DISCUSSION PAPER SERIES

No. 9346

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PUBLIC POLICY

Centre for Economic Policy Research

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Available online at: **www.cepr.org/pubs/dps/DP9346.asp**

ISSN 0265-8003

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Discussion Paper No. 9346
February 2013

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This Discussion Paper is issued under the auspices of the Centre's research programme in **PUBLIC POLICY**. This paper is produced as part of the project Growth and Sustainability Policies for Europe (GRASP), a Collaborative Project funded by the European Commission's Seventh Research Framework Programme, Contract number 244725. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

CEPR Discussion Paper No. 9346

February 2013

ABSTRACT

Cost Efficiency and Subsidization in German Local Public Bus Transit

This paper examines the impact of endogenous deficit-balancing subsidies on the cost efficiency of local public bus companies by using alternative frontier cost models for panel data. Thereby, the multidimensional performance estimation incorporates the subsidy variable directly. The empirical analysis relies on a unique dataset of 33 German companies observed over a period of up to twelve years. We find a positive effect of endogenous subsidies on the standard deviation of cost inefficiency implying that the range of companies' cost inefficiency increases with the level of subsidies relative to total costs. Further, we find that non-subsidized firms perform better.

JEL Classification: C13, D24 and L92
Keywords: cost efficiency, endogenous subsidies, heteroscedasticity, local public bus transportation, panel data and stochastic cost frontier

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Submitted 05 February 2013

Introduction

Globally, local public transit systems require large subsidies in order to secure the provision of the corresponding services.[1] Vickery (1980) outlines three rationales to justify subsidies to local transit: First, because transit operates under conditions of substantial economies of scale,[2] i.e. marginal costs are lower than average costs, and under-pricing average costs, e.g., for social reasons, produces a gap in cost coverage. Second, competing modes of transit receive substantial subsidies. Third, special requirements for the underprivileged or disabled, e.g., an inability to use alternate forms of transportation, justify public financial support. This indicates that public transit subsidies, and in particular operating subsidies, are based upon social objectives rather than economic grounds; see Karlaftis and McCarthy (1998) and the references therein. In addition, public subsidies are a second-best instrument for addressing urban externalities such as noise, congestion, and pollution, helping shift demand from private to public transportation (Button 1993).

Thus, financial support might extend the failure to cover costs instead of compensating for exogenously caused cost increases. Traditionally, one-dimensional key performance indicators, e.g., expense per produced output, revenue-vehicle mile per employee, are used to measure efficiency, effectiveness, and overall performance. However, a large body of literature provides empirical evidence for cost-increasing and performance-impairing effects of subsidies in local public (bus) transit; see e.g., Karlaftis and McCarthy (1998) for a review. More recent frontier models provide a multidimensional measure of relative technical or cost efficiency where each observation is compared to a best-practice frontier derived from the observed sample. The distance to the frontier is considered as inefficiency and represents the proportional increase of output or decrease in inputs given the technology and inputs and outputs, respectively. As shown by Fox (1999), relying on one-dimensional efficiency measures can result in misleading conclusions when comparing firm performances individually. Although, this efficiency concept provides additional and useful information about production processes and cost structures, it has not been used extensively to investigate the effects of subsidies in public bus transit.

Furthermore, operating, capital, and lump-sum subsidies alike are shown to be also endogenous meaning that they may affect the choice of inputs and outputs and, therefore, create allocative distortions and introduce inefficiency (Kim and Spiegel, 1987; Obeng, 1994; Obeng and Sakano, 2000; Obeng, 2011). Endogeneity of subsidies additionally implies that

[1]See e.g., Pucher et al. (1983) for the US, Beesley (1991) for the UK, Filippini et al. (1992) for Switzerland, Odeck and Alkadi (2004) for Norway, and Sakai and Shoji (2010) for Japan.[2] Economies of scale are confirmed in a variety of empirical studies, among them Cambini et al. (2007) and Farsi et al. (2006).

firms have control over it and are obliged to use them for a specific purpose. In many cases, subsidies are fixed, for example, in terms of utilization and amplitude. If endogeneity of subsidies is present, both nonparametric and parametric frontier methods must be able to account for that in order to provide reliable results of subsidy effects.

In the context of the German local public bus transit, we consider a particular type of deficit balancing, i.e. loss absorption, which we assume to be endogenous, and incorporate it appropriately into a single-stage parametric cost efficiency estimation procedure. Cost efficiency is estimated by means of stochastic frontier models for panel data. Thus, we bridge the gap between research on endogenous subsidies in public transport and multidimensional performance measurement. Hence, our analysis broadens the empirical evidence on the effects of subsidization on cost efficiency in local public transportation.

Currently, the German local public transit sector in total receives about 13 billion Euros (about 16 billion US Dollars) of public financing per year.[3] The bus sector is in Germany of particular interest since it supplies more than two-thirds of the demand for general local public transportation[4] and it is notably used in rural areas (VDV 2009a). Several hundred bus companies serve the market and are predominantly publicly owned. The local authorities, i.e. cities and counties, carry the responsibility for the supply of local public transport services. Depending on whether the transportation service can be rendered with or without public co-financing, the local authorities facilitate the provision by directly delegating and awarding or approving operating licenses to companies where the licenses establish local and temporal monopolies. Direct awards still represent the vast majority of service assignments.

