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Potential gains from mergers in local public transport – an efficiency analysis applied to Germany

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Abstract

We analyze potential gains from hypothetical mergers in local public transport using the non-parametric Data Envelopment Analysis with bias corrections by means of bootstrapping. Our sample consists of 41 public transport companies from Germany's most densely populated region, North Rhine-Westphalia. We merge them into geographically meaningful, larger units that operate partially on a joint tram network. Merger gains are then decomposed into individual technical efficiency, synergy and size effects following the methodology of Bogetoft and Wang [Bogetoft, P., Wang, D., 2005. Estimating the Potential Gains from Mergers. Journal of Productivity Analysis, 23(2), 145-171]. Our empirical findings suggest that substantial gains up to 16 percent of factor inputs are present, mainly resulting from synergy effects.

Keywords: Merger; Public Transport; Efficiency; Data Envelopment Analysis

JEL-Codes: L92, C14, L11

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1 Introduction

Local public transport in Germany faces increased calls for reform, primarily because the companies still operate in monopolistic, historically grown, regional market structures. The level of cost coverage is well below 100%. With the number of competitive tenders climbing steadily, the public transport companies now run the risk of losing financial stability.

The market is highly fragmented with almost 800 public transport companies that are loosely organized into around 60 so-called public transport associations. The associations allow the companies to secure e.g. a standardized ticketing. International studies (e.g. Berechman 1993) indicate that the underlying technology for public transport provision is characterized by increasing returns to scale. In the United Kingdom, for example, a concentration process observed during the liberalization of local public transport (see Cowie 2002) developed in response to competition. The fragmentation in Germany seems also not to be efficient and a deeper cooperation, if not outright mergers, is likely to lead to significant cost reductions.[1]

The management of public transport provision in Germany at the local level has been justified on the grounds that strong cooperation with local authorities is necessary and that local circumstances must be considered. Therefore it is doubtful whether a "random" acquisition strategy in geographical distance would be successful.[2] In this paper, we model the potential gains from mergers in public transport in Germany's most densely settled region, North Rhine-Westphalia, whose attributes make the realization of merger gains feasible:

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[1] In analyzing the scale efficiency of German bus companies, Hirschhausen and Cullmann (2008) found that they are characterized by increasing returns to scale. This underlines the importance of a deeper analysis of merger gains.

[2] Failures of such "random" acquisitions include the example of Hamburger Hochbahn withdrawing from their shareholding in WiBus in Wiesbaden, almost 500 kilometers distant from Hamburg, in 2007.

- Cities are close to each other so that combined operation is possible.
- Light railway and tram networks with connecting lines exist, e.g., in Köln and Bonn or in Düsseldorf and Krefeld; until now there have already been two or more public transport companies operating on a common network.

Some companies in North Rhine-Westphalia have either launched mergers (Duisburg, Essen and Mülheim) or at least proposed them (Köln and Bonn in 2003 and 2007). Our empirical analysis is based on nonparametric Data Envelopment Analysis (DEA) with bias corrections through bootstrapping. To model the potential gains, we apply a methodology proposed by Bogetoft and Wang (2005). Within this framework, a decomposition of the overall potential gains into three different effects is possible: a *technical efficiency effect*, a *synergy effect* and a *size effect*. Therefore, the results allow us to quantify the overall potential gains from mergers for German public transport companies as well as the separate role and magnitude of each of the three components. The framework also allows us to identify the most promising merger combinations and their respective characteristics. Possible merger cases that we analyze include cooperative efforts among up to five neighboring public transport companies. We also test the robustness of our calculations by applying different scale properties and introducing structural variables.

Many international studies have analyzed the potential for efficiency improvements through cost reductions or increased technical efficiency at the firm level, in particular looking at single-output bus companies. Pina and Torres (2000) carried out DEA to test if public or private operators are more efficient in the provision of bus services. A good overview for the use of benchmarking analysis, different model specifications, and the evaluation of increasing returns to scale appears in De Borger et al. (2002). Multi-output companies are rarely analyzed, especially in Europe; however there is one quantitative study by Farsi et al. (2007) who used stochastic frontier analysis (SFA) to estimate economies of scale and scope of multi-output public transport companies in Switzerland. Viton (1992) looked at the potential gains from mergers in public transport and analyzed the effects of mergers in San Francisco and the Bay Area also using SFA.

The remainder of this paper is structured as follows: The next section gives an overview of the methodology. Section 3 introduces the data and model specification and introduces the proposed mergers. Section 4 presents average efficiencies for the unmerged firms, compares merger gains under variable and constant returns to scale, with and without incorporating differences in the production of tram and light railway services, and calculates alternative decompositions of synergy and size gains. In Section 5 we present our conclusions and policy recommendations.

