Some Determinants of Cost Efficiency in German Public Transport

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Abstract

This paper evaluates cost efficiency and some of its managerial determinants in Germany's local public transport. A heteroscedastic Stochastic Frontier approach reveals that a high degree of tramcar utilisation and a high outsourcing degree influence the efficiency predictions positively. Mean efficiencies lie between 0.849 and 0.952, depending on the applied panel data models accounting for unobserved heterogeneity and observed heterogeneous output variables for tram, light railway and metro services. The inefficiency levels correspond to a savings potential between 1.40 and 4.43 bn EUR based on the 28.23 bn EUR total costs (in 2006 prices) for 254 observations of 39 companies 1997-2006.

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1.0 Introduction

As local monopolies public transport networks are a natural point of interest for researchers conducting efficiency analysis. The results of such analyses can be very useful for yardstick competition among the transportation companies. However scientific benchmarking has not yet found its way into practical regulation in Germany. Instead, competitive tendering, which is encouraged via EU regulation 1370/2007, is used to provide incentives for efficient transport services, but only in some regions. Hence the question is what conclusions can be drawn from applying efficiency analysis to local public transport. Two possibilities emerge: evaluation of market structure, and supporting strategic firm decisions. This paper focuses on the second point, and evaluates cost efficiency and some of its determinants for multi-output companies. Multi-output companies are those which provide bus services and tram, light railway, and metro (in the sense of underground) services - aggregated as rail-bound services.[1]

The ultimate challenge for the country's local public transport is the very low level of cost coverage across nearly all companies with a mean level of 73.8 per cent (Verband Deutscher Verkehrsunternehmen, 2008). Parts of these losses may be attributed to the reality that local public transport is a public service obligation (*Daseinsvorsorge*). However, as public budgets are tighten, long-term losses may not be sustainable.

This paper focuses on evaluating cost efficiency and some of the major determinants with Stochastic Frontier Analysis (SFA). SFA is a parametric benchmarking method which compares decision-making units relative to the

[1] The companies in the data set used in this paper do not offer suburban (for example S-Bahn) or regional railway services. The analysis is hence restricted to services based on the German passenger transportation law (*Personenbeförderungsgesetz, PBefG*) and the German Ordinance on the Construction and Operation of Rail Systems for Light-Rail-Transit (*Verordnung über den Bau und Betrieb der Straßenbahnen (Straßenbahn-Bau- und Betriebsordnung - BOStrab)*).

best-practice peer. It does not assume as does neoclassical theory (Samuelson, 1983) that all players act optimally. I prefer SFA instead of Data Envelopment Analysis (DEA), which in its basic implementation is deterministic and non-parametric, mainly because of the applicability of panel data models with SFA that incorporates the time horizon into the analysis. Furthermore, SFA is useful because of the possible derivations from the deployment of a functional form, for example, significance levels, and because it can handle data errors.[2] Three SFA models are used in the following analysis because there is substantial difference in how they manage for unobserved heterogeneity and observed heterogeneous output characteristics. Additionally, the vehicle utilisation rate and the outsourcing share are suspected to be determinants of efficiency which are under management's control. For these reasons the usual assumption of independent and identically distributed inefficiencies may not be maintainable.

Since these managerial determinants are endogenous it may not be appropriate to allow them to directly affect the mean of the inefficiency function, unlike the treatment of exogenous variables in Battese and Coelli (1995). I therefore follow the approach of Bhattacharyya et al (1995) and Hadri et al (2003b) who include these managerial determinants as heteroscedastic variables in the inefficiency function and then compare efficiency levels. The analysis is conducted on a unique panel data set which has been implicitly collected for this research project and represents the first of its kind for local public transport in Germany. It consists of 254 observations for 39 multi-output companies from 1997 until 2006.

Pioneering studies in stochastic efficiency analysis of multi-output local public transport operators were carried out by Viton (1992, 1993), who evaluated economies of scale and scope and benefits from organisational restructuring in

[2] I am aware that the a priori assumption of a special functional form imposes some restrictions on the analysis. See Greene (2008) for an in-depth introduction of the econometric approach to efficiency analysis.

the San Francisco Bay area. Viton applied a quadratic cost function to companies with zero outputs for some of the considered outputs, motor bus, rapid or commuter rail, streetcar, trolley-bus, demand-responsive, and other means of public transport. The cost frontier was estimated based on a pooled data set from 1984 until 1986 following the model by Aigner et al (1977), who first introduced the concept of SFA. Viton's results support the formation of larger entities.

Bhattacharyya et al (1995) examined Indian bus operations, analysing the determinants of cost inefficiency, which are under control of management. The determinants are included as heteroscedastic components of the inefficiency function. A translog variable cost function is estimated in a multi-step procedure with firm- and time-specific effects exploring the data's panel structure. The results indicate that, under the threat of closure nationalised operators are the most inefficient, followed by corporations with an independent administrative and managerial structure and units that are operated by transportation departments of state governments. As expected, the breakdown rate negatively influences efficiency whereas the rate of vehicle utilisation positively influences efficiency predictions.

Farsi et al (2006) compared cost efficiency predictions of several Stochastic Frontier models and calculated economies of scale and density for regional bus companies in Switzerland. They suggest that the True Random Effects (TRE) model by Greene (2004, 2005b) could be used as a benchmark model for regulation purposes, mainly because of its ability to differ between inefficiency and unobserved heterogeneity.[3] Conventional models, in particular a pooled model fed with panel data, the applied Random Effects (RE) model (Pitt and Lee, 1981) and the Fixed Effects model (Schmidt and Sickles, 1984), may give inaccurate results.

[3] However, the authors emphasise that a mechanical use transferring efficiency levels into X-factors must be avoided.

