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Regulatory contracts and cost efficiency in the Norwegian Bus Industry: Do high - powered contracts really work?[ψ]

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Abstract
In this paper we investigate the effects of different regulatory contracts on operational cost performance for Norwegian urban transport companies. Exploiting the panel nature of our data (11 years and 1136 company-year observations), we propose a method to estimate regional time varying inefficiency measures that overcomes some of the shortcomings of existing approaches. In particular, the proposed method does not restrict the time pattern of the inefficiency measure (as in Liu (1993)) and, unlike the method proposed by Coelli and Battese (1995) is robust to potential correlation between a firm's inefficiency and input use (right hand side variables). In addition, unlike previous studies on the impact of regulatory contracts on performance, in this paper the potential endogeneity of the regulatory contract is addressed. The main result of this paper is that the contract type does not seem to affect efficiency across counties. This contradicts previous research on this subject. The interpretation of this negative result is an open question. Perhaps in practice, due to the bargaining power of firms, the power of the yardstick and subsidy-cap type of contracts is lower than one would expect from the formal analysis of the regulations. However, this negative result may explain why the authorities have been constantly searching for new regulatory instruments during the last decade. This paper also shows that a careful empirical analysis is required in order to infer the effects of contract types on firm performance, otherwise the results may be quite misleading.

Keywords: urban transport, yardstick regulation, efficiency frontiers
JEL Classification: L9, L5

1. Introduction

In this paper we use an eleven-year panel of Norwegian bus companies (1136 company-year observations) to investigate to what extent different type of regulatory contracts affect company performance. As explained in more detail further below, two main types of contracts are used in Norway to regulate bus companies. On the one hand, regional authorities may bargain individually with transport companies on the subsidy levels to be granted during the next year—a regulatory contract assumed to be of low power in terms of its incentive properties. On the other hand, during the last decade a number of regional authorities have adopted a more high-powered contract based on a yardstick or benchmark model. More recently, regulatory contracts have evolved into a subsidy-cap type scheme.

The present research is important for several reasons. In a recent survey, De Borger and Kerstens (1999) argue that most studies on transit company performance show that there are substantial technical inefficiencies among urban transport operators. These authors also note that the evidence seems to suggest significant variability of measured efficiency among transit companies, both within as well as across countries. Furthermore, few studies have explicitly analyzed the impact of different regulatory contracts in explaining these differences. Thus, given the potential efficiency gains available, a better understanding of the effects of different regulatory contracts on company performance is important.

Other studies on this subject include Kerstens (1996), Jorgensen, Pedersen and Volden (1997), and Odeck and Alkadi (2001)[1]. The first of these applies several Data Envelope Analysis (DEA) models on a cross section of French urban bus companies. The author then uses a Tobit model to explain variations of measured efficiency among companies and finds that the risk-sharing characteristics and the duration of the regulatory contract positively affects company efficiency. However, the cross section nature of the sample, as well as the

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[1] Dalen and Gomez-Lobo (1996, 1997) and Gagnepain and Ivaldi (1999) also study the effects of regulation on cost performance by transit firms. However, they use a structural approach to recover the firm's underlying cost efficiency distribution in order to model the effects of the introduction of an optimal regulatory contract (including network auctions) a lá Laffont and Tirole (1993). These studies are quite restrictive owing to the structural nature of the estimation strategy and may thus introduce unnecessary biases that are avoided by the reduced form approach adopted here.

small sample size (54 companies after more than half of the observations of the original sample was discarded due to 'data' problems), cast some doubts as to the robustness of the results.

Jorgensen, Pedersen and Volden (1997) analyze the performance of Norwegian bus companies in a similar vein to the present paper. They use a cross section for 1991 to estimate a cost frontier model. The inefficiency parameters are then regressed on contract and ownership variables to see their impacts on cost efficiency. They find that the standard cost model improves cost efficiency. However, since it is only one year of data and all inferences are made using this cross section, there is the problem that unobservable network characteristics or other unobservable variables may be influencing the results. The endogeneity of the contract type variable may also be a potential problem.