However, the capability of public bodies to support public transit is limited and even decreasing because public budgets are increasingly stressed. Against this background, in addition to the ongoing discussions about subsidy cutbacks (Peistrup, 2005), it is more likely that financial support will decline and, thereby, compromise local public transit provision. Due to the organizational structure of public transport in Germany, in general the companies have very limited means available to steer revenues, even as legislators and responsible local authorities can decide on revenues (Becker, 2004). For example, bus companies cannot independently change the level of fares and applied requested fare increases are usually evaluated as being against the public interest. Therefore, Becker (2004) recommends concentrating on cost structures.

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[3] Historically, the most significant reason for the sector's fiscal deficit originates in the explosive growth of private vehicle usage during the second half of the twentieth century (Goeverden et al. 2006).

[4] General local public transit refers to modes including buses, trams, light railway, and metros. It is particularly distinguished from regional and suburban railway transportation.

We focus on the effects of loss absorption on the cost efficiency of bus companies, which helps understand the effects of endogenous subsidies, and, hence, helps derive conclusions with respect to improvements in funding dispersion and potential reductions in funding. Loss absorption is particularly distinct from other financial benefits. As aforementioned, generally fare revenues are not enough to cover costs. Therefore, local bus companies are compensated and supported in various ways: For example, they receive supports for providing educational transit and reimbursed for the free-of-charge carriage of handicapped persons (equalization and reimbursement payments). Further, they receive operating and investment grants and are compensated for deferred fare increases. These payments are more or less earmarked and sometimes formula-based to compensate for all kinds of economic drawbacks that may arise from the fact that a sufficient public transit provision is politically intended. Nevertheless, some, but not all, companies run in deficit meaning that the profit and loss account shows a negative figure.

The owners of publicly owned bus companies, which are cities and counties, are obliged to balance these deficits arising from operation, for which there are three main options available: First, companies can forward their losses or use provisions. Second, when the bus companies belong to municipal utilities, profits from other operations, e.g., water and energy, may be used and are, hence, cross-subsidized. However, due to European legislation, the latter type of subsidies is contested because they are rated as aids distorting competition. Third, where cross-subsidies cannot be raised, the local authority or other public owners have to balance the deficits directly from the public budget (Peistrup, 2005). Because public owners are simultaneously the operators of the bus companies, the deficits appear to be related to managerial decisions and abilities to balance revenues and costs during a fiscal year. Loss absorption is not *ex-ante* determined, but *ex-post* computed as residual loss, and, therefore, its amplitude is not bounded. Further, loss absorption has an explicit purpose. Highly likely, the deficits are for example related to the suboptimal choice of inputs and/or outputs as suggested by previous research; see e.g. Obeng (2011) who models operating subsidies as a function of input levels. Against this background, we consider these deficits as well as deficit balancing by loss absorption as influenceable by the bus companies, and thus, endogenous.

To investigate the impact of this type of deficit balancing on the performance of local bus companies we conduct parametric efficiency analysis and, thereby, evaluate their effect on a multidimensional measure of cost efficiency. We link the according variable directly to the distribution of the cost inefficiency term in order to account for the firm-influenceable character of loss absorption. To our knowledge, this approach has not been pursued in the literature on public bus operations, and we believe it promises to broaden our understanding about subsidizing this and other sectors.

The remainder of the paper is structured as follows. Section 2 reviews the literature on cost structures, performance, and subsidization of local public transport. Section 3 discusses the applied methodology and introduces the model specifications and data. Section 4 shows the results of our regressions and discusses in depth our analysis of firm-specific cost efficiencies. Conclusions are given in Section 5.

2 Literature Review

The literature analyzing cost structure and performance of public bus transportation dates to the 1950s and is divided into the two strands: regression analysis and frontier analysis.[5] Early work, including Johnston (1956), Miller (1970), Viton (1981), and Berechman and Guiliano (1985), are chiefly concerned with establishing concepts of cost models and cost functions' properties within the context of public bus transportation,[6] along with determining appropriate regression estimation techniques. The regression analyses concerning subsidies touches on diverse aspects of public transportation, e.g., fares, unit costs, and demand.

Bly et al. (1980) and Bly and Oldfield (1986) find reduced effects on fares and increased effects on demand as well as increased unit costs and reduced labor productivity because of subsidies. The data they use comprises multiple countries, and therefore the findings appear to reflect general trends. Pickrell (1985) examines the relationship between deficits and subsidies in the US transit sector and concludes that government subsidy programs would be more effective if transit operators could gain a measure of control over operating costs, adapt their services to changes in demand, and construct fares that acknowledge the variations in supply costs. In addition, the author proposes that a revision of the subsidy mechanism could also contribute to improving the situation. Thereby, a major effort in revising state and federal programs is re-establishing incentives for operators. Empirical analyses also indicate that the source of subsidies is relevant. The success of subsidies appears to be closely related to the level of government awarding the financial support. For example, Anderson (1983), Pucher (1988), and Filippini et al. (1992) find that subsidies by low-level government bodies cause fewer cost increases than subsidies funded by high-level government bodies. In other words, the impacts of subsidies on costs are less harmful when close relationships exist between funding bodies and companies.

[5] Piacenza (2001) surveys theoretical and empirical issues associated with both approaches.
[6] See Berechman (1983) for a general survey of public transport.