Farsi et al (2007) evaluated economies of scale and scope for a panel data sample of Swiss operators. The three modes of transport, trolley-bus, motor-bus and tramways, are captured by a quadratic cost function. The estimations are based on a pooled heteroscedastic model with autoregressive errors. This econometric framework relies on average functions. The authors find increasing returns to scale across all modes of transport and economies of scope. This paper does not consider economies of scale and scope. The interested reader may consult Nieswand et al (2008) for bus operators and Walter (2009) for multi-output companies in Germany.

The remainder of this paper is structured as follows: Section 2 provides the functional form with its specification as well as the econometric models. Section 3 describes the data in combination with the activity in the German local public transport sector. Section 4 gives the results as well as their interpretation and Section 5 concludes.

2.0 Methodology

2.1 Cost function

The application of a cost function requires the assumption of cost-minimising behaviour with given input prices and output quantities (Coelli et al, 2005). Transport economists have typically applied a cost function[4] instead of a profit function, probably also due to data constraints. Nowadays, it is more difficult to determine whether local public transport companies in Germany minimise costs or maximise profits because of the increasing policy demands for fewer subsidies. The exogeneity of output quantities can be justified with the definiteness of the

[4] See Berechman (1993) for an introduction.

supplied area, typical for a local monopoly, and the requirement to supply, because local transport is a public service obligation. In this case, a total cost (C) function can be written as

$$C = f(Y, Q, w_L, w_K, ID, D_t) \tag{1}$$

dependent on two outputs, the number of seat-kilometres for buses (Y) and the number of seat-kilometres in trams, light railways and metros (Q),[5] on two input prices, for labour (w_L) and capital (w_K), on an inverse density index (ID) which is beyond the firm's control and on the time, represented by year dummies D_t[6]. Seat-kilometres is preferred as output over vehicle-kilometres, because the size of vehicles, a substantial cost driver, is then included. Both measures however represent a pure supply side consideration of output. In contrast, passenger-kilometres, passengers or revenues also take demand into account. Which output specification to use has been discussed intensively in the literature (see e.g. De Borger et al, 2008, or De Borger et al, 2002, in recent years). Management's limited control over network and frequency planning, and political considerations predominate today. The first competitive tenderings carried out in the last decade have also mostly relied on gross contracts, leaving the revenue risk to the public transport authority. Since this paper evaluates management performance, the use of demand-oriented output measures would punish management for requirements imposed by authorities. Hence, I follow Farsi et al (2007), Farsi et al (2006), Margari et al (2007), Roy and Yvrande-Billon (2007) and Piacenza (2006) and use the supply-oriented measure, seat-kilometres. I note that demand-oriented measures are only available as aggregates in the data

[5] Including both sitting and standing room.
[6] Following Farsi et al (2005a) and Farsi and Filippini (2009).

set and the cost of applying an aggregate for losing one output is too high and would inadequately reflect the production technology of local public transport.

The year dummies capture technical progress and other unobserved year-specific factors like changes in collective labour contracts. In contrast to a linear time trend, year dummies assume that technical progress does not follow a linear trend, which is an unrealistic assumption in many cases. The effects of technical progress are assumed to be neutral, thus affecting all firms equally. The most commonly applied flexible functional forms are the first-order flexible Cobb-Douglas and the second-order flexible translog functions. Both allow the variables to enter the estimation in logs in contrast to the quadratic function, which makes them linear in parameters and less fragile to extreme data points. Increased flexibility is usually preferred if the function remains estimable. Additionally, the Cobb-Douglas function follows the same-returns-to-scale for all company sizes. As economies of scale have proved to vary across output levels in central European local public transport (see for example Farsi et al, 2007, and Walter, 2009), this restriction should be avoided if possible. The translog function applied here requires the approximation at a local point which is chosen to be the mean. The median is less influenced by extreme outliers, whereas the mean reflects better the actual position of all data points in the sample. Hence, all variables have been divided by their mean following Farsi et al (2005b). After imposing the linear homogeneity in input prices of degree one by dividing costs and the capital price by the factor price for labour,[7] the function can be written as

[7] The other properties of the cost function, e.g. that all costs have to be strictly positive, are verified in the data and the results sections.

$$
\begin{aligned}
\ln \frac{C_{it}}{w_{L_{it}}} = \ln\ C^*_{it} = \alpha + \beta_Y\ \ln\ Y_{it} + \beta_Q\ \ln\ Q_{it} + \beta_K\ \ln \frac{w_{K_{it}}}{w_{L_{it}}} \\
+ \frac{1}{2}\left(\beta_{YY}(\ln\ Y_{it})^2 + \beta_{QQ}(\ln\ Q_{it})^2 + \beta_{KK}\left(\ln \frac{w_{K_{it}}}{w_{L_{it}}}\right)^2\right) \\
+ \beta_{YQ}\ \ln\ Y_{it}\ \ln\ Q_{it} + \beta_{YK}\ \ln\ Y_{it}\ \frac{w_{K_{it}}}{w_{L_{it}}} \\
+ \beta_{QK}\ \ln\ Q_{it}\frac{w_{K_{it}}}{w_{L_{it}}} + \beta_{ID}\ ID_{it} + \sum_{t=2}^{10}\beta_t D_t
\end{aligned}
\tag{2}
$$

with α representing an intercept term, $i = 1, 2, ..., 39$ denoting the company and $t = 1, 2, ..., 10$ denoting the year (for the year dummies, $t = 1$ (1997) is the omitted year to avoid collinearity).