2 Methodology

2.1 Data Envelopment Analysis

2.1.1 Analytical Framework

Our focus on non-parametric linear optimization using DEA relies on a production frontier where the individual efficiencies of the firms relative to the frontier are calculated by means of distance functions.[3] DEA involves the use of linear programming methods to construct a piecewise linear surface or frontier over the data and measures the efficiency for a given unit relative to the boundary of the convex hull of the input output vectors (see Simar and Wilson 2007).[4] The determination of the efficiency score of the i-th firm in a sample of N firms in the constant returns to scale (CRS) model under input orientation is equivalent to the following optimization (see Coelli et al. 2005):

$$
\begin{aligned}
&\min \theta,_{\theta,\lambda} \\
&s.t. \\
&-y_i + Y\lambda \geq 0 \\
&\theta x_i - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}
$$

with λ being an $N*1$ vector of constants and X, Y representing input and output matrices respectively. θ measures the radial distance between the observation x, y and a linear combination of efficient points, representing the efficiency target for this observation. λ determines the weights of the efficient points for the firms' inputs and outputs. A value of $\theta = 1$ indicates that a firm is fully efficient and thus is located on the efficiency frontier. To determine efficiency measures under the assumption of variable returns to scale (VRS) a further convexity constraint $\sum\lambda=1$ must be considered.

---

[3] The concept of distance functions used to measure efficiency and productivity is closely related to the concept of production frontiers. The framework was independently proposed by Malmquist (1953) and Shepard (1953). By defining these functions the concept of radial contradictions and expansions is used, thus an input distance function considers by how much the input vector may be proportionally contracted with the output vector held fixed. See Färe and Primont (1995) for mathematical derivation of distance functions.

[4] Another technique is the free disposal hull (FDH) estimator, which only assumes free disposability and no convexity constraint. We limit ourselves in this paper to DEA.

DEA can be carried out with either input or output orientation. In this paper input orientation is applied, a realistic assumption for Germany's local public transport when considering the supply side of the public transport sector (the output volume is mostly predetermined by contracts between local authorities and the companies). Thus the companies' intention is to use the fewest possible resources.

2.1.2 Sub-vector efficiency

The radial measure of efficiency commonly used in DEA proposes to reduce inefficiency by a proportional reduction of all employed inputs. This restricts the inefficiency interpretation possibilities. It is useful to understand the sub-vector or input-specific inefficiency, i.e. how to reduce inefficiency by the reduction of only some of the employed inputs. Some inputs may be fixed in the short-term and therefore not reducible, or it may be cheaper to reduce a specific input.

Hence, this paper calculates sub-vector efficiency in addition to overall efficiency values of the unmerged firms according to the methodology proposed by Färe et al. (1994) and used, for example, by Lansink et al. (2002). In this context we do not assume weak disposability.

2.2 Decomposing merger gains

Following a framework proposed by Bogetoft and Wang (2005) for agricultural services and applied by Bagdadioglu et al. (2007) to the energy sector we decompose efficiency gains from mergers[5] into technical efficiency gains, synergies from joint operation, and

[5] It should be noted that merger gains are only feasible for a perfect technology, e.g., that bus services are transferable and scalable.

size gains. The results allow us to quantify both the overall potential gains from mergers and the separate role of the three effects.

Assume that utilities that are geographically close merge into larger units. The merged unit is denoted DMU^J where J determines the number of merged units. By direct pooling of inputs and outputs we obtain a unit that has used $\sum_{j\in J} x^j$ to produce $\sum_{j\in J} y^j$.

Based on Bogetoft and Wang (2005), a radial input-based measure of the potential overall gains from merging the J DMUs under an input orientation is:

$$
\begin{aligned}
&\min \theta^J ,_{\theta^J,\lambda} \\
&s.t. \\
&-\sum_{j\in J} y_i^j + Y\lambda \geq 0 \\
&\theta^J \sum_{j\in J} x_i^j - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}
$$

θ^J is the maximal proportional reduction in the aggregated inputs $\sum_{j\in J} x^j$ that allows the production of the aggregated output $\sum_{j\in J} y^j$. A value below one indicates that merging can reduce costs.[6] As shown by Bogetoft and Wang (2005) the measure θ^J of the potential overall merger gains can be decomposed into the following three effects.

[6] See Bogetoft and Wang (2005) for sufficient conditions about feasible solutions and the requirement of weak gains for arbitrary mergers.

2.2.1 Technical efficiency effect (TE)

The technical inefficiency of the individual utilities in *J* may be captured in θ^J. These inefficiencies could be eliminated by the new management processes, e.g., by imitating the better performers of the same size, sometimes referred to as the peer units, without any benefit from scale or synergy effects. This effect is defined as the technical efficiency effect and it is useful to adjust the overall gains caused by mergers to identify the potential technical efficiency effect. Note that a merger is not ultimately necessary to realize these effects.

Bogetoft and Wang (2005) propose to project the original units to the production possibility frontier and use the projected plans as the basis for evaluating the remaining gains from the merger. Thus, for example, we may project (x^j, y^j) into $(\theta^j x^j, y^j)$, where θ^j is the standard technical efficiency score under an input orientation for a single decision-making unit. In a second step the projected plans $(\theta^j x^j, y^j)$ are used as the basis for calculating the *adjusted overall* or *real merger gains*:

$$
\begin{aligned}
&\min \theta^{*J}, {}_{\theta^{*J},\lambda} \\
&s.t. \\
&-\sum_{j \in J} y_i{}^j + Y\lambda \geq 0 \\
&\theta^{*J} \sum_{j \in J} \theta^j x_i{}^j - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}
$$

Letting $T^J = \theta^J / \theta^{*J}$ we obtain $\theta^J = T^J \theta^{*J}$. T^J indicates what can be saved by individual adjustments in the different units in *J*.