Odeck and Alkadi (2001) apply DEA analysis to examine the performance of Norwegian bus companies using data from 1994. They do not study the effects of regulatory contracts on the performance of companies. However, they do note the limitations of not controlling for unobservable effects. As the authors point out "the major drawback [of the paper] concerns the geographical characteristics of the area in which bus companies operate. Such information would probably help explain some of the differences found in the performance between companies".

Controlling for network structure and spatial characteristics is always a problem when dealing with cross section data to measure performance of transport companies. Although attempts have been made to control for these effects using observable network characteristics, the problems of unobserved differences among observations remain. Unlike the previous studies mentioned above, the main advantage of the present paper is the use of a relatively long panel of observations with several transitions in the data. Thus, unobservable network or other time invariant characteristic of the operating environment can be controlled for.

In addition, we propose a method to estimate regional time varying inefficiency measures that overcomes some of the shortcomings of existing approaches. In particular, the proposed method does not restrict the time pattern of the inefficiency measure (as in Liu (1993)) and,

unlike the method proposed by Coelli and Battese (1995) is robust to potential correlation between a firm's inefficiency and input use (right hand side variables).

Another novelty of our paper is that, unlike previous studies on the impact of regulatory contracts on performance, in this paper the potential endogeneity of the regulatory contract is addressed.

The main result of this paper is that the contract type does not seem to affect efficiency across counties. This contradicts previous research on this subject. The interpretation of this negative result is an open question. Perhaps in practice, due to the bargaining power of firms, the power of the yardstick and subsidy-cap type contracts is lower than one would expect from the formal analysis of the regulations. However, this negative result may explain why the authorities have been constantly searching for new regulatory instruments during the last decade.

2. Regulatory practice in Norwegian bus transport

In Norway, responsibility for local transport is decentralized to the regional governments (counties). They define the network route, schedules, fares and the subsidies given to companies. Each county is free to choose its own regulatory policy. As a consequence, regulatory practice has evolved differently across the various regions of Norway.

Two basic approaches have characterized regulatory practice in Norway. What both approaches have in common, though, is that they involve lump sum grants to companies[2]. Most counties originally bargained annually and individually with each company over both costs and transfers. This scheme exposed companies to a ratchet type effect. If costs are reduced, it becomes harder to argue that the next lump sum grant must be kept at the previous level. On the other hand, if costs rise it may not be too difficult to convince the authorities that subsidies must increase. Therefore, it is reasonable to assume that the individual-bargaining scheme is of low-power in terms of the cost reducing incentives that it provides.

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[2] In 1989 the share of government subsidies amounted to about 40% of the total revenues of Norwegian transport companies. The majority of these companies are privately owned.

In the late eighties some counties started adopting a standard-cost model to determine annual transfers. In such a system, the county and the companies agree upon a set of criteria for calculating costs of operating a bus-network. It is a linear model that links driver costs, fuel costs, and maintenance costs to the number of bus kilometers produced for different categories of routes (from inner-city, low speed to long distance, high speed routes). Given fares and route schedules, the standard-cost model determines the level of transfers that is granted by the regulator. A version of the standard-cost model is presented in more detail in the appendix.

The important aspect of the scheme is that the same standard cost model applies to all companies within a county. This makes the regulatory scheme more high powered: Once the criteria are set, realized costs by one company that happens to deviate from the standard-cost figures, will not affect the level of its next annual lump sum transfer. This gives the standard-cost model a flavor of yardstick competition (see Shleifer, 1985). The main characteristic of yardstick competition is that transfers be based on a benchmark estimated on the basis of cost performance of a larger set of companies.

More recently, both of the previous contracts are being replaced by a third type of contract, a subsidy-cap. The companies and the county agree upon a reduction in the level of governmental transfers by X% per year, over a five years period. This last contract was introduced as a compromise after counties threatened to tender network services.

Table 1 shows how the use of the different types of contracts has evolved over the sample period 1987-1997. It shows the number of counties using each type of contract.