2.2 Econometric models

The focus here is on Stochastic Frontier models exploiting the panel structure of our data. The first proposed models were the RE model (Pitt and Lee, 1981) and the Fixed Effects model (Schmidt and Sickles, 1984). Since the amount of within variation in the data is considerably low (at most 6 per cent within variation based on overall variation for costs, outputs and the remaining factor price)[8] and the Fixed Effects model does not allow the incorporation of efficiency determinants as heteroscedastic factors in the inefficiency function (Kumbhakar and Lovell, 2000), I do not consider this model in the following.[9] This paper uses the RE

[8] I calculated the within variation following Farsi et al (2005a). For further discussion see also Farsi et al (2005b).

[9] I will also discard a pooled model (Aigner et al, 1977, and Meeusen and van den Broeck, 1977) the so-called time-varying inefficiency model (see Kumbhakar, 1990, and Battese and Coelli, 1992). The pooled model considers each observation as independent and

model and its advancements. The Stochastic Frontier RE model as suggested by Pitt and Lee (1981) interprets the panel data random effects as inefficiency. Thus it does not account for firm heterogeneity and the inefficiency measure is time-invariant. Moreover it assumes the explanatory variables to be uncorrelated with the firm-specific effects. The details of the RE model estimated in this paper are as follows:

$$\ln\ C^*_{it} = \alpha + x'_{it}\beta + v_{it} + u_i \tag{3}$$

with $x'_{it}\beta$ representing the parameters and the coefficients to be estimated from Equation 2 and a normal-half-normal distribution of the stochastic term. The time-variant, firm-specific error part $v_{it} \sim iid\ \mathcal{N}(0, \sigma_v^2)$ is independently and identically distributed. u_i represents the non-negative, time-invariant, firm-specific inefficiency component. The usual assumption is that u_i is also independently and identically distributed, particularly when there is no evidence about internal firm determinants. In this case, the outsourcing share and the vehicle utilisation rate are suspected to be such factors. Including these factors directly in the mean of the inefficiency function as Battese and Coelli (1995) for environmental factors would raise the endogeneity discussion in applied econometrics, although endogeneity does not appear to have the same effect in SFA compared to the econometric estimation of average functions (Coelli, 2000). The approach followed here is to include the managerial determinants z_i as heteroscedastic variables in the inefficiency function, directly parameterising the variance of the inefficiency. Formally, $\sigma^2_{u_i} = exp(\gamma' z_i)$ with γ' including

does not allow for firm heterogeneity which is obviously not suitable to the data set. The time-varying inefficiency models assume inefficiency to change systematically over time, which is often not the case in reality, for example due to technological or economic shocks.

an estimated coefficient for an intercept.[10] Such an approach is used by Bhattacharyya et al (1995).[11] z_i are the degree of tramcar utilisation and the outsourcing grade and should be "[...] variables related to characteristics of firm management [...]" according to Hadri et al (2003b). These authors combine the approach with the Battese and Coelli (1995) model, not followed here.

Introducing heteroscedasticity, the mean of u_i then becomes to $E(u_i) = \sigma_{u_i} \frac{\varphi(0)}{\phi(0)} = 0.798 \cdot \sigma_{u_i}$ (where φ is the probability density function of the normal distribution, and ϕ is the cumulative distribution function of the normal distribution) (Greene, 2007).

This approach is especially useful when the instrumental variable approach is not suitable, for example due to data constraints. Two-stage estimations also have not proven to be a generally accepted solution in such cases.

This RE model is estimated using the Maximum Likelihood Method. From the composed error term, the inefficiencies are attained through the Jondrow et al (1982) estimator which uses the conditional mean of the inefficiency term $E[u_i|u_i + v_{it}]$. Disadvantageous to the RE model, the inefficiency is time-invariant and unobserved heterogeneity (likely to exist through the omittance of structural variables for network shapes, altitude differences, environmental conditions etc.) is not accounted for. An example in our case is the track gauge of tram systems which differs from 1000 mm (*Meterspur*) to 1435 mm standard railway gauge in Germany. 1000 mm lead to a constant disadvantage in service provision as vehicles have to be smaller with smaller gauges.

The limitations of the RE model can be overcome with the TRE model proposed by Greene (2004, 2005b). The details of the TRE model (also known as Random

[10] I also estimated a RE model in which I allowed for heteroscedasticity in the stochastic error term by letting the variance of it being dependent on the total volume of seat-kilometres. However, this parameter has not proven to be significant.

[11] See also Wang (2003), for an application of heteroscedastic variables to financing-constrained investment using SFA.

Constant model) estimated in this paper are as followed:

$$\ln\ C^*_{it} = \alpha_0 + \alpha_i + x'_{it}\beta + v_{it} + u_{it} \tag{4}$$

with $\alpha = \alpha_0 + \alpha_i$, α_0 representing the firm-invariant intercept, $\alpha_i \sim iid\, \mathcal{N}(0, \sigma^2_\alpha)$ and representing a firm-specific random intercept term to capture unobserved heterogeneity, $v_{it} \sim iid\ \mathcal{N}(0, \sigma^2_v)$ and u_{it} representing the non-negative, time-variant, firm-specific inefficiency component. There are major differences to the RE model. First, the TRE model has a random intercept being normally distributed and capturing unobserved time-invariant heterogeneity. Second, the inefficiency term is time-variant, allowing a much more realistic image of reality. Third, it also assumes the explanatory variables to be uncorrelated with the firm-specific effects, which may be an unrealistic assumption. However, as Farsi et al (2005b) point out, at least time-*variant* efficiency measures are not very sensitive to such a correlation because such correlations may be captured by the coefficients of the cost function and do not affect residuals.