During the early 1980s, performance measurement using frontier analysis entered the discussion; for a review, see e.g., De Borger et al. (2002) and De Borger and Kerstens (2008). Based on the idea of Farrell (1957), frontier methods determine the best practice behavior in an industry (or a sample) and estimate the unit-specific degree of inefficiency relative to the best-practice benchmark. Frontier approaches mainly estimate the efficient frontier either by nonparametric linear programming, or by parametric techniques, which assume a functional form representing the underlying input-output-transformation. The advantages of parametric efficiency analysis are its accountability for statistical noise, applications to panel data, and incorporation of the time horizon. This paper applies stochastic frontier analysis (SFA), a widely used parametric technique that yields estimation residuals, which are interpreted as measures of inefficiency. Generally, the evidence based on frontier techniques confirms the harming effects of subsidies that are found using regression analysis, but broadens the definition of performance measures. Even though there is continued interest in performance measurement focusing on public bus operators, the empirical evidence on subsidies derived from frontier analysis is limited.

In a nonparametric analysis, Obeng (1994) investigates the technical efficiency of 73 US single mode bus systems in 1988 by comparing the efficiency scores from a base model to its re-estimation including subsidies (measured as total operating and capital subsidies from all sources) as an additional variable. He finds higher technical efficiencies when subsidies are considered. However, it is unclear whether this result is truly subsidy-related, or is driven by the curse of dimensionality.[7] Likewise, Kerstens (1996) uses a nonparametric technology references to estimate the technical efficiency of 114 French bus operators in 1990. To analyze the effect of subsidies, the author conducts, in a second stage, a Tobit regression and finds that subsidies (measured as the share of subsidies in total operating costs) subvert technical efficiency.

Filippini et al. (1992) estimate the cost efficiency of a panel of 62 Swiss bus operators in 1988 parametrically by displaced ordinary least squares. The subsequent ordinary least square (OLS) regression reveals that cost efficiency is positively influenced by the low-level government share in deficit subsidies and the amount of compensatory payments. Examining the technical and allocative inefficiency of 134 US single mode bus firms in 1988 estimated by the stochastic frontier approach developed by Schmidt and Lovell (1979, 1980), Sakano and Obeng (1995) find that firm size rather than operating and capital subsidies affects the

[7] The curse of dimensionality is a well-known phenomenon in Data Envelopment Analysis; it is the overestimation of efficiency when the number of variables is high relative to the number of observations. For theoretical considerations see Simar and Wilson (2008) and Adler and Yazemsky (2010); for an empirical investigation see e.g., Nieswand et al. (2010).

allocative inefficiency between labor and capital. Similar to Filippini et al. (1992), the authors investigate the effects of firm size and subsidies in a second stage using OLS.

Sakano et al. (1997) extend Sakano and Obeng (1995) by incorporating the operating and capital subsidies directly in the cost minimization problem such that firms minimize costs net of subsidies subject to the production function constraints. This specification allows them to distinguish allocative inefficiency due to subsidies or due to internal factors. They pool data on US urban bus companies from 1983 to 1992 and find that allocative inefficiency mainly originates in factors internal to the firms, not the subsidies. Further, Sakano et al. (1997) indicate that subsidies cause notable deviations from optimal input factor proportions, i.e. the excess use of labor relative to capital and the excess use of fuel relative to capital and labor.

Unlike previous research, we directly incorporate the firm-influenced subsidy as a heteroscedastic variable in the standard deviation of inefficiency term, i.e. the half-normal error term. This approach is proposed by Bhattacharyya et al. (1995) and Hadri et al. (2003) who suggest, among others, assigning factors that are under the control of firms (managerial determinants) to the inefficiency term.[8] Our approach accounts for endogeneity of inefficiency and the considered deficit-balancing subsidies, enabling us to capture a potential bias due to heteroscedasticity. Caudill et al. (1995) argue that the residuals in frontier estimation are especially sensitive to heteroscedasticity because the frontier changes when the error dispersion increases.[9] This sensitivity is likely to carry over to the inefficiency measures and, therefore, must be considered.[10]

This paper contributes to the existing literature by investigating the impact on firm-influenceable subsidies on a multidimensional measure of cost efficiency. In this context, we consider a sample of German local public bus operators for the first time and applying recent panel data model specifications of SFA that account for unobserved heterogeneity and provide time-varying and firm-specific efficiency estimates. Moreover, to allow for variations in the optimal (reference) production technology, one of our two model specifications relaxes the strong assumption of equal output and price parameters by randomizing them.

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[8] The association of factors under the control of firms (managerial determinants) and inefficiency is particularly distinguished from exogenous factors that are instead associated with the noise term.

[9] In regression estimation this is a minor problem because average cost functions are usually estimated by least squares and estimators based on means are no longer efficient but still unbiased when symmetric error dispersion is present (Caudill et al., 1995).

[10] Using a Monte Carlo study for the estimation of a cross-sectional cost frontier of banking institutions, Caudill et al. (1995) find overestimation of inefficiency for small firms and underestimation of inefficiency for large firms when heteroscedasticity is ignored.

3 Methodology and data

3.1 Cost function

Public transit can be considered a production process whereby inputs, e.g., labor and capital, are transformed into one or multiple outputs, e.g., vehicle-kilometers. The production process is well-known by now and the corresponding cost function of public bus operators is discussed at length. Kumbhakar (1997) notes that independent from the output produced, it is important to use inputs in order to minimize the cost of producing a given level of output. Cost-minimizing behavior is required when a cost function is applied (Coelli et al. 2005). Further, output quantities are predetermined by public (government) entities that make decisions about the public transport services to be supplied. Therefore, we apply an input-oriented approach and the total cost function can be written as

$$C = f\left(Y, p_L, p_K, di, D_{east}, t\right) \tag{1}$$

where total costs (C) depend on the level of output (Y), two input factor prices for labor (p_L) and capital (p_K), and structural variables that are beyond the control of companies. These structural variables are the density index (di) and a dummy variable (D_{east}), which realizes the value of one if a company operates in one of the former East German territories. A linear time trend (t) captures neutral technological change.

