COST EFFICIENCY IN REGIONAL BUS COMPANIES: AN APPLICATION OF ALTERNATIVE STOCHASTIC FRONTIER MODELS*

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Abstract

This paper evaluates cost and scale efficiencies of Switzerland's regulated rural bus companies operating in regional networks. The adopted methodology can be used in benchmarking analyses applied to incentive regulation systems. Moreover, the estimations can be used to evaluate the bidding offers for the tendering processes predicted by the ongoing reform policies. Since these companies operate in different regions with various characteristics that are only partially observed, it is crucial for the regulator to distinguish between inefficiency and exogenous heterogeneity that influences the costs. A number of stochastic cost frontier models are applied to a panel of 94 companies over a 12-year period from 1986 to 1997. The main focus lies on the ability of these models to distinguish inefficiency from the unobserved firm-specific heterogeneity in a network industry. The estimation results are compared and the effect of unobserved heterogeneity on inefficiency estimates is analyzed.

1. Introduction

In many European countries the regional public bus services are being reorganized. In line with the EU policy the Swiss government has introduced important regulatory reforms in the public transport system, including regional bus companies. The new policy act predicts a tendering process for the provision of regional bus services. With the implementation of the new system, the applying companies will bid in competitive auctions and the access rights will be granted to the company with the lowest subsidies request. This system is believed to introduce greater incentives for competitive behavior. However, given the limited number of bidding companies in most regions, it is not clear to what extent the new policies lead to efficient production. Moreover, the incumbents, mostly public companies, might have an advantageous position in such auctions. Benchmarking methods can be used to evaluate the requested subsidies and proposed costs by individual companies or to adjust the minimum bidding prices.

Benchmarking analysis is based on comparing the costs of individual companies to the 'best' (most cost-efficient) observed practice. These deviations, often labeled as 'cost-inefficiency' can also be used to adjust the amount of subsidies paid to individual bus operators. Moreover, predicted costs of the benchmark practice could be used to gain information regarding the future evolution of costs incurred by the companies operating in a service area, and to re-evaluate the claimed subsidies.[1]

In order to use the efficiency estimates of individual companies in regulation, it is important to have precise measurement methods. In particular, because of

[1] See Farsi and Filippini (2004) for a discussion on the use of cost prediction in the regulation of public utilities.

considerable cost differences across various networks, it is crucial to distinguish the cost difference due to unobserved heterogeneity in external factors from the excess costs due to the company's inefficiency. Benchmarking can be conducted using econometric methods such as stochastic frontier models, which have been developed in a variety of forms during the past two decades.[2] All these models in one way or another separate the heterogeneity from cost-inefficiency. Especially, with panel data at hand, the unobserved heterogeneity can be better identified because the time-invariant elements of heterogeneity can be separately specified by firm-specific effects.

The first application of panel data models in stochastic frontier analysis was introduced by Pitt and Lee (1981). These authors formulated the firm-specific error component as a half-normal distribution, which they interpreted as inefficiency. In the following years, several models have been developed to incorporate the observed firm-specific heterogeneity. For instance, Jha and Singh (2001), Piacenza (2002) and Dalen and Gomez-Lobo (2003) use single equation models[3] proposed by Battese and Coelli (1995) to incorporate some exogenous variables to explain the determinants of the inefficiency component in the bus transportation industry. However, most of these models have a shortcoming in that they cannot disentangle firm's inefficiency from cost differences due to unobserved characteristics of the service area. Especially, transport companies operate in networks with different shapes and structures, which result in different coordination problems and thus lead to different costs. These characteristics are usually given and cannot be controlled by the companies. Some of these exogenous factors are either unavailable or too complex to be measured by

[2] Kumbhakar and Lovell (2000) provide an extensive survey of this literature.
[3] For the advantages of single stage models, see Wang and Schmidt (2002).

single indicators. Unfortunately, when unobserved heterogeneity is present the inefficiency estimates can be biased.

Greene (2004, 2005) proposes alternative panel data models, which can better distinguish between unobserved firm-specific heterogeneity and inefficiency. These models extend the previous models by adding an additional stochastic error component for the heterogeneity.[4] Such models are particularly useful in transport industries where the network and environmental characteristics are mostly unobserved or hard to measure, but play an important role on the operating costs.

The purpose of this study is to analyze the performance of different panel data frontier models with regard to estimated coefficients, inefficiency scores and estimates of economies of scale and density. Especially, we focus on the ability of different models to distinguish unobserved heterogeneity from inefficiency. Alternative models are applied to a sample of 94 Swiss rural bus companies from 1986 to 1997. It is concluded that in the studied sample, Greene's "true" random effects model has a considerable advantage over other models in separating heterogeneity from inefficiency.

The rest of the paper is organized as follows: Sections 2 and 3 present the model specification and the methodology respectively. The data are explained in section 4. Section 5 presents the estimation results and discusses their implications, and section 6 provides the conclusions.

[4] A similar model but with a three-stage estimation procedure has been proposed by Kumbhakar (1991) and Heshmati and Kumbhakar (1994).

2. Model Specification

A bus transit company can be considered as a production unit that operates in a given network and transforms labor and capital services and energy into units of transport services. Since in most cases not only the network but also the schedule of a bus operator is regulated and predetermined, it is common to estimate a cost rather than a production function.[5] Different specifications have been used in the literature.[6] Often, output is measured in terms of either passenger- or seat-kilometers. To capture some of the heterogeneity of different service areas, most specifications include additional output characteristics such as the number of stops, network length or average commercial speed. Most of these studies also include a time trend to capture the potential changes in technology.