The conditional expectation of the inefficiency term $E[u_{it}|r_{it}]$ with $r_{it} = \alpha_i + u_{it} + v_{it}$ is calculated by Monte Carlo simulations (Greene, 2005a) in order to be able to approximate the maximisation of the log-likelihood (Greene, 2005b). All estimations for this model are done in one step. Apart from this, the model is very similar to that proposed by Kumbhakar (1991), also applied by Kumbhakar and Hjalmarsson (1995), who use a two-step estimation. The estimations presented in the following again allow for heteroscedasticity in the inefficiency component, so that $\sigma^2_{u_{it}} = exp(\gamma' z_{it})$. The model is a special case of the Random Parameter (RP) model. A RP model with not only random intercept, but also random output parameter is the third model estimated in this paper. The randomness of output parameters is justified by the different technological systems summarised in the rail-bound output category. A relatively slow overground tram in Dresden definitely uses a different technology than a metro-similar light railway system in Stuttgart, with lots of tunnels and a railroad embankment separated from motorised individual transport (MIT). The heteroscedastic specification is the same as for the TRE model. All the models estimated here assume that the regressors are uncorrelated with the explanatory variables.[12]

3.0 Data and sector characteristics

The data set consists of an unbalanced panel of 254 observations of German multi-output local public transport operators from 1997 until 2006. In total, 39 companies are included with a mean of 6.5 observations per company.[13] The physical data (output quantities, input quantities, etc.) was taken from the annual statistics of the Association of German Transport Companies (Verband Deutscher Verkehrsunternehmen (VDV), 2007, and preceding years). All monetary data was extracted separately from annual reports. Table 1 shows the descriptive statistics for the data set. The monetary values are given in 2006 prices and inflated by the German producer-price-index (Destatis, 2008). Total expenditures include: labor, materials, other operating expenses, depreciation, interest on borrowed capital and opportunity costs of capital. Cost of equity was not directly available from the data set, and was calculated by taking the equity base for each company and year and multiplying by the interest rates for corporate bonds at that time plus 2 per cent risk premium (source for interest rates: Deutsche Bundesbank, 2007). Notably

[12] For a more detailed and structured overview of panel data models see the publications by Farsi et al, for example 2006.

[13] The exact data structure is as follows: 1997: 22 observations, 1998 and 1999: 23 obs., 2003: 24 obs., 2004 and 2006: 25 obs., 2000 and 2005: 26 obs., 2002: 29 obs. and 2001: 31 obs.

this approach treats all companies equally. This may be justified by the public ownership of the vast majority of Germany's local public transport companies.

For the purpose of calculating factor prices, all cost items except labour costs are included into capital and operating expenses. The shares for personnel costs as well as capital and operating expenses show a relatively wide range from 0.20 to 0.66 and 0.34 to 0.80 respectively. The reason for this is outsourcing of services to private partners, and particularly to privately organized subsidiaries, which often employ significant amounts of transport labour. In the profit and loss accounts, expenses for such employments are classified as expenses for purchased services.

The labour price is calculated as personnel costs divided by the number of full-time-equivalents (FTE). The high range from 30 639 to 82 610 EUR is related to regional wage differences, different age structures, outsourcing of low-paid functions and different handling of pension accruals. The capital price is calculated as residual costs (total costs minus personnel costs) divided by a measure of capital quantity, the number of seats in buses and rail-bound cars (both standing and sitting), following Farsi et al (2007). The number of seats was not directly available from the VDV statistics, but approximated by the number of seat-kilometres multiplied by the number of buses and cars divided by the number of vehicle-kilometres. The underlying assumption is that the deployment of each bus and railcar is uniformly distributed.

Assuming a common factor price for capital and operations for both kind of outputs has two shortcomings. First, buses and rail-bound cars are treated equally which may diverge from actual fixed and variable costs proportions. Second, dividing the number of seats is a pure capital measure neglecting operational costs like energy costs. However, absent more detailed information about the structure of non-personnel costs, this is the best approach available.

The two outputs are seat-kilometres in buses and seat-kilometres in rail-bound cars. Tram, light railway, and metro services are not split into different outputs because there is no clear definitional separation between these services, and transitions are smooth.[14] The inverse density index is defined as population in the supplied area divided by the sum of bus line length and rail-bound track length.[15]

Turning to the heteroscedastic variables, the outsourcing share is defined as purchased services (part of material costs) divided by total costs. According to the German Commercial Code (*Handelsgesetzbuch, HGB*), purchases, e.g. for energy or line services, are always considered material costs. The outsourcing share has steadily increased from 0.09 in 1997 to 0.24 in 2006.[16] Some companies like Leipziger Verkehrsbetriebe (LVB) and Verkehrsgesellschaft Frankfurt (VGF) have founded subsidiaries for bus and tram operations. The subsidiaries Leobus and Leipziger Stadtverkehrsvertriebe (LSVB) and In-der-City-Bus (ICB) pay lower wages that are not bound to civil service tariffs (see Walter et al, 2009, also for a description of other strategies to react on local public transport challenges).[17] These subsidiary operations have been classified as purchased services. This can also be seen in the correlation matrix in Table 2. The capital price and the outsourcing share show a relatively high correlation (0.653) because outsourcing shifts personnel costs into the capital block. With the capital quantity remaining unchanged, a higher capital price without any real price

[14] Tram services are usually characterised as pure overground services often with no separate railroad embankment (from MIT). Examples include the major East German cities like Dresden and Leipzig and the smaller West German cities. Light railway services are typically characterised by higher average speeds and inner-city tunnels, although their overall operations are similar to suburban tramways. In the 1970s, many bigger West German cities invested in new infrastructure for light railways to transform their existing tram services.

[15] In a preliminary estimation I introduced the network length as alternative network variable. This resulted in significance problems.

[16] I am aware that, in an unbalanced panel, this increase can also be due to the data structure, e.g. firms in early years with low outsourcing share and firms in late years with high outsourcing share. However, a closer look on the data provides no evidence to defend this hypothesis.