We now describe the two most interesting "production" effects of a merger: the synergy effect (*H*)[7] and the size effect (*S*).

2.2.2 Synergy Effect (H)

As a merger typically involves different input and output combinations, it may prove advantageous when the result is a more productive use of the product space and hence savings can be raised by a more efficient joint production of several outputs. This is termed the synergy effect (*H*). Bogetoft and Wang (2005) propose to capture the synergy gains by examining how much of the average input can be saved in the production of the average output, i.e. by the measure (*H*), which can be expressed in the DEA optimization by:

$$
\begin{aligned}
&\min H^J, _{H^J,\lambda} \\
&s.t. \\
&\alpha \sum_{j \in J} y_i^j + Y\lambda \geq 0 \\
&H^J \alpha \sum_{j \in J} \theta^j x_i^j - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}
$$

where $\alpha \in [0,1]$ is a scalar determining the size of the firm evaluated with the synergy measure. To eliminate the size effect, α is typically chosen to be equal to $|J|^{-1}$. As shown by Bogetoft and Wang (2005), the mean input and the average output reveal what can be saved at most by a pure reallocation of inputs and outputs. Other values for α can be used for sensitivity testing. H^J <1 indicates a savings potential due to

[7] Bogetoft and Wang (2005) refer to the synergy effect as harmony, scope or input mixture effects.

improved harmony, while $H^J > 1$ indicates a cost of harmonizing the inputs and outputs. This cost of harmonizing can only occur when not looking at the mean input and average output because of the assumed convexity.[8]

2.2.3 Size Effect (S)

To analyze the scale effects we must consider the properties of the underlying production technology. A merger results in a unit that operates at a larger scale. The outcome depends on the scale properties of the underlying technology. A positive size effect is characterized as follows: assuming that the original productions of firm $A=(x_1, y_1)$ and firm $B=(x_2, y_2)$ are efficient and improvement potentials are present in the merged unit $A+B$ using x_1+x_2 to produce y_1+y_2, it is sufficient for unit $A+B$ to use $(\theta^*(x_1+x_2))$ in the production process to produce (y_1+y_2).

In the next linear optimization we can capture the size gains by asking how much is saved by operating at full scale rather than at α-scale. This can be reflected by the measure S^J:

$$
\begin{aligned}
&\min S^J,_{S^J,\lambda} \\
&s.t. \\
&-\sum_{j\in J} y_i^j + Y\lambda \geq 0 \\
&S[H^J \sum_{j\in J} \theta^J x_i^j] - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned}
$$

[8] However, there is one merger shown in the following with a synergy effect slightly higher than 1. This results from the bias correction obtained through the use of bootstrapping in the merger gains decomposition because this value is below one when applying standard DEA.

$S^J < 1$ indicates that rescaling is advantageous given the synergy improvements, whereas $S^J > 1$ shows that the return to scale property does not favor larger units and thus the merger is costly.

Summarizing the effects using the definition from the linear optimization leads to $\theta^{*J} = H^J * S^J$ and by means of $\theta^J = T^J * \theta^{*J}$ we obtain the basic decomposition $\theta^J = T^J * H^J * S^J$. In turn it corresponds to a decomposition of the basic merger index θ^J into a technical efficiency index T^J, a synergy index H^J, and a size index S^J.[9]

2.3 Bias correction with bootstrapping

The deterministic nonparametric frontier models offer the great advantage of flexibility. However, the two major drawbacks are the sensitivity to outliers and extreme values, and the disallowance of noise in the data (see Simar and Wilson 2000, 2007). Therefore, we conduct statistical inference using bootstrapping to correct for the bias in our empirical deterministic efficiency estimates. We begin by briefly summarizing the statistical properties of the nonparametric DEA estimators; a detailed discussion about statistical inference appears in Simar and Wilson (2000, 2007).

With respect to consistency it is sometimes difficult to prove convergence of an estimator in nonparametric statistics and to obtain its rate of convergence (see Simar and Wilson, 2007).[10] The rates of convergence depend on the dimensionality of the problem. When there are large numbers of inputs and outputs, the imprecision of the

[9] For a survey on alternative decomposition concepts see Bogetoft and Wang (2005).

[10] The convergence properties for the DEA estimators for the univariate input and multivariate output case were shown by Korostelev et al. (1995); the convergence rates for the multivariate input and multivariate output case were established by Kneip et al. (1998).

results will be reflected in large biases, large variances, and wide confidence intervals (Simar and Wilson, 2007). As we dispose of a relatively small number of observations it becomes important within our framework to conduct bias correction.