Concerning the functional form we opt for a flexible form, i.e. the translog cost function.[11] We choose the mean to be the local point around which the function is approximated. Hence, the variables for output, factor prices, and density index are divided by their respective mean. This transformation allows interpreting the estimated coefficients as elasticities. After imposing linear homogeneity of costs in input prices of degree one by dividing cost-related measures by the factor price of labor, the translog cost function is

$$\begin{aligned}\ln\left(\frac{C_{it}}{p_{L_{it}}}\right) = \ln C^*_{it} = \beta_0 + \beta_Y \ln Y_{it} + \beta_{pK} \ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right) \\ + \frac{1}{2}\left[\beta_{YY}\left(\ln Y_{it}\right)^2 + \beta_{pKpK}\left(\ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right)\right)^2\right] \\ + \beta_{Y_{pK}} \ln Y_{it} \ln\left(\frac{p_{K_{it}}}{p_{L_{it}}}\right) + \beta_{di} \ln di_{it} + \beta_{D_{east}} D_{east} + t\end{aligned} \tag{2}$$

[11] For previous applications, see e.g., Bhattacharyya et al. (1995); Farsi et al. (2006), Filippini and Prioni (2003).

where β_0 represents the intercept, and all other βs represent the variables' coefficients to be estimated. The indices i and t indicate the unbalanced panel structure of our data where $i = 1,2,...,33$ denote the companies, and $t = 1,2,...,12$ the period of the specific observation.

3.2 Econometric model

To estimate the translog cost function we employ stochastic frontier models for panel data. The advantage of using panel data models is that they allow accounting for both unobserved heterogeneity between firms and dynamics. The first panel data models for SFA were proposed by Pitt and Lee (1981) and Schmidt and Sickles (1984). Both models allow for firm-specific inefficiency estimation but regard only time-invariant inefficiency. Thus, they are no longer considered here. Numerous approaches include time-varying inefficiency, such as Kumbhakar (1990) and Battese and Coelli (1992, 1995). This paper uses the true random effects (TRE) model proposed by Greene (2005), who extends conventional models by including an additional random intercept that captures unobserved heterogeneity. This model can be illustrated as

$$\ln (C_{it}^{*}) = \alpha_0 + \alpha_i + x_{it}'\beta + v_{it} + u_{it} \tag{3}$$

with C^* depicting the transformed cost variable and $x'\beta$ collecting the explanatory variables and the respective parameters. α_0 is a common intercept and $\alpha_i \sim iid\ N(0, \sigma_\alpha^2)$ a firm-specific random intercept that captures unobserved time-invariant heterogeneity. Noise is captured by a two-sided error term, $v_{it} \sim iid\ N(0, \sigma_v^2)$, while $u_{it} \sim iid\ N^+(0, \sigma_u^2)$ denotes a one-sided, non-negative random variable that represents the firm-specific inefficiency. Since we wish to include a managerial determinant as heteroscedastic variable z in the inefficiency function, we parameterize the standard deviation of the one-sided inefficiency term such that $\sigma_{u_{it}} = \exp(\delta' z_{it})$ after Bhattacharyya et al. (1995). z collects an intercept (z_0) and the heteroscedastic variable, which represents our measure of deficit-balancing subsidies (z_1). This variable is divided by its standard deviation to improve the estimation. δ denotes the vector of coefficients to be estimated in the heteroscedastically specified inefficiency function. Introducing heteroscedasticity in the half-normal model implies an individual-varying mean of the inefficiency since $E[u_i] = \sigma_{u,i}\, \phi(0)/\Phi(0) = 0.79788\sigma_{u,i}$ where ϕ denotes the probability density function of the inefficiency function of the normal distribution and Φ is its cumulative distribution function (Greene, 2007).

Several extensions of heteroscedastic models have been proposed: Hadri (1999) introduces double heteroscedasticity (heteroscedasticity in both the one-sided and the two-sided error terms) for cost frontiers; Hadri et al. (2003) extend this approach to the cases of production frontiers and panel data. We concentrate only on the heteroscedasticity of the one-sided error term. According to Kumbhakar (1997), from an economic view, it makes more sense to model heterogeneity in the variances of firm-specific components, especially when there are unobserved firm-specific components.

The TRE model assumes that the explanatory variables are uncorrelated with the firm-specific effect. Farsi et al. (2005) point out that at least time-variant efficiency measures are not very sensitive to such correlations because the correlations may be captured by the coefficients of the cost function and do not affect residuals. The TRE model is a special case of the random parameters (RP) model that also allows other coefficients to be randomized. We let the coefficients of output (β_Y) and the price ratio (β_{p_K}) vary between companies. Hence, the frontier estimated by this RP model does not assume the same optimal technology for every firm. Justifications for assuming a different technology may originate, first, in different bus types, e.g., diesel versus hybrid, or low floor versus conventional, and second, in different optimal input factor ratios according to a company's environment.[12] The heteroscedastic formulation of the inefficiency term and all other assumptions are the same as before.