[17] LVB achieved an outsourcing share of approximately 59 per cent in 2006 with 133 m EUR of purchased services.

increases results. This favours companies with higher outsourcing shares almost automatically because the capital price is assumed to be exogenous in the cost function specification. Hence, a higher capital price explains the variation of the dependent variable and firms become more efficient.

This potential bias could be overcome with the introduction of a third factor price for purchased services. Unfortunately no information is available for the quantity of purchased services and the only price index would be a country-wide one assigning a common factor price to all companies. Therefore, the results must be interpreted with care. On the other hand, some concurrent tendencies in the covered period may partially explain the high correlation, e.g. the capital price includes purchased energy which showed a steady price increase in past years, corresponding to an increasing outsourcing share. Furthermore this is a luxury problem in comparison to the evaluation of technical efficiencies with production or distance functions which very often neglect the presence of outsourcing.

The second heteroscedastic component is the vehicle utilisation rate of railcars per day defined as vehicle-kilometres divided by the number of railcars and 365 days. The broad range from 47.33 for Jena in 1997[18] to 250.23 for Oberhausen (STOAG) in 2005 indicates an improvement potential. The indicator is a measure for the actual deployment time and for the average speed of these transport systems.[19] The low correlation coefficient between the utilisation rate and the inverse density index (0.082) shows that a low utilisation rate is mostly unrelated to congestion costs, and may be related instead to technological constraints and

[18] 47.33 relies on construction activities in Jena's inner city in 1997, though many tram services were replaced by bus services in that year. The second-lowest value is 72.98 with similar other values in the near range.

[19] A similar vehicle utilisation rate could be calculated for bus operations. However, I was not able to estimate a model in which all managerial variables, outsourcing share, utilisation rate for railcars and vehicle utilisation rate for buses, were significant. This may be due to the high dependency between outsourcing and bus utilisation. Many firms employ small- and medium-sized bus companies from the surrounding areas that can be called up on short notice as subcontractors.

network characteristics which are supposed to be manageable, at least in the long-term, especially for the municipal owners of local public transport firms. The utilisation rate is furthermore also related to pure managerial factors like maintenance time planning, vehicle scheduling, and to a certain degree peak demand levels, which are outside the influence of the management. For these reasons I use the utilisation rate as influenceable by management, acknowledging that it could also be interpreted as exogenous (e.g. Piacenza, 2006).

The quality of services throughout Germany is generally considered quite high, for instance, nearly all buses are low-floor buses for ease of entry and exit. No consistent data basis for amenities such as the availability of air conditioning exists. We can deduce from the data that speed matters, causing many potential customers to choose private auto over local transport.

Although the data offers rich interpretation possibilities, there are some aspects to consider. First, the asset valuation excludes subsidies from the public sector (and hence distorts the opportunity cost of capital), and second, the land for stops and the road bed is very often public property. Still, it is valuable to examine total costs instead of variable costs, because the measure of efficiency can be biased when looking only at parts of the total costs.

4.0 Results and interpretation

4.1 Regression results

Table 3 shows the regression results for the Random Effects (RE), for the True Random Effects (TRE) and for the Random Parameter (RP) models.[20] All

[20] I have conducted the estimations with Limdep 9.0, using 1000 Halton draws for the RP models after initial estimations using 50 Halton draws. Accuracy, as Train (2003) points out, improves with an increasing number of Halton draws.

first-order coefficients show the expected signs and are significant at the 1 per cent level. The positive coefficients of output quantities and input prices verify the non-decreasing-conditions of the cost function. All model parameters are in logs, so the output coefficients can be interpreted as cost elasticities at the local point of approximation, which is represented here by the mean. Across all models, the cost elasticities for rail-bound services are substantially higher (between 0.493 and 0.500) than for bus services (between 0.387 and 0.430).[21] An additional seat-kilometre in a bus is hence approximately 25 per cent cheaper than in a tram, light railway or metro. This may be reflected by the high fixed-cost proportion in rail-bound services for the network and the cars which are mostly custom-made for each single operator. These higher cost elasticities accompany the greater comfort of rail-bound cars which are wider and quieter.

The capital price coefficient varies slightly around 0.47, closely representing the 54 per cent share of capital and operational costs.[22] The year dummies are significantly negative from 2000 on, suggesting cost decreases because of technological progress between 7 and 10 per cent in comparison to 1997. Further cost decreases are observable until 2004 when cost savings between 18 and 23 per cent are established. Afterwards the level remains stable. This trend is obviously not linear, leading my preliminary estimations with a linear time trend to implausible results. Applying the approach by Saal et al (2007) and allowing for technical change to vary with input and output levels did not produce significant interaction terms between independent variables and time. The technological progress may be represented by new buses and tramcars, e.g. East Germany's old Tatra tramcars have been replaced. The use of innovative information technology

[21] The random output coefficients of the RP model hereby should be interpreted with care, because, through the randomisation, there is no unique parameter to assess, only a mean coefficient given.

[22] Through imposing the linear homogeneity in input prices, a labour price coefficient of 0.53 follows.

may also play a role. The coefficient of the inverse density index is significantly positive indicating that higher population per network length leads to higher costs, for example through reduced speed in urban areas, wait times at traffic lights, higher wages and so on. The inverse density index can be seen as an efficiency determinant outside the influence of management.

The coefficient of the second derivative of the cost function with respect to the capital price is positive across all models, violating the concavity property of the cost function (Cornes, 1992). According to Farsi et al (2005b) and Farsi and Filippini (2009), this may originate from some constraints in the cost-minimising strategy. For instance, competitive pressure may not be too strong and responses to input prices are quite small. The reasons are that publicly owned local transport firms are vulnerable to political concerns and the transfer of losses from municipalities and affiliated energy companies.