The total cost frontier can therefore be written as the following function:

$$TC = f(Y, N, P_L, P_C, t), \tag{1}$$

where *TC* is the total annual cost and Y is the output represented by the total number of seat-kilometers. *N* represents the network length. P_C and P_L are respectively the capital and labor prices. We considered an alternative specification including energy prices. The estimated coefficients did not change significantly and the coefficient of the energy price was generally insignificant. Moreover, because of a number of missing values for energy costs a two-input model allows a larger sample. Therefore,

[5] See Berechman (1993) for an overview of the application of cost functions in public transport.
[6] See among others Fazioli et al. (1993), Filippini and Prioni (1994, 2003), Matas and Raymond (1998), Fraquelli et al. (2001) and Fazioli et al. (2003).

we consider labor and capital as the main input factors. However, as we see later, the capital price is calculated from all non-labor expenses, thus includes the variations in energy prices.

It is generally assumed that the cost function given in (1) is the result of cost minimization given input prices and output and should therefore satisfy certain properties namely, linear homogeneity and concavity in input prices and monotonicity in input prices and output.[7] Input prices and output are assumed to be exogenous, thus beyond the firm's control. In the case of Swiss bus transport companies, the municipalities and the cantons specify the output by regulating the frequency of the service. The input prices can also be regarded as given, because these companies have a relatively small share in the labor and capital markets, thus cannot influence the prices through monopsony.

To estimate the cost function (1), a translog functional form is chosen. This flexible functional form is a local, second-order logarithmic approximation to any arbitrary twice-differentiable cost function. It places no *a priori* restrictions on the elasticity of substitution and allows the economies of scale to vary with the output level. The translog approximation to (1) is written as:

$$\begin{aligned}\ln\left(\frac{TC_{it}}{P_{L_{it}}}\right) = {} & \alpha_0 + \alpha_Y \ln Y_{it} + \alpha_N \ln N_{it} + \alpha_K \ln \frac{P_{K_{it}}}{P_{L_{it}}} \\ & + \frac{1}{2}\alpha_{YY} (\ln Y_{it})^2 + \frac{1}{2}\alpha_{NN} (\ln N_{it})^2 + \frac{1}{2}\alpha_{KK} \left(\ln \frac{P_{K_{it}}}{P_{L_{it}}}\right)^2 \\ & + \alpha_{YK} \ln Y_{it} \ln \frac{P_{K_{it}}}{P_{L_{it}}} + \alpha_{YN} \ln Y_{it} \ln N_{it} \\ & + \alpha_{KN} \ln \frac{P_{K_{it}}}{P_{L_{it}}} \ln N_{it} + \alpha_t t,\end{aligned} \tag{2}$$

with *i= 1, 2, ..., N and t = 1,2,...,T,*

[7] For more details on the properties of the cost function, see Chambers (1988), p. 52.

where subscripts i and t denote the company and year respectively. The technical change is specified as a linear trend and is assumed to be neutral with respect to cost minimizing input ratios.[8] The translog form requires that the underlying cost function be approximated around a specific point like the sample mean or median. Here, the sample median is chosen because it is less affected by outliers and thus the approximation will have better precision. As can be seen in equation (2), linear homogeneity in input prices is imposed by dividing total costs and input prices by labor price. The other theoretical restrictions are verified after the estimation.

Apart from estimating cost inefficiency, the estimation of a cost function enables us to derive important characteristics of bus supply technology such as economies of density and scale. The distinction between scale and density economies is particularly important in network industries. In such cases, a company's size is related to both its output level and its network size, which do not necessarily vary with a simple one-to-one relationship. For this reason it is important to distinguish cost changes that occur uniquely because of output changes within a fixed network and cost changes resulting from a proportional change in both network and output.

Economies of density are defined as the inverse of the elasticity of costs with respect to output that is, the relative increase in total cost resulting from an increase in output, holding all input prices and the network size fixed:[9]

$$ED := \left(\frac{\partial \ln C}{\partial \ln y}\right)^{-1} = \left(\alpha_Y + \alpha_{YY} \ln y + \alpha_{YK} \ln \frac{P_K}{P_L} + \alpha_{YN} \ln N\right)^{-1}. \qquad (3)$$

[8] In other words the technical change does not alter the optimal input bundles.
[9] See also Caves, Christensen and Tretheway (1984).

The existence of economies of density implies that the average costs of a bus operator decrease as physical output increases. Economies of density exist if the above expression (*ED*) has a value greater than one. For values of *ED* below one, we identify diseconomies of density. In the case of *ED* = 1, the company's output minimizes its average costs given the network's size.

Slightly different is the definition of economies of scale (*ES*). Here, the increase in total costs is brought about by an increase in company's scale that is in both output and the network size, holding the factor prices constant. However, since the changes in output and network size are inter-related, the definition of scale economies requires an assumption in this respect. The commonly used definition is the one proposed by Caves, Christensen and Tretheway (1984), which assumes that any increase in size raises the network size and the outputs with the same proportion. Based on this assumption, *ES* is defined as:

$$\begin{aligned} ES &:= \left(\frac{\partial \ln C}{\partial \ln y} + \frac{\partial \ln C}{\partial \ln N} \right)^{-1} \\ &= \left(\alpha_Y + \alpha_{YY} \ln y + \alpha_{YK} \ln \frac{P_K}{P_L} + \alpha_{YN} \ln N + \alpha_N + \alpha_{NN} \ln N + \alpha_{YN} \ln y + \alpha_{KN} \ln \frac{P_K}{P_L} \right)^{-1}. \end{aligned} \tag{4}$$

Similarly, economies of scale exist if *ES* is higher than 1.