3.3 Data

The dataset incorporates an unbalanced panel of 33 German bus operators in urban and rural areas. The time period covers twelve years (1997-2008) for a total of 231 observations. The panel structure is such that 50% of the companies are observed seven years or less, and 25% are observed ten years or more. Table 1 presents the data characteristics. The data are derived from multiple sources, i.e. the physical data (e.g., kilometers of network length) is from the annual statistics of the German Association of Transportation Companies (VDV), and the

[12] Alternatively, heterogeneous technologies can be modeled using the latent class model, as proposed by Greene (2002) and extended by Orea and Kumbhakar (2004). In these models distinct technologies and efficiency distributions can be identified for different groups of companies. The affiliation to one of the groups is determined by so called separating or switching variables (Cullmann, 2012). An application of this model for transit systems is provided by Sakano and Obeng (2011), who contrast a single class stochastic cost frontier accounting for heterogeneity by including background variables with a latent class model. They find that the alternative efficiencies estimates differ significantly and conclude that the latent class model is superior in capturing differences in the technologies that would otherwise be considered inefficient. We owe this reference an attentive referee.

monetary data (e.g., personnel expenditures, loss absorption) is from the balance sheets published in annual reports and the Federal Gazette (*Bundesanzeiger*).

Table 1: Descriptive statistics for German local public bus companies

Variable	Mean	Median	Std. Dev.	Min	Max
Total costs (Y) [mn Euro] [a]	39.47	33.47	24.22	3.82	95.04
Seat-kilometers (skm) [km]	750	719	423	55	1,870
Labor price (p_L) [Euro/ FTE] [a]	46,896	46,689	11,566	10,693	86,243
Capital price (p_K) [Euro/seat] [a]	1,360	1,237	590	568	3,517
Density index (di) [inhabitants/ km] [b]	412	344	333	61	2460
Dummy East (D_{east}) [level] [c]	0.26	0.00	0.44	0.00	1.00
Subsidy ratio (z_1) [percent] [a, d]	0.14	0.14	0.14	0.00	0.55

Source: German Association of Transportation Companies, Federal Gazette. Notes: observations = 231, companies = 33, years = 1997-2008. [a] Base year 2008. [b] Population in operating area per km of network length. [c] Dummy East; 1: company operates in Eastern Federal States (59 observations), 0: company operates in Western Federal States (173 observations). [d] Loss absorption in Euro divided by total costs in Euro.

Total costs (Y) include personnel expenditures, material costs, other operating expenses, depreciation, interest on borrowed capital,[13] and opportunity costs of equity. The latter is measured by multiplying the individual equity base of each observation with the corresponding interest rates of corporate bonds (Deutsche Bundesbank, 2010) plus a 2% risk premium. We note that this approach treats the companies equally and is justified by the fact that our dataset includes operators that are predominantly publicly owned. Only five companies[14] have a mixed ownership structure (public and private), and none are purely privately owned. Dividing personnel expenditures by the number of full-time equivalents (FTE) provides the input factor price for labor (p_L). To approximate capital costs we use the residue from subtracting personnel expenditures from total costs, and thus consider all non-labor costs as capital costs. This approach is frequently used when companies do not report capital costs directly or it is not possible to apply the capital inventory method (e.g., Farsi et al. 2006; Filippini and Prioni 2003). We then calculate the input factor price for capital (p_K) as the ratio of capital costs to the number of seats.[15] Seats are our preferred unit measurement, because unlike the number of buses, the number of seats accounts for different bus sizes. Both input factor prices vary notably. Walter (2011) argues that labor and capital cost shares are significantly related to outsourcing because outsourcing moves internal labor costs into

[13] We use the account "interest paid and similar costs" reported in the financial reports.
[14] These companies are ASEAG in Aachen, KVG in Kiel, KVG in Koblenz, KVS in Saarlouis, and KVIP in Uetersen.
[15] The number of seats is calculated by the number of seat-kilometers multiplied by the number of buses divided by the number of vehicle-kilometers. This approach assumes a similar deployment of all buses in the fleet, which should be the usual case.

purchased services, which are then part of material costs. The large variation in labor prices furthermore depicts the interregional wage differentials, particularly for the distinction between wage levels in Eastern and Western parts of Germany.[16] The differences in capital prices seem to be due to rural and non-rural characteristics of the operating environments.[17] The capital price is lower for rural operating areas where companies tend to employ older buses with fewer comfort devices. Cost reductions due to lower depreciation costs appear to outweigh the higher maintenance costs associated with old buses. All cost data is inflation-adjusted to 2008 using the German producer price index (Destatis, 2009).

Seat-kilometers (skm) are the supply-oriented measurement of output. De Borger and Kerstens (2008) note that objectives and heterogeneity of public bus transit imply that both supply- and demand-oriented approaches are relevant. We use the former approach since local public transport is a public service obligation with pre-determined service levels that, at least in the short-run, are not open to companies' influence.

For comparability between operators, we use a density index (di) capturing the network characteristics beyond firm's control, e.g., differences in the service accessibility for customers, in speed, and in network complexity. We define di as the ratio of population living in the operating area over the kilometers of network length. A dummy variable (D_{east}) addresses the cost differences between companies operating either in former East German states (D_{east} equals 1) or in West German States. A substantial restructuring of public transport in the newly formed German States, supported by state aid, followed Germany's reunification in 1991 and, hence, affects cost structures.