I will next consider the model-specific heteroscedastic (z-) variables and the random parameter. There are two heteroscedastic variables: outsourcing rate and tramcar utilisation. These variables are not significant for the RE model. I conducted likelihood-ratio tests in order to check the explanatory power of the heteroscedastic variables. A model with tramcar utilisation rate (UR) as only heteroscedastic variable is preferred to a basic model without heteroscedasticity at a p-value of 1.4 per cent. Adding the outsourcing share does not lead to any improvement and is rejected at a p-value of 99.1 per cent. The coefficient for UR is negative suggesting that firms with high utilisation rates tend to have less variability in efficiency; hence it appears to introduce planning reliability (see Hadri et al, 2003a, on how to interpret heteroscedastic variables). For the TRE and RP models, Wald tests have been used to check for the explanatory power of the heteroscedastic components. The hypothesis that the coefficient of the tramcar utilisation rate is equal to zero is rejected at a p-value of 0 per cent for both models. The hypothesis that the coefficient of the outsourcing share is zero is rejected at p-values of 7.3 and 6.7 per cent respectively. The coefficient for both models is also significantly negative, meaning that a higher outsourcing share leads to less variability in efficiency. The delegation of services to third parties on short notice appears to reduce risks and introduces stability in economic efficiency.

The random output parameters for the RP model are both significant, supporting the use of this model. The variation for bus services appears to be even higher than for tram, light railway and metro services. This can be related inter alia to the deployment of standard and articulated buses.

4.2 Efficiencies

Table 4 shows statistics for the efficiency predictions. Efficiency predictions which are given as levels in a range between greater than 0, and 1. The cost savings potential is given by the difference from 1, that is, a global minimum efficiency level of 0.650 means 35 per cent excess costs.

As expected, the mean for the RE model is much lower than for the TRE model, because the latter treats all persistent inefficiency (as Kumbhakar, 1991, calls it) as unobserved heterogeneity. From the descriptive statistics, the TRE model and the RP model appear quite similar with a slightly higher standard deviation of efficiency predictions for the RP model which allows more diversity. As Farsi and Filippini (2009) point out, the true efficiencies should lie somewhere between the RE model, which is supposed to underestimate efficiency, and the TRE model, which is supposed to overestimate efficiency. The happy medium is around 0.9, which is in a realistic albeit relatively high range. Restructuring and increased cost efficiencies throughout Germany appear to be somehow successful. An example for substantial efficiency differences between the two models is Bremer Straßenbahnen AG (BSAG) with an efficiency prediction of 0.768 in the RE model and up to 0.957 for 2005 in the TRE model. The question remains whether this is related to unobserved heterogeneity (Bremen's tram system does not rely on a sophisticated infrastructure with tunnels etc.) or if it is persistent inefficiency. Interestingly, in 2005 BSAG achieved a very low level of cost coverage of only 50.95 per cent.[23]

Around 0.9 was also the mean efficiency at the onset of incentive regulation for German electricity and gas distribution companies (Agrell et al, 2008, taking a best-of value of SFA and DEA values), which makes this number a reasonable value for local network monopolies.

The inefficiencies refer to a savings potential of 1.40 to 4.43 bn EUR in 2006 prices, depending on the applied panel data model, for all 254 observations from 1997 until 2006. I note that for the TRE model at least 117 m EUR could have been saved by the 25 firms considered in 2006.[24]

Table 5 shows the efficiency correlations with high consistencies. The rank correlations shown in Table 6 show similar results. However, a comparison of individual efficiency levels (mean over years) in Figure 1 shows that unobserved heterogeneity plays an important role for some specific firms with differences up to 20 per cent between the RE and TRE models.

A detailed look at the Kernel Density Estimate in Figure 2 also shows that the distribution of efficiency predictions differs most between the RE and the other two models. All curves suggest the efficiency to be negatively skewed which is the usual assumption in Stochastic Cost Frontier models. The bimodal distribution in the RE model however goes against the assumption of a half-normally distributed inefficiency. As Farsi and Filippini (2009) point out, this may be explained by "[...] cost differences that are not due to inefficiencies but to other external factors." In such a case, a RE model would not be appropriate for the given data.

[23] Calculated as revenues (corrected from subsidies) divided by the total cost definition applied here.

[24] Savings potential is calculated as the sum of individual inefficiency scores multiplied by individual total costs.

I now look at the efficiency determinants under managerial control, the outsourcing share and the vehicle utilisation rate. To check whether observations with low values of these indicators really are less efficient, I split the sample into values below, and values equal or above the median (for both indicators). Mean efficiencies for these sub samples are given in Table 7. In all three models, mean efficiencies for low outsourcing shares and low vehicle utilisation rates are significantly lower. For the outsourcing share the differences in mean efficiencies are somehow lower (between 0.007 and 0.019) resulting in p-values between 0.02 per cent and 1.98 per cent. These p-values are still low enough to reject the hypothesis of equal distribution of efficiency values in the groups with low respectively high outsourcing share. Outsourcing therefore appears to increase efficiency. Still, this variable has to be interpreted carefully. Compared with the vehicle utilisation rate, higher values do not necessarily mean better values, for there could be an optimal outsourcing grade.

The results are even clearer for the vehicle utilisation rate. Differences in mean efficiencies of the group with a low vehicle utilisation rate compared to the group with a high vehicle utilisation rate account for approximately 0.03-0.07, depending on the applied panel data model. These distribution differences are all significant with very low p-values. Higher values of the railcar utilisation rate have a positive influence on efficiency, as expected. This is related to higher average speeds, better deployment times and lower maintenance and stop times and costs. The effect on efficiency also appears to be stronger than for the outsourcing share.