To make inferences about empirical applications, the asymptotic sample distributions of the envelopment estimators are required (see Simar and Wilson, 2000, 2007). The bootstrap algorithm remains the only practical way of making inferences when using the multivariate DEA approach (Simar and Wilson, 1998, 2000, 2007 provide an extensive discussion). This paper applies the bootstrap algorithm established in Simar and Wilson (1998) that is based on the bootstrap idea by Efron (1979, 1982) and Efron and Tibshirani (1993) who approximated the sampling distributions of interest by simulating, or mimicking, the data generating process (DGP). Its use for nonparametric envelopment estimators was developed by Simar and Wilson (1998, 2000). The following discussion is based on Simar and Wilson (2007).

Simulating by means of bootstrapping provides approximations of the sampling distributions of $\hat{\theta}(x,y)-\theta(x,y)$, the difference of the estimated score $\hat{\theta}(x,y)$, and the true value $\theta(x,y)$. The logic is as follows: DGP generates the original data X_n and is completely characterized by knowledge of ψ, the production possibility set, and the probability density function $f(x,y)$. Assume $\hat{P}(X_n)$ to be a consistent estimator of the DGP. The true P, ψ and $\theta(x,y)$ are unknown (we only observe the data X_n, and this set must be used to construct estimates of P, ψ and $\theta(x,y)$). Assume also that the simulated world, i.e. the bootstrap world is analogous to the real world, but that estimates take the place of the real world. Thus in the simulated bootstrap world, a new dataset $X_n^* = \{(x_i^*, y_i^*), i = 1...n\}$ can be drawn from the estimated DGP. By using the usual linear program an estimator $\hat{\theta}^*(x, y)$ based on the new sample can be computed. Ergo $\hat{\theta}^*(x, y)$ is an estimator of $\hat{\theta}(x, y)$ based on the pseudo sample $X_n^* = \{(x_i^*, y_i^*), i = 1...n\}$. The sampling distribution of $\hat{\theta}^*(x, y)$ is approximated by Monte Carlo simulations (see Simar and Wilson 1998, 2000, 2007 for an in-depth discussion). This paper uses the bootstrap algorithm by Simar and Wilson (1998) known as the smoothed homogeneous bootstrap to conduct bias correction in each step of the different linear programming problems of merger gains decomposition.

DEA estimators are biased by construction as follows:

$$BIAS(\hat{\theta}(x, y)) = E(\hat{\theta}(x, y)) - \theta(x, y)$$

The same relation holds for the bootstrap bias estimate for the original estimator $\widehat{BIAS}_B(\hat{\theta}(x, y)) = B^{-1}\sum_{b=1}^{B}(\hat{\theta}^*{}_b(x, y)) - \hat{\theta}(x, y)$. Following Simar and Wilson (1998) we construct a bias corrected estimator of $\theta(x, y)$ by computing

$$\hat{\hat{\theta}}(x, y) = \hat{\theta}(x, y) - \widehat{BIAS}_B(\hat{\theta}(x, y)) = 2 * \hat{\theta}(x, y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*{}_b(x, y)$$

3 Data and model specification

3.1 Dataset

Our dataset consisting of 43 local public transport companies in North Rhine-Westphalia in 2006 was retrieved from the annual statistics of the Association of German Transport Undertakings (Verband Deutscher Verkehrsunternehmen, VDV). Since the dataset does not include the degree of personnel outsourcing by which the companies have organized their operations, the number of employees (full-time equivalents) in the dataset may be underestimated. The dataset does include the number of chartered buses which can be used as a proxy for the degree of outsourcing, and on this basis the number of full-time equivalents (FTE) can be updated. Following Leuthardt (1986 and 2005) we assume two additional FTEs per chartered bus.[11] After the adaptation of the dataset two of the 43 companies were identified as outliers due to a very low ratio of FTE to employed vehicle capacity. For these companies the FTE numbers are apparently not correctly stated in the statistics.

Of the remaining 41 companies, 38 are under complete private ownership and three are under mixed, public and private, ownership; 12 are multi-output companies (in addition to bus services they also offer tram, metro-similar light railway, and, in Wuppertal, aerial cableway services); and 29 are purely bus operators (including trolley buses in Solingen).

[11] The analyses have also been conducted with 1.5 and 2.5 additional FTEs per chartered bus. No significant different results could be observed.

To evaluate the efficiency of mergers under a variable returns to scale technology, the dataset must contain firms of at least similar size in comparison to the mergers. To study merging of larger firms, we collected additional data points of local public transport firms that are larger than those in our original 43-company dataset.[12] After eliminating outliers, we arrived at a dataset of 44 companies for the reference technology. The reason of comparability and the reduced sample (because of outliers) limited our maximum evaluated number of merged companies to five.

3.2 Model

Our model specifications were limited by data availability, e.g., the dataset does not include cost and input factor prices. Thus we examine only the companies' technical efficiency. Under input orientation two different input-output specifications are possible and summarized in Table 1:

1) The first specification contains the inputs "number of seats in the bus fleet" and "number of seats in the railcar fleet" (both include standing room) and the outputs "seat-kilometers in buses" and "seat-kilometers in railcars".
2) The second specification contains the inputs "pure number of buses" and "number of railcars" and the outputs "vehicle-kilometers for buses" and "vehicle-kilometers for railcars".