To determine the firm-influenced subsidies, we use the amount of loss absorption directly paid by the firm owners (shareholders) to balance losses [18]. The subsidy ratio (z_1) is then constructed by the ratio of loss absorption over total costs.

4 Empirical evidence and interpretation

4.1 Regression results

Table 2 provides the regression results for the TRE and the RP models.[19] The obtained results are robust and show significant coefficients with small standard errors.

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[16] The average labor factor price p.a. is 50,616 Euro/FTE in the old West German States, and 36,050 Euro/FTE in former East German states.

[17] The average capital price is 1,133 Euro/seat in rural and 1,563 Euro/seat in non-rural operating areas, respectively.

[18] We also consider withdrawals from equity (reserves) as loss absorption because in our sample, whenever equity withdrawals are observed, the equity was obviously enlarged by the public owner by the exact amount of the deficits that would have been balanced by loss absorption otherwise. Hence, the purpose and nature of those equity withdrawals do not differ from those of loss absorption.

Table 2: Regression results

		TRE model		RP model	
		Coefficient	Std.Dev.	Coefficient	Std.Dev.
Parameters of the cost function					
Constant	α_i	-7.042 ***	0.014	-6.970 ***	0.011
Std.dev. of α_i	σ_α	0.246 ***	0.009	0.190 ***	0.006
Output (Seat-km)	β_Y	0.457 ***	0.019	0.622 ***	0.013
Std.dev. of output	σ_y			0.263 ***	0.009
Capital price	β_{pK}	0.413 ***	0.012	0.415 ***	0.011
Std.dev. of prices	σ_{pK}			0.320 ***	0.013
Output^2	β_{YY}	-0.363 ***	0.020	-0.215 ***	0.015
Capital price^2	β_{pKpK}	0.074 ***	0.019	-0.066 ***	0.023
Output * Capital price	β_{YpK}	-0.285 ***	0.021	-0.185 ***	0.018
Density index	β_{di}	0.042 ***	0.007	0.024 ***	0.006
Dummy east	β_{Deast}	-0.235 ***	0.015	-0.238 ***	0.014
Linear time	β_t	-0.006 ***	0.001	-0.011 ***	0.001
Parameters of the inefficiency function					
Constant of σ_u	δ_0	-4.348 *	2.223	-4.567 ***	1.675
Subsidies ratio	δ_{z1}	1.681 **	0.799	1.906 ***	0.625
Std.dev. of v	σ_v	0.066 ***	0.002	0.043 ***	0.001
Lambda	σ_u/σ_v	0.326		0.483	
Wald test H_0: $\delta_0=\delta_{z1}=0$			5.533 ^{a}		13.879 ^{b}
Loglikelihood function			218		263

Notes: ^{a} p-value = 0.063, ^{b} p-value = 0.001. ***,**,* indicate statistical significance at the 0.01, 0.05, 0.1 level, respectively.

The first order coefficients, β_Y and β_{p_K}, have the expected, positive signs and are statistically significant at the 1% level. Given that all variables of the cost function are in logarithmic form, we can interpret the estimates as cost elasticities. The TRE model shows an output cost elasticity of 0.457 for the mean company, indicating an under-proportional increase of costs when output enlarges. With the same implication of existing economies of scale, β_Y is substantially higher in the RP model (0.622) and exhibits a significant standard deviation of 0.263. Based on the significant standard deviation, our results indicate that cost elasticities vary across the observations meaning that scale economies are not identical, even if all observations belong to the same transportation system, i.e. motor-buses. The capital price coefficients are similar across models (0.413 and 0.415). However, the randomized capital price coefficient in the RP model has a large standard deviation of 0.320. Since the

[19] We conduct the estimation with Limdep 9.0 using 1,000 Halton draws for each model.

price coefficient can be interpreted as the optimal cost share of the individual input factor, σ_{p_K} indicates an optimal input mix that varies across companies. This is likely to be related to firm size and emphasizes the necessity to account for different production structures and operating frameworks.[20] Moreover, varying prices and marginal costs can be explained by the diversity of input virtues. For example, regarding capital diversity, De Borger and Kerstens (2008) mention that bus fleets are heterogeneous in terms of vintages and, therefore, lead to diverse depreciation patterns. They also mention that different drive systems are applied. Even though hybrid power technologies might not have an important impact over the sample period, low-floor technologies, quality improving devices, e.g., air conditioning, and different types of buses, e.g., standard and articulated buses, are relevant. While hybrid technologies might not have important impacts during our sample period, we note that low-floor technologies, quality improvements, e.g., air conditioning, etc. are relevant.

The second order coefficients, β_{YY}, $\beta_{p_K p_K}$, and the interaction coefficients**,** β_{Yp_K}, are statistically significant but do not always show the expected negative sign. The positive coefficient $\beta_{p_K p_K}$ in the TRE model violates the concavity property of cost functions in input prices and suggests a non-cost-minimizing behavior of firms in response to changes in prices. The same result is found in Karlaftis and McCarthy (2002), Farsi et al. (2005), and Farsi and Filippini (2009), who explain it by the considerable barriers of cost-minimizing strategies.[21] Plausibly, these constraints could also apply to the German public local bus transport as a highly state-influenced sector. However, the more flexible technology shows a negative sign of the second-order coefficient $\beta_{p_K p_K}$ and, thus, the RP model satisfies the theoretical requirements of cost functions. Applying the Wald test we cannot confirm the hypothesis of Cobb-Douglas-typed technologies at the 1% level.[22]

For the coefficients of the structural variables, β_{di} and β_{Deast}, both models show consistent implications of the estimates. Commonly, urban transportation systems are characterized by lower average speeds and higher network complexity, which explains the positive sign of the density index coefficient β_{di}. In addition, the coefficient contains some costs associated with network length, e.g., costs for bus stops. Thus, operating areas with a higher population density yield higher costs. The dummy variable's coefficient β_{Deast} implies lower costs for companies operating in eastern Germany. Apparently, restructuring after

[20] The mean share of capital costs in total costs is 55.1% with a standard deviation of 12.6%.