5.0 Conclusions

In this paper, I estimated state-of-the-art models of Stochastic Frontier Analysis incorporating unobserved heterogeneity and allowing for heteroscedasticity in the inefficiency function. Incorporating unobserved heterogeneity is important when the data set omits environmental/structural variables which are likely to influence the production process. This is an important application, although I also showed that observed heterogeneity plays a significant role as well. The inverse density index defined as population living in the network area has a cost-increasing influence.

Two efficiency determinants under managerial control were included as heteroscedastic variables in the inefficiency function. I conducted tests on the influence of these managerial determinants on mean efficiencies of groups with high vs. low outsourcing and high vs. low vehicle utilisation. All Kruskal-Wallis tests indicated that the high values show a higher efficiency distribution. This implies great potential for improvements. Optimisation of outsourcing should be in focus for businessmen emphasised for firms that have neglected it in the past. The options include establishing subsidiaries or cooperating with small- and medium-sized firms. The vast differences in the vehicle utilisation rate for railcars (shown in the descriptive data statistics) are somewhat surprising. Improvement options can be related to enhancing speed through infrastructure measures (separate rail embankments, prioritisation at traffic lights, tunnels in inner-city areas, new tracks, express trains similar to those in Karlsruhe, etc.). Furthermore maintenance times could be reduced and procurement optimised.

In an international context, the analysis shows how cost efficiency and hence economic success of local public transport relates to the utilisation degree of vehicles. For example, local public transport must achieve intermodally competitive average speeds, supported by adequate transport planning and policy measures.

Considering Germany's low mean level of cost coverage with 73.8 per cent (Verband Deutscher Verkehrsunternehmen, 2008), the problem is likely to extend beyond the cost side. I found mean efficiencies roughly about 0.9, meaning that full efficiency would also imply a negative level of cost coverage. Some past improvements have often been attributed to wage reductions. The revenue side should bear further optimisation potential and should be analysed in the future. These results impact corporate strategies and point to the need for a comprehensive, national regulation.

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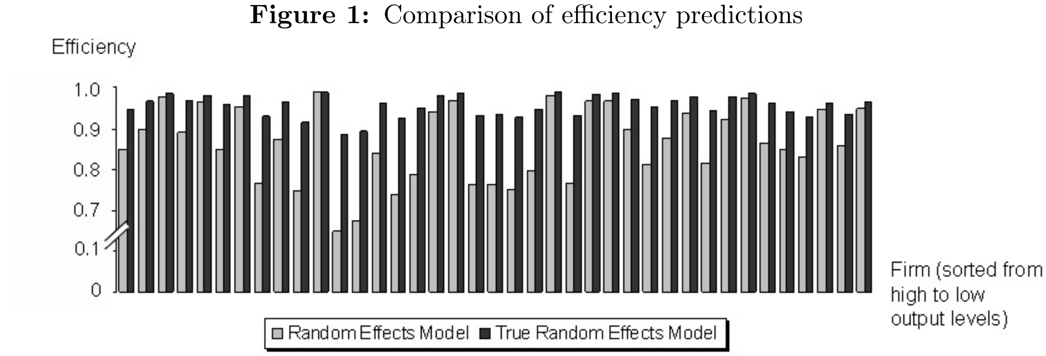
Figure 1: Comparison of efficiency predictions



Source: Own calculation

Table 1: Descriptive statistics

	Sum[a]	Min.	Mean	Median	Max.	Std. Dev.
Total cost (C) [m EUR]	2822.67	11.70	111.14	70.13	363.23	86.82
Share personnel costs		0.19	0.46	0.46	0.62	0.08
Share capital costs		0.38	0.54	0.54	0.81	0.08
Labour Price (w_L) [EUR/FTE]		30 639	49 636	50 409	82 610	8714
Capital Price (w_K) [EUR/seat]		934	1917	1679	5064	766
Output in m seat-kilometres						
Bus (Y)	17 122	4	656	459	2303	503
Rail-bound (Q)	27 482	50	1018	644	4800	974
Inverse density index (ID)[b]		138	862	787	2958	458
Outsourcing share (OUT)[c,d]		0.00	0.16	0.12	0.59	0.19
Railcar utilisation rate (UR)[e,d]		47.33	135.66	128.11	250.23	39.27
Vehicles						
Bus	3650	2	146	103	470	106
Rail-bound	2855	6	124	85	513	106

[a] *Sum values for 2006* [b] *Inhabitants per km network length* [c] *Based on total costs* [d] *Calculated over 254 observations (note that the RE model uses group means in z-variables)* [e] *Vehicle-km per day and vehicle*