Table 1: Number of counties using each type of contracts

Contract type	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
Individual negotiation	16	13	12	11	11	9	8	7	2	1	0
Standard Cost	4	6	7	8	8	9	9	9	10	7	3
Subsidy cap	0	0	0	0	0	1	2	3	7	11	16

During the first part of the sample period, most counties used the relatively low-powered individual negotiation type of contract. By 1992-1993, the yardstick model had become the most popular contract with 9 out of 19 counties using this type of regulation. From 1992 onwards, counties that previously used the low-powered contract switched to a subsidy-cap. In the last two years of our sample period, many counties using yardstick contracts have also switched to the subsidy-cap contract.

3. Empirical issues

The general problem addressed in this paper is as follows. Consider a firm i in county m in year t. The logarithm of observed costs are C_{imt}. Observed costs are a function of the logarithm of firm specific or county level time varying variables, X_{imt}, some network characteristics of the county (in logarithm if continuos), Y_m, a firm specific inefficiency term μ_{imt} (assumed positive in the cost frontier literature) and an *iid* random error term, ε_{imt}. For example, a typical specification would be:

$$C_{imt} = \beta_0 + \beta_1' X_{imt} + \beta_2' Y_m + \mu_{imt} + \varepsilon_{imt} \tag{1}$$

We are interested in examining the evolution of μ_{imt} for different counties and the effects that different types of regulatory contracts had on this variable during the last decade. Problems analogous to this have been studied in the international trade debate (see Liu (1993), Liu and Tybout (1996) and Pavcnik (2002)), deregulation and productivity (Olley and Pakes (1996)) and in several other fields.

If only cross section data is available, a simple regression of costs on explanatory variables, including some dummy variables for the regime type (contract type) can be undertaken. In the frontier literature—following the pioneering work of Lee and Pitt (1981)—this is often done through a two step procedure. First a stochastic frontier method is used to estimate the expected value of μ_{imt} for each firm, and then in a second-stage these estimates are regressed on other variables, including the regime indicators, in order to explain variations across firms in their performance. A typical specification for the second-stage regression would be:

$$\mu^{\wedge}{}_{imt} = \alpha_0 + \alpha_1 I_{imt} + \eta_{imt} \tag{2}$$

where $\hat{\mu}_{imt}$ is the estimate of the inefficiency term from the first stage and I_{imt} is a dummy variable associated with the application of a certain regime.

This is the approach taken by Jorgensen, Pedersen and Volden (1997) to study the same issue as in this paper, but using only one cross section of data (for 1991). After estimating firm specific inefficiency effects, these are regressed on the contract type variables. They find that the standard cost contract decreases costs between 1.7 and 3.5 percent, depending on the distributional assumption made for the inefficiency term.

However, the previous approach has several shortcomings. First, apart from the loss of some estimating efficiency, the two-step method is internally inconsistent since the inefficiency error terms are assumed to be identically distributed for each firm in the first stage. This assumption is then contradicted in the second stage when the expected value of these error terms is assumed to depend on some other explanatory variables.

Second, if there are some unobservable firm (or county in our context) effects, say some of the variables in the vector Y_m, then the first stage estimates of the inefficiency term will be biased[3]. In this case it is not possible to separate the impacts on costs due to the unobservable effects from the true inefficiency of the observation. For example, the inefficiency term may be very high for one firm, but this may be due to unmeasured congestion on the routes used by that firm rather than inefficiency.

This is a potentially serious problem for studies of transit firms. It is well known that the network structure and spatial characteristics significantly affect transit company costs. Although attempts have been made to control for these effects using observable variables, it is reasonable to assume that there are some characteristics that are not included in an analyst's data and thus unobservable effects remain.

Panel data offers the potential to overcome this last problem. Note that estimating the μ_{imt}'s as a time invariant fixed effects (as in Schmidt and Sickles (1984)) or as time invariant non-symmetric random effects (as in Battese and Coelli (1988)) does not solve the problem. In the first approach it would not be possible to disentangle the effects of observable and unobservable time invariant characteristics from inefficiency proper. That is, the fixed effect estimated for each unit would include the effects of both network, demand or spatial characteristics (such as the average congestion level, for example) and cost inefficiencies. In addition, if actual efficiencies are not time invariant and they are correlated with input choice, the fixed effects model will generate biased estimates. The second approach (time invariant random effects) also suffers from this last problem. It requires assuming that the inefficiency is not correlated with any right hand side variable. This is clearly a strong assumption in the present context since cost inefficiency may well be related to input choice decisions. In addition, any time invariant inefficiency measure (either from a fixed or random effects model) would not be very useful in the present context where the interest lies in identifying the impacts of regime changes (the introduction of different regulatory contracts).