[21] For example, input prices that are constrained by regulation and a less-distinctive sensitivity to price changes in public sectors can be considered barriers.

[22] The test statistics take value of 481 (TRE model) and 217 (RP model) which clearly exceed the critical value of 12.84 at the 0.5% significance level.

German reunification shows a significant cost-reducing impact. The expected negative coefficient value of the linear time is small (0.006 and 0.011), which implies only minor technological advances associated with cost reductions. De Borger and Kerstens (2008) explain the small time trend with the established technology of bus driving, increasing congestion levels impeding performance improvements, and improvements in technical efficiency rather than technological progress.

The focus of this paper is on the heteroscedastic variable, i.e. on the effect of the subsidy ratio on the cost inefficiency's variance. The two models reveal positive and statistically significant coefficients for the subsidy ratio. δ_{z_1} is 1.681 in the TRE model and 1.906 in the RP model which implies an increasing standard deviation in cost inefficiencies for larger z_1. Conducting a Wald test on the heteroscedasticity of the inefficiency's standard deviation fails to confirm the hypothesis of zero values for δ_0 and δ_{z_1} at the 10% significance level in the TRE model and at the 1% level in the RP model. Since efficiency is half-normally distributed, the distribution's probability function flattens with increasing z_1 and the probability mass shifts towards the tail. Therefore, we conclude that the performance range increases when the proportion of subsidies to total costs increases.

4.2 Cost Efficiencies

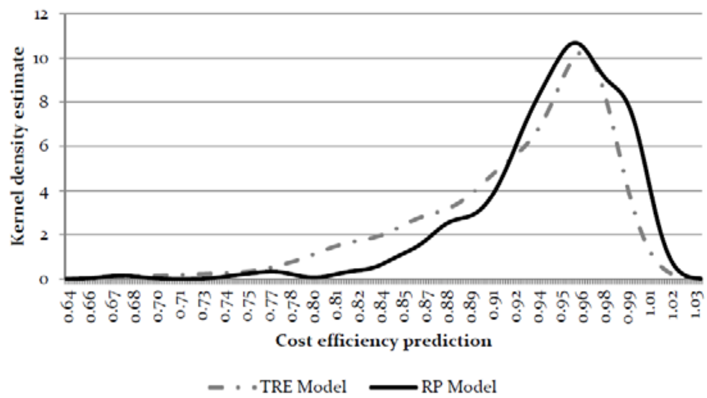
Table 3 shows the characteristics of the predicted cost efficiencies. For the 231 observations considered, the econometric models show an overall mean cost efficiency of 92% and 93% in the TRE model and RP model, respectively. The minimum value of cost efficiency is 69% in the TRE model and 66% in the RP model while the highest is close to 99% in both.

Table 3: Cost efficiency estimates

Model	Mean	Median	Std. Dev.	Min	Max
TRE Model	0.9214	0.9398	0.0582	0.6908	0.9886
RP Model	0.9280	0.9368	0.0475	0.6599	0.9873

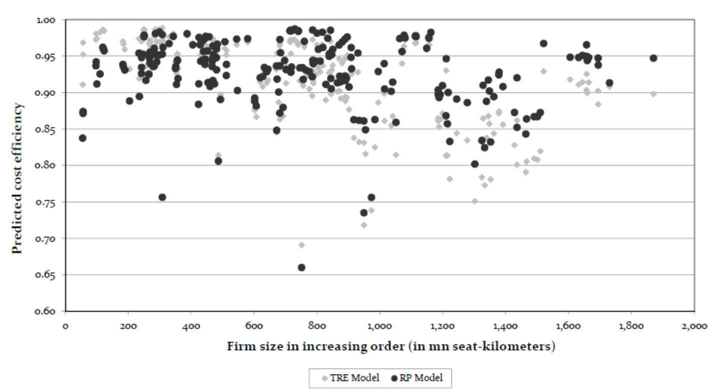
Figure 1 depicts the distribution of the cost efficiency predictions. Both curves support our assumed half-normal distribution of efficiency and so we conclude that the underlying models are appropriate for the given data. However, the probability mass in the RP model is closer to the efficient tail of the distribution representing the model's characteristic of allowing more heterogeneity between companies without attributing the cost differences to inefficiency.

Figure 1: Kernel density of cost efficiency predictions



A detailed look at firm-specific efficiency estimates with respect to firm size in Figure 2 reveals that larger firms especially benefit from the RP model with a more flexible underlying technology. This has two implications. First, there is no clear indication for size-related differences in performance between smaller and larger local public bus operators. Second, the TRE model appears to miss important information on technology characteristics.