It should be noted that the above definitions of scale and density economies are in terms of cost elasticity and do not necessarily correspond to the definitions derived from the production function. In fact, only in homothetic production functions, where the optimal input bundles vary proportionately, the two definitions are equivalent. Here, we do not impose such an assumption. However, as in this paper we are interested in the cost effects of output, we define the scale and density economies as the inverse of the corresponding cost elasticities.[10]

3. Methodology

The effects of unobserved heterogeneity on inefficiency estimates are studied by a comparative analysis of four econometric models. These models are a pooled cross section model in line with Aigner, Lovell and Schmidt (1977); a random effects model as in Pitt and Lee (1981); a fixed effects model as in Schmidt and Sickles (1984); and a random intercept frontier model (also known as "true" random effects model) proposed by Greene (2004, 2005). The deterministic part of all models is based on the specification given in equation (2).

Model *I* (Aigner, Lovell and Schmidt, 1977) is a pooled frontier model, in which the error term is divided into two components: a normally distributed error v_{it}, capturing general measurement errors and heterogeneity and a half-normal random term u_{it}, representing the inefficiency as a one-sided non-negative disturbance This model can be written as:

$$\ln TC_{it} = \alpha_0 + \mathbf{x'_{it}\beta} + v_{it} + u_{it}, \qquad (5)$$
$$\text{where } \mathrm{v_{it}} \sim iid\ N(0,\sigma_v^2) \text{ and } u_{it} \sim iid\ N^+(0,\sigma_u^2).$$

$\alpha_0 + \mathbf{x'_{it}\beta}$ represents the deterministic part of the cost function as in equation (2), and $N^+(0,\sigma_u^2)$ stands for the positive part of a normal distribution. Both error components are assumed to be uncorrelated with each other and the regressors. This

[10] See Chambers (1988) for more details about this issue. To avoid confusion this author refers to the inverse of cost elasticity as the "economies of size" rather than economies of scale (see page 72).

model is estimated by Maximum Likelihood and the inefficiency component is estimated from the residuals $\varepsilon_{it} = v_{it} + u_{it}$ by the conditional expectation $E(u_{it} \mid \hat{\varepsilon}_{it})$, proposed by Jondrow et al. (1982). In this model, the observations of a same company are considered as independent sample points. Therefore, the panel structure of the data is completely ignored. This issue can be addressed by considering a random effects model (model *II*) as in Pitt and Lee (1981). Similar to model *I*, a normal-half-normal composite error term is considered. The difference is that here, the observations for a specific company possess a common error component. This model can be formulated as:

$$\begin{aligned} &\ln TC_{it} = \alpha_0 + \mathbf{x'_{it}\beta} + v_{it} + u_i, \\ &\text{where } \mathrm{v_{it}} \sim iid\ N(0,\sigma_v^2) \text{ and } u_i \sim iid\ N^+(0,\sigma_u^2). \end{aligned} \tag{6}$$

The model is estimated by Maximum Likelihood method. The firm-specific inefficiency is estimated using the conditional mean of the inefficiency term (u_i) proposed by Jondrow et al. (1982),[11] that is: $\mathrm{E}\left[u_i \mid \hat{\varepsilon}_{i1}, \hat{\varepsilon}_{i2}, .., \hat{\varepsilon}_{iT}\right] = \mathrm{E}\left[u_i \mid \overline{\varepsilon}_i\right]$, where $\varepsilon_{it} = u_i + v_{it}$ and $\overline{\varepsilon}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} \hat{\varepsilon}_{it}$.

A limitation of this model is the assumption that the firm-specific stochastic term is assumed to be uncorrelated with the explanatory variables. In fact, most frontier models assume that inefficiency is uncorrelated with explanatory variables included in the cost function.[12] However, the firm-specific term (u_i in this model) may also contain other unobserved environmental factors, which may be correlated with explanatory variables and thus may bias the coefficients. For example, larger networks are likely to be more spread, thus incur higher coordination and

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[11] See also Greene (2002a).

[12] This assumption can be justified based on the fact that the apparent excess costs that are correlated with exogenous variables may be due to factors beyond the firm's control.

maintenance costs. In this case as the overall spread of the network is not observed, its positive correlation with the network's size may create an upward bias in the coefficient of the network's size. .

The fixed effects model (model *III*) can overcome this heterogeneity bias problem, by taking the firm-specific effects as constants. In this model the estimated coefficients are unbiased even in the presence of such correlations. The inefficiency estimates are obtained using the procedure proposed by Schmidt and Sickles (1984). This model is given by:

$$\ln TC_{it} = \alpha_0 + \mathbf{x'_{it}\beta} + v_{it} + u_i, \tag{7}$$

where $\mathrm{v_{it}} \sim iid\ (0,\sigma_v^2)$, and $u_i = \alpha_i - \alpha_0$. The firm-specific α_i's are the so-called fixed effects.[13] The model can therefore be re-written as:

$$\ln TC_{it} = \alpha_i + \mathbf{x'_{it}\beta} + v_{it}. \tag{8}$$

This model is estimated by applying Ordinary Least Squares. The positive inefficiency scores are then calculated as $\hat{u}_i = \hat{\alpha}_i - \min_i(\hat{\alpha}_i)$. From this expression, it can be seen that the company with the smallest firm-specific component is regarded as fully efficient and defines the common intercept: $\hat{\alpha}_0 = \min_i(\hat{\alpha}_i)$.