Clearly, time varying relative efficiency estimates are required. These could be estimated following Cornwell, Schmidt and Sickles (1990). They assume that the inefficiency term, μ_{imt} follows a time patter given by:

$$\mu_{imt} = \delta_{i0} + \delta_{i1}t + \delta_{i2}t^2 \tag{3}$$

This is the approach taken by Liu (1993) and Liu and Tybout (1996) to study the effects of trade liberalization on plant level productivity. They first estimate the parameters of a production function (equation (1)) using a fixed effect model, calculate the residual ($\mu_{imt} + \varepsilon_{imt}$) for each observation and then regress these residuals on time and time squared for each unit. With the latter estimates it is possible to construct time varying firm specific efficiency measures. However, this approach has several shortcomings. First, it requires a particular parametric specification for the evolution of efficiency. A more flexible approach would be

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[3] The county effect will also control for any unobservable heterogeneity across firms within a county as long as this heterogeneity remains constant through time. In other words, this variable will control for the average firm

preferable. Second, many degrees of freedom are lost since the parameters of the efficiency equation are firm specific. Third, as pointed out by Pavnick (2002), if efficiencies are not really time invariant and they are correlated with input choice, then the first stage fixed effects estimation will generate biases coefficients and thus biased residuals from which to estimate the parameters of equation (3).

Still another alternative is to use frontier models such as Kumbhakar (1990), Battese and Coelli (1992) and others. However, all of these methods suffer from at least one of the following problems. First, the time variation of efficiency is the same or similar for all firms, or, second, they do not solve the problem of correlation between the efficiency term and input choice variables.

Within this literature the model of Battesi and Coelli (1995) merits special attention. They assume the inefficiency effects to be independently distributed as truncated normal $N(\mu_{imt}, \sigma_\mu^2)$, with mean,

$$\mu_{imt} = \gamma' r_{imt}$$

where r is a vector of firm specific variables that affect inefficiency across firms. The advantage of the above specification is that cost inefficiency measures are estimated considering certain explanatory variables that may account for differences in performance across firms. Thus it would be possible for example to include the contract type as an explanatory variable and examine the impacts on efficiency. Furthermore, estimating the cost function parameters together with the parameters that explain efficiency variations across firms is statistically more efficient and less ad-hoc than the two-stage methods usually used in the literature.

However, this method does not overcome the simultaneity problem between the efficiency and input choice variables (right hand side variables). Unless the input (price or quantity) variables are included in the vector r, any correlation between inefficiency and input choice

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specific unobservable effects within a county.

will generate biased and inconsistent estimated. Including these right hand side variables in r, however, creates important identification problems.

A different approach altogether from the frontier literature to estimate time varying productivity was developed by Olley and Pakes (1996)[4]. They assume that the industry in question (telecommunication equipment manufacturers) can be characterized by a Markov Perfect Equilibrium for plant's exit and investment decisions. Using the resulting equilibrium investment rule it is possible to estimate the parameters of the production (or cost) function consistently using observable variables. Thus, time varying plant specific productivity measures are estimated even when unobserved productivity is correlated with input choices.

Unfortunately, this last approach is not applicable to the sector analyzed in this paper. It is unlikely that the transit bus industry—at least in Norway—can be modelled as an oligopoly characterized by a Markov Perfect Equilibrium. Urban transit is a heavily regulated industry where the authorities set prices and quality variables. Most often companies do not compete head to head for passengers.