Additionally, both input-output specifications have in common the input "number of employees in full-time equivalents" (FTE).

[12] We do not want to extend our dataset to all of Germany because different demographic, geographical and political circumstances could bias the results. Therefore we only included three additional companies: BVG (Berlin), HHA (Hamburg), and MVG (Munich).

[Insert Table 1 here or further back]

We now evaluate the possible input-output specifications. The first input-output specification with seat-kilometers is the most appropriate because the variables incorporate as much information as possible. In comparison to the second input-output specification with vehicle-kilometers, the capacity of vehicles is included. This capacity can differ substantially, e.g., between articulated buses in urban areas and normal buses in rural areas, or between large light railways in Dortmund and the aerial cable cars in Wuppertal. We note that a public transport company may have little influence over capacity utilization, since they are not directly responsible for marketing, ticketing, traffic planning, and the like. Thus our model's supply side focus is economically justified.

Companies may also have little control over structural variables representing environmental conditions or those represent additional specifications of input or output variables beyond the scope of management during a merger. Following Coelli et al. (2005), our analysis includes two structural variables introduced on the output side:[13]

- Some companies have difficulties producing output because of the network's dispersion connected with a low population density. An *inverse density index* is defined as total track length for trams and light railways and line length for buses divided by the number of inhabitants in the operation area of a local public transport provider. With our approach companies operating in these areas will obtain a better efficiency score, because they obtain additional "output".

[13] Within the DEA framework there is also another approach to capture conditions which are not under the control of management. It was first proposed by Banker and Morey (1986) who formulated a DEA model in which one only seeks radial input reductions over some variables of the input vector, the discretionary set.

- The provision of metro and possibly light railway services requires greater infrastructure investments that cannot be discussed in this paper due to the lack of cost data. On the other hand the average speed of tram services is much lower and therefore output production is more difficult with given inputs.[14] A *tram index* measures the tram capacity as percentage of all rail-bound capacity. Hence our model supports companies offering tram[15] services in comparison to those offering light railway or metro services.

3.3 Mergers

In general, proposed mergers should fulfill two criteria:

1) A tram or light railway network with connecting lines, operated by more than one company at present, should be operated by only one company after the merger in order to facilitate operations planning and to encourage the use of shared facilities (A network with connecting lines is the case for three mergers).[16]
2) All other companies are assigned to mergers where it makes geographical sense, since the realization of efficiency gains from mergers in public transport relies on the geographical nearness of the cities and companies. Only under this constraint, gains in the production process, e.g., from combined operations,

[14] The data for the non-discretionary variables is obtained from the VDV statistics 1998 and 2006, validated by company information.

[15] Also aerial cableway because the average speed is similar to trams (approximately 30 km/h).

[16] These three networks are of the companies from Köln and Bonn, Düsseldorf and Krefeld as well as Essen and Mülheim. Duisburg with its connecting lines to Düsseldorf and Krefeld is assigned to Essen and Mülheim because of an ongoing actual merger process. Apart from these mergers, there is only one additional tram network in Germany with connecting lines between different cities. Interestingly, the joint-venture Rhine-Neckar-Verkehrsgesellschaft (the public transport companies of Mannheim, Heidelberg and Ludwigshafen in the Rhine-Neckar area) has already been set up on this network.

appear feasible (North Rhine-Westphalia in comparison to the rest of Germany best fulfills this constraint).

We selected 14 out of 80 potential mergers as shown by the patternings in Figure 1. For Herten, Lüdenscheid and the two companies from Münster, no adequate merger combinations could be found; thus these four remain unmerged. We achieve three mergers with trams and light railways operating on a network with connecting lines; four mergers of one tram and light railway operator with several pure bus operators; and seven pure bus mergers.

[Insert Figure 1 here or further back]

4 Results and interpretation

We first calculate average efficiency estimates for the unmerged companies and analyze input-specific inefficiency as well as the impact of structural variables on company performance. Second, we present merger gains under variable and constant returns to scale. Third, we compare technical efficiency and real merger gains with/without a structural variable and calculate alternative decompositions of the real merger gains into synergy and size effects. The robustness of the results is checked and guaranteed by means of bias correction.

4.1 Average efficiencies for the unmerged firms with structural variables

Table 2 shows the average efficiencies for the unmerged firms with seat-kilometer as output for different model variations. Our intention is to analyze sub-vector efficiency as well as the effects of the structural variables under variable returns to scale and constant returns to scale and draw conclusions for the impact on company performance level. In addition, we compare standard DEA results with bias-corrected results based on bootstrapping.[17] In general the bootstrapping results show the expected lower average efficiencies (e.g., 0.792 bias-corrected in comparison to 0.851 standard DEA of overall efficiency under VRS without structural variables) because we assume the true frontier to be on a higher efficiency level than the estimated frontier with standard DEA. The ranking and the proportional magnitude of results between the models under standard DEA and bias-corrected DEA do not differ; therefore we focus on the bias-corrected values in the following explanation.