Finally, Greene's true random effects model (model *IV*) is an extension of Aigner et al.'s frontier model that includes an additional time-invariant random term to capture the firm-specific heterogeneity effect on cost by a random intercept component. It can be written as:

$$\begin{aligned} &\ln TC_{it} = \alpha_0 + \alpha_i + \mathbf{x'_{it}\beta} + v_{it} + u_{it}, \\ &\text{where} \\ &\alpha_\mathrm{i} \sim iid\,N(0,\sigma_\alpha^2),\ v_{it} \sim iid\,N(0,\sigma_v^2) \text{ and } u_{it} \sim iid\,N^+(0,\sigma_u^2). \end{aligned} \tag{9}$$

[13] See Hsiao (2003) for details.

As before, all distributions are assumed do be independent from each other and from the regressors. This model is estimated using Simulated Maximum Likelihood method.[14] The inefficiency is estimated using the conditional mean of the inefficiency term (u_{it}) given by $\mathrm{E}\left[u_{it} \middle| \hat{\omega}_{it}\right]$, where $\omega_{it} = \alpha_i + \varepsilon_{it}$.[15]

Aigner et al.'s model (model *I*) is formulated as a cross sectional model and thus, ignores the panel aspects of the data. This might lead to inaccurate results due to misspecification by ignoring firm-specific unobserved factors. In the true random effects model (model *IV*), this problem is addressed by including a separate stochastic term for firm-specific heterogeneity. Such heterogeneity is also accounted in the fixed and random effects models (models *II* and *III*). However, both these models impose additional restrictions that might affect the inefficiency estimates. In fact in both models, the firm-specific unobserved effects are interpreted as efficiency differences. Moreover, inefficiency is assumed to be constant over time. Both these assumptions might be quite restrictive. Given that in network industries, a considerable part of the unobserved factors are related to the network complexity and are beyond the firm's control, thus cannot be considered as firm's inefficiency. As the time-invariant part of unobserved heterogeneity is primarily captured by the firm-specific effects, the inefficiency estimates are likely to be biased in these models. As for the second assumption, both economic theory and empirical evidence suggest that cost-inefficiency varies with time. New technology shocks and learning are among the reasons why inefficiency varies over time and across individuals. Using a translog production function, Alvarez, Arias and Greene (2003) have shown that even in cases

[14] See Greene (2001, 2005) for a discussion of the estimation method. For the simulation, 100 Halton draws were used. Our estimations with higher numbers of draws showed that the results are not sensitive to the number of draws.
[15] See Greene (2002a) for more details.

when the management's efficiency is constant, the technical efficiency could vary with time.[16] Moreover, the assumption of time-invariant inefficiencies is not realistic in a relatively long panel such as our sample.

The true random effects model does not require any of these assumptions. However, if the firm-specific heterogeneity is correlated with the explanatory variables, the estimated parameters of the cost function might be biased. In another paper (Farsi, Filippini and Kuenzle, 2003), we proposed an adjustment based on Mundlak (1978)'s formulation to reduce the possible biases in this model.[17] However, in the present study, our analysis (not reported here) indicates that the estimation results are fairly close with or without this adjustment. Thus, we decided to focus on the model without adjustment. With two heterogeneity terms, this model is expected to provide a better distinction between inefficiency and other unexplained variations. This advantage is especially important in network industries, in which a significant part of unobserved differences is due to time-invariant factors.

In our comparative analysis we consider two aspects of the models' performance. The first dimension is the estimation of the cost function's coefficients. In cases such as bus companies (or in general network industries), explanatory variables and costs can be influenced by a number of unobserved network characteristics. For instance, increasing density of stops will increase the costs due to higher infrastructure expenditures, or a ramified network will lead to a higher labor and capital demand than a single-line network. But longer networks might be relatively more complex, in which case complexity is an unobserved factor that is correlated with the network length. A Hausman test is used to confirm that the firm-

[16] In translog form this time variation is due to interaction of time-invariant inefficiency with explanatory variables.
[17] See also Farsi, Filippini and Greene (2004) for an application of this method in railway companies.

specific effects are correlated with the explanatory variables.[18] In this case a fixed effects estimator would be unbiased and could thus be used as a benchmark. Therefore, the extent of heterogeneity bias across different models can be compared according to the overall distance of their parameter estimates with respect to those of the fixed effects model.

One can argue that models with more general error structures, such as model *IV*, have lower biases because the residuals can capture a larger part of the correlations between unobserved heterogeneity and explanatory variables, thus leaving the coefficients less affected. However, the residuals are by definition uncorrelated with explanatory variables and the extent to which they may confound such correlations with errors may significantly vary from one sample to another. Especially, since the frontier estimators are non-linear, the prediction of the biases is not straightforward. This theoretical discussion is beyond the scope of this paper. Here we rather focus on the evaluation of the models with respect to our sample.

The second aspect of the models' performance concerns the estimation of inefficiency scores. The specification of inefficiency in each model relies on certain assumptions on its error components, which do not violate the consistency of estimated parameters. Therefore, an unbiased estimation of the cost function is not a sufficient condition for a reliable estimation of inefficiency.[19] Given that the "real" inefficiency scores are not known, a high correlation between the inefficiency estimates from different models is usually considered as an indication of the validity of individual approaches. However, as we will see, our results show a rather weak

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[18] This test performed on a GLS random effects model (not reported here), rejects the hypothesis of nocorrelation between regressors and firm effects.
[19] See Farsi and Filippini (2004) for an example of overestimation of inefficiency in the fixed-effects model, which in principle gives unbiased estimates of cost function's coefficients.

correlation. Therefore, our assessment of various models relies on plausibility arguments.

In particular, the purpose of this paper is to study whether the true random effect model can help solve some of the mentioned problems. It should be noted that the validity of the results depends on the study sample and may vary from one case to another. Therefore, our purpose is not to identify a unique all-purpose model. Rather, our comparative analysis highlights in each one of the models, the effect of unobserved heterogeneity on inefficiency estimates.