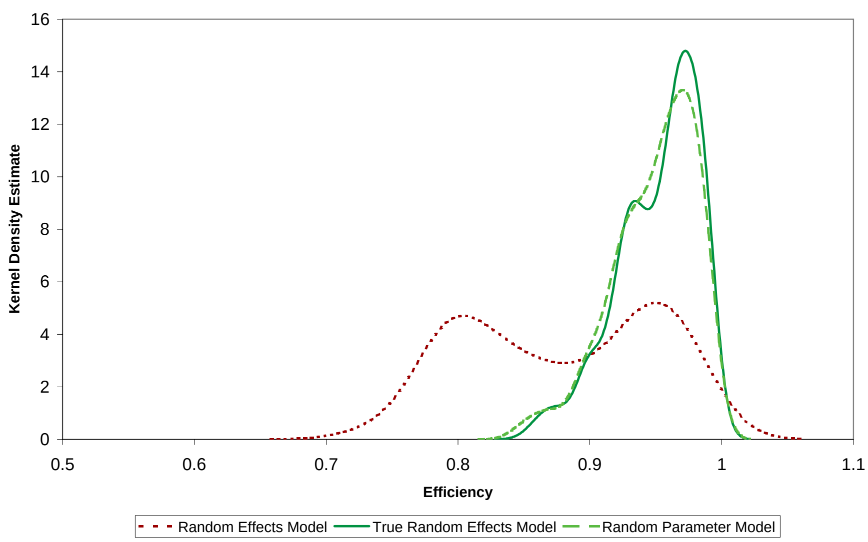
Source: Own calculation

Table 2: Data correlations

	Y	Q	w_L	w_K	ID	OUT	UR
C	0.837	0.920	0.242	0.218	0.227	0.208	0.357
Y		0.707	0.253	0.007	0.060	0.131	0.342
Q			0.105	0.061	0.239	0.110	0.335
w_L				0.201	0.083	0.268	0.226
w_K					0.154	0.663	0.501
ID						-0.123	0.082
OUT							0.391

Source: Own calculation

Figure 2: Kernel density of efficiency predictions



Source: Own calculation

Table 3: Regression results

Model	**RE**	**TRE**	**RP**
Parameter	Estimate	Estimate	Estimate
α	$-.105^{**}$	$.036$	$.013$
	(.044)	(.022)	(.020)
σ_α	—	$.095^{***}$	$.096^{***}$
	—	(.004)	(.004)
β_Y	$.430^{***}$	$.406^{***}$	$.387^{***}$
	(.053)	(.008)	(.007)
σ_{β_Y}	—	—	$.103^{***}$
	—	—	(.005)
β_Q	$.494^{***}$	$.500^{***}$	$.493^{***}$
	(.026)	(.007)	(.006)
σ_{β_Q}	—	—	$.030^{***}$
	—	—	(.003)
β_K	$.464^{***}$	$.467^{***}$	$.473^{***}$
	(.040)	(.011)	(.010)
β_{YY}	$.145^{**}$	$.165^{***}$	$.159^{***}$
	(.071)	(.007)	(.006)
β_{QQ}	$.151^{***}$	$.150^{***}$	$.162^{***}$
	(.038)	(.008)	(.007)
β_{KK}	$.381^{*}$	$.276^{***}$	$.252^{***}$
	(.230)	(.047)	(.044)
β_{YQ}	$-.098^{**}$	$-.149^{***}$	$-.152^{***}$
	(.049)	(.008)	(.008)
β_{YK}	$.061$	$.019$	$.024$
	(.059)	(.019)	(.018)
β_{QK}	$-.058$	$-.058^{***}$	$-.059^{***}$
	(.040)	(.018)	(.017)
β_{1998}	$-.058$	$-.033$	$-.032$
β_{1999}	$-.057$	$-.041$	$-.041$
β_{2000}	$-.098^{**}$	$-.074^{**}$	$-.073^{***}$
β_{2001}	$-.126^{***}$	$-.091^{***}$	$-.091^{***}$
β_{2002}	$-.160^{***}$	$-.121^{***}$	$-.122^{***}$
β_{2003}	$-.212^{***}$	$-.162^{***}$	$-.161^{***}$
β_{2004}	$-.235^{***}$	$-.186^{***}$	$-.186^{***}$
β_{2005}	$-.236^{***}$	$-.182^{***}$	$-.183^{***}$
β_{2006}	$-.237^{***}$	$-.184^{***}$	$-.185^{***}$
β_{ID}	$.064^{**}$	$.047^{***}$	$.050^{***}$
	(.029)	(.008)	(.008)
γ_0	—	6.072^{***}	6.134^{***}
	—	(1.616)	(1.563)
γ_{OUT}	—	$-.260^{*}$	$-.252^{*}$
	—	(.145)	(.134)
γ_{UR}	-2.744	-6.749^{***}	-6.722^{***}
	(2.331)	(2.037)	(1.970)
σ_u	$.714$	$.035$	$.036$
$\lambda = \sigma_u/\sigma_v$	12.948	$.799$	$.888$

***significant at 1 per cent, **significant at 5 per cent, *significant at 10 per cent; standard errors in parentheses (omitted for year dummies for reasons of space)

Source: Own calculation

Table 4: Descriptive efficiencies

Model	RE	TRE	RP
Minimum	0.650	0.855	0.844
Mean	0.862	0.952	0.949
Median	0.866	0.960	0.954
Maximum	0.990	0.993	0.993
Standard deviation	0.090	0.031	0.032
N	39	254	254

Source: Own calculation

Table 5: Efficiency correlations

Model	RE	TRE	RP
RE	100.00%	95.58%	96.11%
TRE		100.00%	98.52%[98.75%]
RP			100.00%

Based on average firm values (39 obs.)
In brackets based on all observations

Source: Own calculation

Table 6: Rank correlations

Model	RE	TRE	RP
RE	100.00%	94.99%	95.50%
TRE	-	100.00%	97.70%[98.77%]
RP	-	-	100.00%

Based on average firm values (39 obs.)
In brackets based on all observations

Source: Own calculation

Table 7: Efficiency comparisons and Kruskal-Wallis tests

Model	RE	TRE	RP
Outsourcing (OUT)			
Mean efficiency for low OUT	0.837	0.948	0.944
Mean efficiency for high OUT	0.855	0.955	0.953
χ^2_1-value	5.432	9.712	14.353
Probability	1.98%	0.18%	0.02%
Vehicle utilisation (UR)			
Mean efficiency for low UR	0.811	0.936	0.934
Mean efficiency for high UR	0.881	0.967	0.963
χ^2_1-value	34.979	63.114	52.008
Probability	0.01%	0.01%	0.01%

Low and high groups with 127 obs. each, split at the median of the efficiency determinant

Source: Own calculation