We begin with the base model (Model 1) absent the inclusion of any structural variables. The average efficiency for the unmerged firms is 0.792 for VRS and 0.769 for CRS. The average firm therefore would be able to save 20.8% of their inputs for VRS and 23.1% of their inputs for CRS if produced on the efficiency frontier. Concerning the input-specific efficiency estimates we see that the efficiency value of the input capital (buses and railcars) with 0.782 for VRS is approximately on the level of overall efficiency, yet the efficiency value of the input labor (FTEs) with 0.598 is significantly below overall efficiency. These conclusions hold for constant returns to scale. It appears that there is more potential for improvements in labor inefficiency. This finding

[17] Bootstrapping was conducted with 2,000 replications.

corresponds with the recent move to reduce the number of FTEs while subsequently producing more output, a trend that we expect to continue.

Models 2 and 3 introduce structural variables in order to compare the overall efficiency of Model 1. Model 4 includes both structural variables at the same time. Under VRS the impact of the inverse density index with an efficiency value of 0.804 in Model 2 is slightly higher than 0.799 for the tram index in Model 3. But under CRS, the impact of the tram index with an efficiency value of 0.789 in Model 3 is substantially above 0.779 for the inverse density index in Model 2. When including both structural variables at the same time in Model 4, we see a significant difference from Models 2 and 3 with 0.813 as the efficiency value under VRS. However, there is no large difference for Model 3 under CRS in comparison to Model 4 with an efficiency value of 0.791 and a calculated difference of 0.002.

[Insert Table 2 here or further back]

4.2 Merger gains under variable and constant returns to scale

The following discussion of the merger gains omits the inverse density index included in Models 2 and 4 to avoid over-specifying of the general DEA model regarding the relatively small dataset. We hence focus on Models 1 and 3 because the tram index shows a higher impact in the preceding analysis.

We calculate the overall potential merger effects for VRS and CRS absent structural variables (Model 1), based on the bias-corrected efficiency estimates. We decompose these overall effects into real merger effects (synergy and size effect together) and technical efficiency effects. Table 3 presents the mergers in descending order by company size. The most important result is the existence of significant real merger gains, i.e. gains that are only possible when merging the operational processes. Under VRS and CRS the largest merger 1 with two large bus, tram and light railway operators and one bus operator shows significant real merger gains of 12%. Under VRS only, we also find mergers with negative real merger gains (the mergers result in increased inefficiency in terms of synergy and size). However, mergers 6, 7, 9, and 11 can still have a positive overall impact if the technical efficiency is brought to the frontier level. The negative real merger effects can be explained by looking at the specifics. Merger 6 is of an economic nature: Wuppertal has an aerial cableway with which synergies to bus services are not probable, at least not for maintenance, technology and substitutability. Mergers 7, 9, and 11 are big bus companies which do not yet exist in the German market.[18] Therefore the negative effects could stem from the missing references. In reality, however, real merger gains appear possible.

In the following we adhere to the VRS assumption because it allows us to further decompose the real merger gains into synergy and size gains.

[Insert Table 3 here or further back]

4.3 Merger gains with/without incorporating differences in the production of tram and light railway services

Figure 2 shows the VRS results from Table 3. We observe substantial real merger gains (synergy and size) for the mergers of companies operating on a common tram and light

[18] The integrated transport company Deutsche Bahn with its bus subsidiary DB Stadtverkehr, which would be big enough to serve as a benchmark, is not included in our dataset.

railway network (dark-shaded) and mergers of bus, tram and light railway operators (light-shaded) with the exception of merger 6. The mergers of companies operating on a common tram and light railway network are at the same time the largest in terms of output seat-kilometers (bus, tram and light railway; indicated by the size of the bubble). The results for smaller pure bus mergers vary and must be evaluated on a case-by-case basis.

[Insert Figure 2 here or further back]

We now include the tram index as structural variable with the largest impact. Since the mergers consist of companies of different sizes, the tram index is input-weighted. Comparing Figures 2 and 3, we observe some heterogeneity and can thus group the mergers into four clusters: *pure bus mergers 7 and 9-14 with no changes* (reasonable because the tram index itself is not directly affecting the results for the bus companies); *bus, tram, and light railway mergers 1, 4 and 8 with no significant changes* (the level of tram services differs little in comparison to their benchmarks and hence the incorporation of the structural variable does not change the results; *bus, tram, and light railway mergers 2a and 3a that are still favorable* (but to a lesser extent and with few firms -- Krefeld removed from merger 2 and Oberhausen and Moers removed from merger 3); and *mergers 5 and 6 that are no longer beneficial* (hence not included in Figure 3).

[Insert Figure 3 here or further back]

All of the mergers in Model 1 (except merger 6) have been highly beneficial without including the tram index. However, not all the non-beneficial mergers in Model 3 are likely to be really disadvantageous. As Table 2 shows, the individual efficiency increases with the number of structural variables. Hence, a careful interpretation and evaluation of these mergers seems necessary.