4. Data

The data used in this paper are extracted from the annual reports of the Swiss Federal Office of Statistics on public transport companies. The companies operating in main urban centers are excluded from the sample. Most of these companies operate both inner-city tramways and buses, whose functioning is quite different from rural bus transport. Our data set includes information on all the 170 rural companies operating in Switzerland during the study period. However, the data is not available for all years. In several cases lack of information is due to closure or merging with other companies. We decided to exclude the companies that have fewer than four observations.[20] That is, all the companies in the final sample have at least four years of non-missing data. Therefore companies that were closed or taken over by other companies after a short period of operation are excluded. Obviously, such companies are not comparable with other companies because their closure may have been related

[20] We also dropped one observation that we suspected as erroneous because of extremely low reported total costs compared to the same company's total costs reported in other years.

to their excessive costs or other peculiar reasons. Moreover, since the panel models used in this study require in one way or another the estimation of firm-specific effects, four observations per firm appears to be a reasonable minimum. We also excluded Swiss Post[21] and all its sub-contractors from the sample, because a considerable part of these companies' revenues is related to package transport and other postal services. Therefore, all the companies included in the sample are mainly involved in passenger transport.

The final data set is an unbalanced panel with 985 observations including 94 operators over a 12-year period from 1986 to 1997. The number of periods per firm varies from 4 to 12 with an average of 10.5 years. The available information includes total costs, total number of employees, network length, total numbers of bus-kilometers and passenger-kilometers as well as those of buses and seats. Table 1 provides a descriptive summary of the main variables used in the analysis.

The variables for the cost function specification were calculated as follows. Total costs *TC* are calculated as the total expenditures of the bus companies in a given year. The output *Y* is measured by the number of seat-kilometers, which is calculated by multiplying the total number of bus-kilometers in any given year by the average number of seats per bus in that year. It should be pointed out that this calculation is based on the assumption that the number of seats in a bus does not vary considerably in a given company's fleet in a given year. This is a reasonable assumption because a typical bus company in Switzerland possesses a uniform fleet. Generally, in order to reduce their maintenance costs, companies purchase their vehicles in large quantities from the same supplier and the same model. The number of seats includes both sitting and standing places. In other studies such as Windle (1988), Bhattacharyya et al.

[21] Swiss Post, a public company funded by the federal government, mainly in charge of mail delivery and financial services, operates public transport in about 60% of Switzerland's rural bus network.

(1995) and Jha and Singh (2001), the number of passenger-kilometers is used as output. However, since in Switzerland the rural buses are rarely running at full capacity and they have to run according to the frequency set by the regulators, a considerable number of seats are likely to be empty in a typical bus travel during an off-season period. Therefore, the number of passenger-kilometers is not a representative measure of output. Alternatively, several authors like Berechman (1987), Matas and Raymond (1998) and Fazioli et al. (2003), use bus-kilometers as the output measure. Given that the average vehicle size is likely to vary across different bus companies in our sample, this measure can distort the output in favor of companies with smaller thus less costly buses. The number of seat-kilometers measures the kilometers traveled by the fleet capacity, which is not sensitive to occupancy rate and at the same time account for the variation of vehicle size across companies. In Switzerland the minimum required frequency of bus services (set by the communities) does not considerably change with the actual occupancy rates. Especially in remote areas, it is not unusual that buses occasionally run with few passengers. Therefore, we contend that in the context of Switzerland's rural bus systems, this measure is more relevant for cost estimations.[22]

[22] In any case, the three mentioned output measures are highly correlated in our data and our preliminary estimations suggest that the results are similar regardless of the adopted measure.

Table 1: Descriptive statistics based on 985 observations

Variables	Mean	Standard Deviation	1. Quartile	Median	3. Quartile
Total annual costs (TC) Thousand CHF	3106	4802	425	1270	3410
Output (Y) Thousand seat-kilometers	47986	85556	5715	16403	53127
Network length (N) km	43	70	13	26	55
Capital price (P_C) CHF/Seat	1343	606	927	1225	1612
Labor price (P_L) CHF per employee per year	80749	27133	66417	80872	91586
Number of seats	1067	1721	184	439	1215
Number of employees	22	35	3	9	23

- All monetary values are in 1997 Swiss Francs (CHF), adjusted for inflation using Switzerland's consumer price index.

Input prices are defined as factor expenditures per factor unit. Labor price (P_L) is defined as the ratio of annual labor costs to the total number of employees.[23] Following Friedlaender and Chang (1983), the capital price (P_C) is calculated as residual cost divided by the total number of seats (both standing and sitting), where residual cost is total cost minus labor cost.[24] Unfortunately, we do not have the required data to calculate the capital stock using the capital inventory method. The use of a simple indicator is justified by the fact that the bus companies do not possess a significant stock of capital apart from the rolling stock, which could be considered as a relatively uniform stock. All the costs and prices are adjusted for inflation using the Switzerland's consumer price index and are measured in 1997 Swiss Francs. The network length is also included in the explanatory variables as an output characteristic. It is expected that due to organization and coordination problems, all

[23] Given the range of variation of salaries in the data we can safely assume that a large majority of the employees in our sample are full-time.
[24] See also Filippini and Prioni (2003) for a similar approach.

other factors being constant, longer networks are expected to be more costly. Other output characteristics such as the number of stops per kilometer of network were initially considered. However, given that these variables and some of their interactions proved to be highly correlated with other explanatory variables, we decided to exclude them from the equation to avoid the possibility of multi-collinearity.[25]

5. Estimation Results

The estimation results for the four models are given in table 2. These results show that the output and input price coefficients are positive and highly significant across all models. The estimated coefficient of output from the pooled model (*I*) is particularly different from those of other models. Noting that model *I* completely ignores the panel structure of the data, its estimates are likely to be biased through omitted firm-specific factors.