Figure 2: Cost efficiency and firm size



Since we are interested to find whether less-subsidized operators perform better, we conduct a Welch test, which compares the mean cost efficiency of two groups while allowing for any underlying distribution of the standard deviation. We divide the companies into two groups where group 1 comprises all observations that record zero loss absorption (95 observations) and group 2 comprises all others (136 observations). The test first calculates the mean cost efficiency of all group members for each group and then tests whether the means differ significantly from each other. The obtained test results are illustrated in Table 4.

Table 4: Welch test on group mean cost efficiency

	Group size	TRE model		RP model	
		Mean	Std. Dev.	Mean	Std. Dev.
Overall mean efficiency	231	0.9214	0.0582	0.9280	0.0475
Mean cost efficiency for group 1 [a]	95	0.9322	0.0050	0.9423	0.0369
Mean cost efficiency for group 2 [b]	136	0.9139	0.0054	0.9181	0.0044
t -value		2.484		4.171	
p -value		0.014		0.000	

Note: [a] indicates that the loss absorption equals zero. [b] indicates that the loss absorption is greater than zero.

Both models consistently show that group 1 performs better in terms of cost efficiency. Those companies with a subsidy ratio of zero achieve a mean cost efficiency of 93.22% and 94.23% in the TRE model and the RP model, respectively, while companies with a positive subsidy ratio achieve mean cost efficiencies of 91.39% (TRE model) and 91.81% (RP model). We cannot confirm the null hypothesis of non-differing mean cost efficiency values, since the respective average values are different at the 5% (TRE model) and at the 1% significance levels (RP model). From this we conclude that operators demanding no subsidies in the form of loss absorption, on average, perform better, i.e. more cost efficient. This coincides for example with De Borger and Kerstens (2008), who conclude from their empirical evidence that subsidies have cost-increasing and performance-worsening effects. Our results extend the empirical evidence of efficiency-decreasing effects of subsidies, which are firm-influenced, target-unspecific, unlimited, and, hence, endogenous.

5 Conclusion

Subsidies are commonly allocated to public bus transportation in order to compensate for exogenously caused cost increases. However, the empirical evidence implies reversing effects of financial supports on costs, i.e. cost increases due to subsidies. Interest in curtailing Germany’s generous public budgets and previous empirical findings spurred our examination of the effect of subsidies on operator performance. We considered loss absorption, i.e. a payment by a public firm owner (cities and counties), who is simultaneously the company operator, to balance deficits from ordinary activities, as endogenous for the following reasons: First, a wide range of subsidies exists to compensate for exogenously caused cost disadvantages. Therefore, further deficits are likely to be related to managerial decisions, e.g. overuse of inputs. Second, losses can be balanced via different accounting treatments. Thus, the utilization of loss absorption also depends on the ability of the companies to balance deficits by equity withdrawals. Third, loss absorption is not determined *ex-ante* but calculated *ex-post* and, therefore, not limited in its extent. Fourth, loss absorption refers to one specific purpose, i.e. deficit balancing.

We hypothesize that bus operators with higher subsidies would perform worse and, thus, exhibit reduced cost efficiencies. Using a heteroscedastic stochastic frontier cost function, we analyze an unbalanced panel of 33 German bus companies observed over a period of twelve years for a total of 231 observations. To estimate the translog cost function, we use two stochastic cost frontier models (true random parameter model and random parameter model) that differ in their ability to allow for varying optimal cost structures among companies. The random parameter model is preferable to the true random parameter model in three respects: First, it achieves a higher loglikelihood function; second, it satisfies the concavity property of the cost function; and third, it shows significant standard deviation coefficients for output and prices. To ignore the latter leaves important information unexploited. The finding of a positive effect of subsidies on the standard deviation of cost inefficiency shows that the inefficiency of local public bus companies is not equally distributed across subsidy levels. Relative to total costs, the larger the subsidies the greater the range of companies' cost efficiency. We also found that German bus companies are more cost efficient when they do not require loss absorption.

The contribution of the paper to the literature is as follows: For the first time, we introduce endogenous subsidies as a heteroscedastic variable directly in the parametric estimation of cost efficiency using frontier analysis. This enables us to account for its endogenous nature in frontier analysis and to demonstrate its impact on efficiency derived in a multidimensional framework. Consequently, we link previous findings on the endogeneity of subsidies and multidimensional performance measurement. For our sample, we find an increasing variation of cost efficiency for an increasing ratio of loss absorption to total costs. Thus, companies perform more differently when the ratio of loss absorption to total costs is high. Further, we provide the first analysis of German local public bus companies with respect to subsidies, which supplements the empirical evidence.

The findings imply that subsidies that are under control of firms can be addressed to decrease subsidies and, therefore, relax public budgets. Particularly those bus companies with high deficit-balancing subsidy shares in costs differ most in their performance. Consequently, the potential to improve cost efficiency is large and attainable also for deficit-making companies as their peers spanning the efficient frontier prove. However, these implications are based on the assumption that wasting resources has no inherent value. This needs to be more explored in future research. Similarly, further research is required to identify where and how exactly the endogeneity of subsidies takes effect and, consequently, creates inefficiency.

Acknowledgement

We thank Pio Baake for fruitful discussions and Anne Neumann, Astrid Cullmann, Christian von Hirschhausen, Arne Beck, two anonymous referees and the participants of the Graduate Center seminar at DIW and the North American Productivity Workshop VI for helpful comments. Further, we thank Marika Geissler, Stefan Seifert, and Samuel Schneider for help with the data collection as well as Adam Lederer and Ann Stewart for excellent proof reading. The usual disclaimer applies.

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