4.4 Alternative decompositions of synergy and size gains

So far we have only looked at the real merger gains generally. We did not differentiate between a synergy effect from a better input mixture and the common provision of different outputs and a size effect resulting from the production at bigger scale. We want to calculate this decomposition with three different values for α, the scalar determining the size of the firm evaluated with the synergy measure (see Section 2.2). First we follow Bogetoft and Wang (2005) with the default value of *1/n* where *n* is the number of firms merged. As the structural variables have been recalculated for the mergers and are not just the sum of the original unit values, there is an additional technical rational for this robustness check on the synergy and size allocation of gains. For inputs and outputs only, it is the natural choice to divide the number of units being merged since this corresponds to the maximum of what can be gained by a pure reallocation. We therefore halve and double the default value of *1/n* for a sensitivity analysis. This also gives us some indication on the magnitude of the merger effects if there is a quite small firm operating with this input mixture or if the merger consists of a very big firm and additional smaller firms.

Table 4 gives the result for the described decomposition. The most obvious result is the much more advantageous status of synergy gains, in particular for mergers 1 and 4 where this conclusion holds for all the three different values of α. For the scalar values of *1/n* and even more *2/n*, the synergy gains are in majority higher than the size gains. However, that these input mixtures in the mergers seem beneficial is not purely related to synergy. Size over a specific threshold can be conditional in order to reach this beneficial input mixture, e.g. for automated maintenance activities. Furthermore, the question remains which input mixture and output combination determines the synergy gains. We leave this to further research.

[Insert Table 4 here or further back]

5 Conclusions

This paper has applied new methods of DEA to evaluate the potential efficiency gains from mergers in Germany's local public transportation sector. We motivated our approach with prior international research indicating inefficiency, the high fragmentation of public transport in Germany and the suitable geography of the proposed mergers. We found that the incorporation of differences in rail-bound local public transport services is necessary, but must be analyzed on a case-by-case basis. Population and network density plays no substantial role in this already very densely populated area. We determined that substantial merger gains can be expected for bus, tram, and light railway mergers and smaller bus mergers and that larger bus mergers deserve further research. A sensitivity analysis for decomposition of real merger gains revealed the importance of synergy gains over size gains. Nevertheless the two effects can only be addressed together.

Following our analysis, the implementation of mergers with companies operating on a common tram and light railway network should be high priority from both political and operational perspectives. The merger process assists companies to prepare for a market environment defined by an increasing number of tenders. Companies that are active in several cities learn to diversify their risks, and are no longer dependent on contracts with one city. It is furthermore an issue of transport and competition policy to aim at a framework and measures for a new industry structure. Increasing financial pressure and changes in demography as well as settlement structures will also raise the topic again. There is plenty of room for further research in this sector, especially with monetary data. Revenue and cost efficiency especially should be analyzed to produce more knowledge about the existence of economies of scale and scope vis-à-vis allocation.

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Table 1: Possible input-output specifications

	Specification 1	Specification 2
Inputs		
Number of employees		*
Number of seats in bus fleet	*	
Number of seats in railcar	*	
Number of buses		*
Number of railcars		*
Outputs		
Seat-kilometers in buses	*	
Seat-kilometers in railcars	*	
Vehicle-kilometers in buses		*
Vehicle-kilometers in railcars		*
Structural Variables		
Inverse density index	(*)	(*)
Tram index	(*)	(*)

Table 2: Average efficiency estimates with seat-kilometers as output

	Model 1 **Without** structural variables			**Model 2**	**Model 3**	**Model 4**
	Overall efficiency	Labor-specific efficiency	Capital-specific efficiency	With inverse density index	With tram index	With tram **and** inverse density index
VRS						
Standard DEA	0.851	0.680	0.838	0.870	0.863	0.882
Bias-corrected	0.792	0.598	0.782	0.804	0.799	0.813
CRS						
Standard DEA	0.806	0.583	0.806	0.825	0.841	0.845
Bias-corrected	0.769	0.526	0.768	0.779	0.789	0.791

Table 3: Decomposition of bias-corrected potential merger effects for variable and constant returns to scale (Model 1)

	Merger	Overall potential effect Θ^{J} (VRS)	Real merger effect Θ^{*J} (VRS)	Technical efficiency effect T^{J} (VRS)	Overall potential effect Θ^{J} (CRS)	Real merger effect/ Synergy effect Θ^{*J} (CRS)	Technical efficiency effect T^{J} (CRS)
1)	**Köln**, **Bonn,** Siegen	0.70	0.88	0.80	0.63	0.81	0.77
2)	**Düsseldorf**, **Krefeld**, Neuss	0.72	0.87	0.82	0.77	0.88	0.88
3)	**Duisburg, Mülheim**, **Essen**, **Oberhausen**, Moers	0.68	0.89	0.77	0.67	0.90	0.74
4)	**Dortmund**, Hagen	0.68	0.84	0.81	0.70	0.84	0.83
5)	**Bochum**, Herne	0.71	0.91	0.78	0.71	0.91	0.78
6)	**Wuppertal**, Ennepetal	0.88	1.11	0.79	0.75	0.99	0.76
7)	Aachen, Geilenkirchen	0.90	1.13	0.80	0.75	0.99	0.76
8)	Detmold, Extertal, **Bielefeld**	0.71	0.88	0.81	0.72	0.93	0.77
9)	Troisdorf, Euskirchen, Düren	0.79	1.17	0.67	0.66	0.97	0.68
10)	Gummersbach, Remscheid, Solingen	0.73	0.97	0.75	0.75	1.00	0.75
11)	Dormagen, Gladbach, Viersen	0.88	1.10	0.80	0.78	0.96	0.81
12)	Hamm, Kamen	0.72	0.97	0.74	0.74	0.99	0.75
13)	Monheim, Leverkusen	0.83	0.91	0.91	0.84	0.94	0.90
14)	Gütersloh, Soest	0.70	0.95	0.73	0.70	0.96	0.73