Since total costs and all the continuous explanatory variables are in logarithms and normalized by their medians, the estimated first order coefficients can be interpreted as cost elasticities evaluated at the sample median. For instance, the output coefficients suggest that on average a one percent increase in seat-kilometers will increase the costs by about 0.25 to 0.73 percent depending on the adopted specification. The cost elasticity of the network length is as expected positive (α_N) and significant. This implies that the increase in network length will increase total

[25] We only dropped the variables that had extremely high correlation with other variables (the correlation coefficient of about 0.99). The omission of these variables would not significantly bias the results, because their effects are captured by other variables. However, including such variables creates a near-singularity problem, which might cause high estimation errors.

costs. This result is consistent with previous empirical studies such as Filippini and Prioni (1994, 2003) and Windle (1988).[26]

The median cost elasticity with respect to the factor price is positive and of similar magnitude in all models. The estimated coefficient for capital price (α_{PC}) represents the share of costs attributed to capital at the median production unit, which varies from 51 to 54 percent depending on the model. This result is more or less consistent with the actual data that show a capital share of about half for the sample median. Additionally, the estimated cost function is concave[27] in input prices suggesting that the companies have a cost-minimizing behavior in response to changes in prices.

The coefficient of the linear time trend is significant and positive in all models except in model *I*, which shows an insignificant effect. These results suggest an annual increase of about 1% in total costs. This result can be explained by the fact that the production technology has not much changed in bus transport. The increase in costs may be related to higher quality of service and increased security requirements.

Although the Hausman specification test's results suggest that the firm specific effects in a GLS model are correlated with the regressors, the results in table 2 indicate that most of the coefficients do not vary considerably across models *II*, *III* and *IV*. In particular the estimated coefficients of model *IV* are within a reasonable range of the unbiased estimates of the fixed effects model. Several likelihood ratio tests[28] were performed to test whether the cost function coefficients are similar across models. As expected model *I*, that ignores the panel structure of the data, is

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[26] It should be noted that Filippini and Prioni (2003) studied the Swiss bus systems though using a different sample in a shorter time period and without cost frontier models.

[27] In this context the concavity condition reduces to $\alpha_{PCPC} \leq 0$.

[28] In the case of true random effects model, as the likelihood function is simulated, a Wald test was used instead. Note that the two tests are asymptotically equivalent.

significantly different from all other models. These tests also suggest statistically significant differences across the other three models. However, these differences are mainly limited to the output coefficient (α_Y). In fact, a test on the similarity of all other coefficients was not rejected at p=.05, suggesting that apart from the output coefficient the estimated cost function is similar across these three models.

Table 2: Regression results

Coefficient	*Model I* **Pooled**	*Model II* **RE (ML)**	*Model III* **FE**	*Model IV* **True RE**
α_Y	0.734* (0.013)	0.326* (0.040)	0.247* (0.024)	0.351* (0.009)
α_N	0.122* (0.019)	0.244* (0.023)	0.240* (0.033)	0.264* (0.018)
α_{PC}	0.512* (0.025)	0.535* (0.008)	0.540* (0.015)	0.525* (0.006)
α_{YY}	0.079* (0.018)	-0.027* (0.009)	-0.010 (0.018)	0.014* (0.004)
α_{NN}	0.083* (0.042)	0.063 (0.054)	0.027 (0.064)	0.119* (0.016)
α_{PCPC}	-0.162* (0.041)	-0.262* (0.015)	-0.264* (0.025)	-0.278* (0.013)
α_{YN}	0.003 (0.026)	-0.026 (0.023)	-0.026 (0.032)	-0.094* (0.010)
α_{YPC}	-0.067* (0.029)	-0.095* (0.009)	-0.098* (0.016)	-0.115* (0.006)
α_{NPC}	0.129* (0.042)	0.093* (0.011)	0.102* (0.024)	0.116* (0.008)
α_T	-0.005 (0.003)	0.011* (0.001)	0.015* (0.002)	0.010* (0.001)
α_0	-0.275* (0.030)	-1.085* (0.040)	-1.458* (0.108)	0.054* (0.011)
σ_α	-	-	-	0.526* (0.011)
$\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$	0.433* (0.0004)	1.306* (0.387)	-	0.163* (0.002)
$\lambda = \sigma_u / \sigma_v$	1.038* (0.090)	9.738* (3.464)	-	0.980* (0.034)

- Standard errors are given in brackets. * means significantly different from zero at least at 5%.

Table 3 provides a descriptive summary of the inefficiency estimates from different models. These estimates represent the relative excess cost of a given firm compared to a minimum level that would have been achieved if the firm had operated as efficiently as the 'best practice' observed in the sample, since $u_{it} = \ln TC_{it} - \ln \widehat{TC}_{it}$, were $\widehat{TC}_{it}$ are the predicted costs of the regression model, including the random error term v_{it}.[29] In comparing different models it should again be stressed that models *II* and *III* assume constant inefficiency over time. Moreover, in these models all the unobserved firm-specific differences are interpreted as inefficiency. As expected, model *II* and *III* predict rather implausible inefficiency scores averaging about 1.15 and 1.46. At their face values these numbers suggest an excess cost of more than 100 percent for a typical company. These high values indicate that the heterogeneity across companies is an important driver of cost differences and that neglecting it may create a substantial upward bias in inefficiency scores.