Bold: companies with tram/light railway

Table 4: Evaluation of bias-corrected synergy and size effects for variable returns to scale

	Merger	Synergy merger gains 1/(2n)	Synergy merger gains 1/n	Synergy merger gains 2/n	Size merger gains 1/(2n)	Size merger gains 1/n	Size merger gains 2/n
1)	**Köln**, **Bonn,** Siegen	0.81	0.80	0.84	1.08	1.10	1.06
2)	**Düsseldorf**, **Krefeld**, Neuss	1.02	0.96	0.90	0.85	0.91	0.96
3)	**Duisburg, Mülheim**, **Essen**, **Oberhausen**, Moers	1.00	0.94	0.88	0.89	0.95	1.01
4)	**Dortmund**, Hagen	0.92	0.86	0.84	0.92	0.98	1.00
5)	**Bochum**, Herne	1.02	0.97	0.91	0.89	0.94	1.00
6)	**Wuppertal**, Ennepetal	0.96	0.94	1.11	1.15	1.17	1.00
7)	Aachen, Geilenkirchen	0.96	0.94	1.13	1.18	1.20	1.00
8)	Detmold, Extertal, **Bielefeld**	1.19	0.98	0.90	0.74	0.89	0.97
9)	Troisdorf, Euskirchen, Düren	1.04	0.98	0.95	1.12	1.19	1.23
10)	Gummersbach, Remscheid, Solingen	1.01	1.00	0.99	0.96	0.97	0.98
11)	Dormagen, Gladbach, Viersen	1.09	1.02	0.97	1.01	1.08	1.13
12)	Hamm, Kamen	1.06	1.00	0.98	0.92	0.98	1.00
13)	Monheim, Leverkusen	1.01	0.95	0.91	0.91	0.97	1.00
14)	Gütersloh, Soest	1.05	0.99	0.95	0.90	0.96	1.00

Bold: companies with tram/light railway

Figure 1: Geography of local public transport mergers in North Rhine-Westphalia

Legend: *Tram or light railway operators in **bold** font*
Different shadings relate to the mergers
○ Not merged companies

Figure 2: Bias-corrected merger gains decomposition for variable returns to scale without structural variables (Model 1)

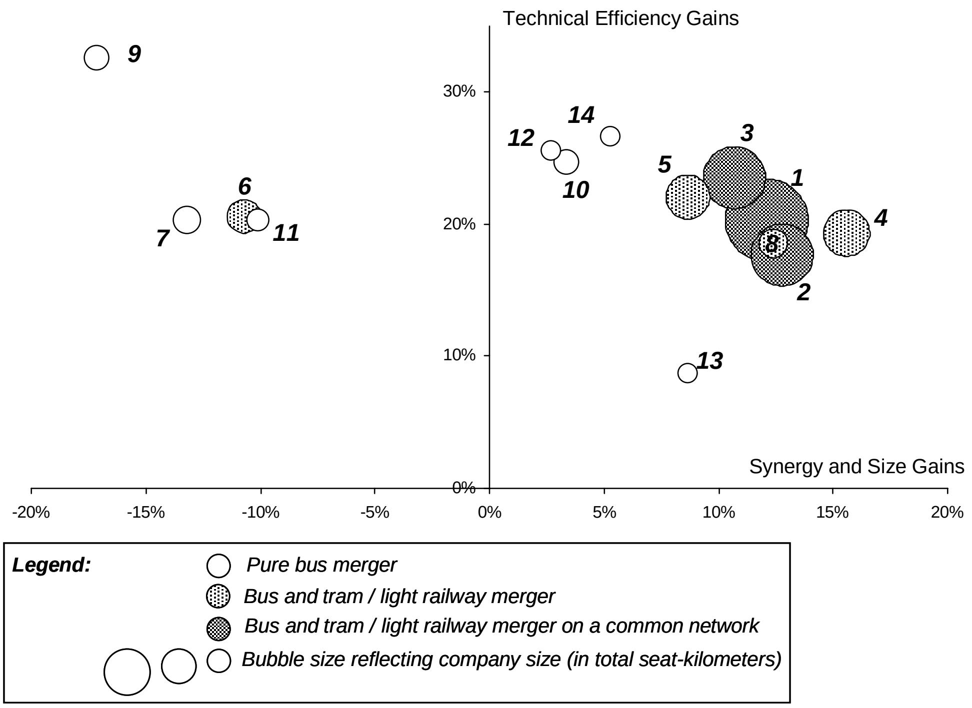

Figure 3: Bias-corrected merger gains decomposition for variable returns to scale with a tram index (Model 3)