In model *I* the inefficiency estimates are in a more realistic range, with an average of 0.25 and a maximum value of 0.73. These values, though still arguably quite high, are substantially lower than those predicted by models *II* and *III*. However, the inefficiency scores obtained from model *I* are likely to be overestimated, because in fact they might capture some of the network-specific unobserved heterogeneity, which is not accounted for separately. Model *IV*, which has two separate stochastic terms for inefficiency and firm-specific heterogeneity, has inefficiency estimates of about 0.09 on average, which stands for a cost saving potential of about 9 percent.[30] Although the maximum value of 0.47 appears as excessive, this model's results

[29] Note that cost efficiency can be alternatively defined as the optimal costs divided by actual costs that is, $CE = \exp(-u)$, where u is the relative excess cost given in table 3.
[30] This result is consistent with the average inefficiency levels reported in Dalen and Gomez-Lobo (2003) for the Norwegian bus industry.

suggest that in 95 percent of the cases the relative excessive cost is below 15 percent. The high value of estimated inefficiency in the remaining 5 percent can be explained by statistical errors. Therefore, compared to the other models the inefficiency estimates from model *IV* are plausible and remain within a reasonable range of variation.

Table 3: Inefficiency measures

	Model I Pooled	*Model II* RE (ML)	*Model III* FE	*Model IV* True RE
Mean	0.249	1.147	1.457	0.090
Median	0.228	1.070	1.408	0.082
Maximum	0.732	2.825	3.383	0.473
95th Percentile	0.472	2.316	2.854	0.153
Minimum	0.042	0.031	0	0.019

The pair-wise correlation coefficients between the inefficiency estimates from different models are listed in table 4. In order for the correlation coefficients to be comparable, they are calculated at the firm level using 94 observations (one observation for each firm). Namely, in models with time-variant efficiency, the inefficiency score is calculated as the firm's average inefficiency score over the sample period. For models with time-variant inefficiency the correlation coefficients are also given over the total of 985 observations. As expected, in most cases the correlation coefficients are rather low, suggesting substantial differences across models. Some of these differences can be explained by large sampling errors incurred for the estimation of inefficiency for individual companies, especially in cases where the inefficiency can vary with time. This problem for cross-sectional data and short panels is documented by Horrace and Schmidt (1996), Street (2003) and Jensen

(2000). Obviously, to the extent that inefficiencies remain constant over time, a longer panel can help. Nevertheless, the assumption of constant inefficiency can be unrealistic in long panels.

However, the weak correlation between efficiency estimates across different models suggests that these models differ not only with respect to individual companies' inefficiency scores but also give significantly different efficiency rankings.[31] In particular, model *IV* shows a negative correlation with models *II* and *III* and a weak positive correlation with model *I*.[32] Such weak correlation implies that the individual companies might get completely different evaluations depending on the adopted model. To the extent that model *IV* is a legitimate model that separates unobserved heterogeneity from inefficiency, these results suggest that other models might give a misleading assessment of individual companies. For instance, our estimations show that the company regarded as fully efficient in the fixed effects model (model *III*), is a company that operates in a relatively short network with a single line. However, this company's relatively low costs might be related to its simple network, rather than high efficiency. This explanation is consistent with the results of the true random effects model (model *IV*) that ranks the same company as highly inefficient.[33]

As table 4 shows, the high correlation between inefficiency estimates from models *II* and *III* (coefficient of .987) is a striking exception to the rule. This result can be explained by the fact that the inefficiency estimates in both models mainly represent the network-specific heterogeneity. Therefore, the high correlation between

[31] The rank correlations show a pattern similar to table 4. These results are omitted to avoid repetition.
[32] All three coefficients are significantly different from zero at 5% significance level.
[33] Model *IV* suggests that with an inefficiency score of about 10%, this company is less efficient than the average company in the sample.

these two models can only suggest that the estimation of unobserved network effects is not much sensitive to whether fixed or random effects specification is used.

Table 4. Pair-wise Pearson correlation between inefficiency estimates

	Model I Pooled	*Model II* RE (ML)	*Model III* FE	*Model IV* True RE
Model l	1			
Model II	0.496	1		
Model III	0.426	0.987	1	
Model IV	0.083 (0.371)	-0.082	-0.098	1

- The correlation coefficients have been estimated over the firms (94 observations).
- Correlation coefficient based on 985 observations is given in brackets.

To further test whether the inefficiency estimates differ across various models a series of t-tests have been performed. The results unequivocally reject the hypothesis that the inefficiency estimates across any pair of models are on average identical. Table 5 shows the estimates of scale and density economies as given in equations (3) and (4), obtained from different models. The results are listed for three representative companies at the first quartile, median and the third quartile outputs. We identified the median ($1^{st}/3^{rd}$ quartile) company as the company that produces the sample median ($1^{st}/3^{rd}$ quartile) of the number of seat-kilometers and considered that company's corresponding network length in the estimation of density and scale economies.[34] Since the factor prices are assumed to be exogenous, they are held constant at their median values for all three cases.

[34] We considered alternative definitions for representative companies, e.g. median of both output and network. However, the results are mainly the same insofar as the following discussion is concerned.

Table 5. Economies of scale and density estimates

	Model I Pooled	*Model II* RE	*Model III* FE	*Model IV* True RE
ED at 1st Quartile	1.545	2.592	3.468	2.224
ED at Median	1.370	2.780	3.571	2.115
ED at 3rd Quartile	1.208	3.544	4.485	3.086
ES at 1st Quartile	1.500	1.719	1.910	1.490
ES at Median	1.343	1.915	2.059	1.713
ES at 3rd Quartile	1.008	1.907	2.248	1.879

The results listed in table 5 show a considerable amount of variation between different models. As can be seen in this table, both economies of density and scale are greater than one in all three representative cases, suggesting the presence of unexploited economies in most companies in the sample.[35] In particular, the relatively high values of density economies indicate that a more intensive use of a given network would considerably lower the average cost per seat-kilometer. However, it should be noted that the intensity of demand in a given network is beyond the company's control. An increase in output usually requires some extension in the network, which can be represented by scale economies.

The estimated scale economies from all models also suggest the existence of considerable potential for cost saving through extending the networks. As expected, the economies obtained from an increase in output density in a given network (density economies) are relatively higher than those gained by extending a company's network (scale economies). The presence of unexploited scale economies in all three

[35] Only the estimated value of economies of scale for the third quartile for the pooled model is not significantly different from one.

representative cases suggests that most companies are smaller than the cost-minimizing size at which such economies are fully utilized. The small size of rural bus companies in Switzerland is related to the development of this industry that has been historically associated with the growth of small and fragmented user communities.

The high variation of scale and density economies across various models (see table 5) can be partially explained by the models' differences with respect to the unobserved network effects. If these effects are correlated with explanatory variables (such as output and network length) the values obtained from the fixed effect model (model *III*) are unbiased and those of the other three models are biased. Particularly, the values estimated by the pooled model (model *I*) are likely to be biased downward. This model's estimates are comparable to those reported by Filippini and Prioni (2003), who applied a cross-sectional cost-frontier model to a panel data of 34 bus companies in Switzerland. In one of their specifications, the median company's size (about twice as our sample median) has been found to be very close to the cost-minimizing size. These results suggest that ignoring the unobserved firm-specific effects can bias the estimated coefficients. In fact such biases are driven by possible correlation of unobserved effects with output and network length. For instance it is plausible that larger networks are more complex in terms of unobserved factors, thus more costly. Such correlations are likely to be positive, thus lead to an underestimation of scale economies.

Theoretically, an unbiased estimation of scale and density economies can be obtained from the fixed effect model (*III*), because it allows with the regressors correlated firm specific effects. If such correlation is present and positive, then the coefficients of model *II* and *IV* are biased upwards. However, because of the large number of parameters in this model (at least as many as the companies in the sample), the precision of the results depends on the number of periods in the sample and the companies' output variation over the sample period. As indicated in table 2, the coefficients of most of the second order terms are statistically insignificant in this model. This can be explained by the relatively high standard errors in the fixed effects model. Therefore, estimated economies of scale and density for the fixed effects model might be imprecise.

Interestingly, model *I* predicts a decreasing scale and density economies with output, which appears to be consistent with the common perception that sources of scale economies are exhaustible. However, models *II* to *IV* suggest that if the unobserved heterogeneity is taken into account, this result may be reversed. As table 5 shows, according to these models, the unexploited scale and density economies are greater in relatively large companies in the sample. This result can be explained by some of the special features in relatively small network industries: Noting that the smallest companies in our sample are bus companies with a single line and a few employees, the potential gains of increasing the size are limited to savings in distributing the same fixed costs over a higher output. On the other hand, large companies have complex multiple-line networks. By increasing their size, such companies can benefit not only from savings in the fixed costs but also from a better possibility of reallocation of input factors over the network, thus reducing their variable costs.

6. Conclusions

The application of alternative cost frontier models to a panel of rural bus companies in Switzerland indicates that the inefficiency estimates are sensitive to the adopted model. From a methodological point of view, the results largely depend upon how the unobserved firm-specific heterogeneity among firms is modeled. Our comparative analysis suggests that models that do not distinguish between unobserved network effects and inefficiency can overestimate the inefficiency scores. In particular, if the inefficiency estimates are derived from the firm-specific effects (cf. Schmidt and Sickles, 1984 and Pitt and Lee, 1981), they include an important part of the unobserved exogenous factors related to the network. Our sample shows that such factors can account for a considerable part of cost differences, thus bias the inefficiency estimates to implausibly high values.

This paper also highlights possible differences in cost function coefficients across models. A (pooled) cross-sectional model does not account for network heterogeneity. Since such heterogeneity is likely to be correlated with some of the explanatory variable, this model can give biased coefficients. A fixed effect model can solve the heterogeneity bias in the coefficients. However, because of the large number of parameters (incidental parameters problem), this model might lead to relatively large estimation errors especially for the second-order terms of the cost function. These latter coefficients might be important for the estimation of scale and density economies.

This study suggests that an econometric specification that includes separate stochastic terms for firm-specific effects and inefficiency can improve the estimations regarding both inefficiencies and slopes. We considered a random-constant cost frontier model ("true" random effects model) proposed by Greene (2004, 2005). The results indicate that the main coefficients of the cost function are fairly close to the unbiased estimators obtained from the fixed effects model. Given that we do not have the true values of efficiency, we cannot conclude the validity of any model regarding inefficiency estimates. However, our analysis suggests that while conventional models could give implausible estimates, the true random effects model's estimates are within a reasonable range. These results underscore the importance of modeling unobserved firm-specific heterogeneity in efficiency measurement of network industries.

The results also indicate that the unexploited scale economies might be greater for relatively large companies, which can benefit from better possibilities of reallocation over larger networks. Such effects could be masked by unobserved network factors, which if neglected could lead to inaccurate results. It should be pointed out that the results of this paper are valid for the specific sample used here and cannot be directly extended to other cases.

From a policy point of view, this study suggests that the "true" random effects model could be a valuable alternative for setting a benchmark in regulating network industries. However, it has to be emphasized that a mechanical use of any of these models in regulation could be misleading. Since each industry has its specific cost characteristics that are not equally well reproduced by these models, establishing a reliable benchmark requires a careful analysis of the cost structure of the industry under consideration. Consequently, these models should be used as one among different instruments in the assessment of subsidy requests.

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