In summary, there are many methods that could be used to estimate firm efficiency measures to analyze the impact of different regulatory contracts. However, all of them suffer from some drawback. The approach we propose below allows us to obtain time varying efficiency measures that are consistent even when efficiency is correlated with input choices and when there are county specific unobservable characteristics that may affect costs. In addition, no parametric assumption is made regarding the dynamic properties of the efficiency measure.

Before presenting the estimation strategy, one final potential empirical problem must be discussed. In empirical applications it is often assumed that the regime variables are exogenous in equation (2). For example, in the trade and productivity literature, trade reform is assumed to be exogenous. However, in our particular application this may be untenable.

As is seen in Table 1, there are many transitions in the data. That is, counties that change regulatory contracts during the period. It is reasonable to expect that these transitions are not

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[4] See also Pavnick (2002).

exogenous but may be a function of the performance of the transit firms in that county. For example, it may be that a regulator introduced a new contract because firms in the past years were notoriously inefficient. Or, it may be that more proactive or innovative regulators—perhaps due to civil or political pressure—introduced the high powered contracts first. At the same time, in these counties it would also be reasonable to assume that past regulation was also strong—due to the character of the regulator—and thus past performance was above average for that county. These arguments imply that the contract variable may be endogenous in equation (2), biasing our estimates of their impact on efficiency.

To explain this formally, let's assume that we are able to estimate unbiased time varying efficiency measures, $\hat{\mu}_{imt}$. As will be shown below, these estimates will include a county specific fixed effects. In order to get rid of the fixed effect we could take the first difference of equation (2) for each observation[5]:

$$\hat{\mu}_{imt} - \hat{\mu}_{imt-1} = \alpha_1 I^*_{imt} + \eta_{imt} - \eta_{imt-1} \qquad (2')$$

where I^* is an indicator variable that takes the value of one in the year that the new contract was introduced. Now, if the introduction of the new contract was in part motivated by high inefficiency during the last year, then the indicator variable and the error term are negatively correlated and:

$$E\left[\eta_{imt} - \eta_{imt-1} \middle| I^*_{imt} = 1\right] \neq 0 .$$

Thus, OLS estimate of α_1 would be biased and we would make the wrong inference regarding the effects of each contract.

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[5] First differencing in this context to get rid of the fixed effect is preferable to estimating the model using a fixed effects panel data model. In this second approach the endogeneity problem may be more sever since the error term will include the average of all past and future inefficiency shocks.

4. Estimation strategy

In this section we explain the estimation strategy used in this paper to obtain consistent estimates of time varying efficiencies. We also explain how we control for the potential endogeneity of the contract variables when analyzing the impact of different regulatory contracts.

4.1 First stage: obtaining consistent time varying efficiency measures

We first rewrite equation (1) in a slightly different form:

$$C_{imt} = \beta_0 + \beta_1' X_{imt} + \beta_2' Y_m + (\mu_{imt} - \overline{\mu}_{mt}) + \overline{\mu}_{mt} + \varepsilon_{imt} \tag{1'}$$

where $\overline{\mu}_{mt}$ is the average inefficiency for county m in period t. Now, if we subtract from each observation the county average values for each period we can eliminate $\overline{\mu}_{mt}$ from equation (1'):

$$(C_{imt} - \overline{C}_{mt}) = \beta_1'(X_{imt} - \overline{X}_{mt}) + (\mu_{imt} - \overline{\mu}_{mt}) + (\varepsilon_{im} - \overline{\varepsilon}_m) \tag{4}$$

The crucial assumption that is made in this paper is that the deviation of efficiency of each firm from the county average in each period, $(\mu_{imt} - \overline{\mu}_{mt})$, is not correlated with the deviation of input choice by the firm from the county average $(X_{imt} - \overline{X}_{mt})$. If this is the case then the vector β_1 can be estimated consistently.

With $\hat{\beta}_1$, we can obtain an estimate of the average inefficiency for each county. In particular form equation (1), it is possible to obtain an average county residuals for each period:

$$\begin{aligned}
\hat{\gamma}_{mt} &= \beta_0 + \beta_2 Y_m + \overline{\mu}_{mt} + \overline{\varepsilon}_{mt} \\
&= \beta_m + \overline{\mu}_{mt} + \overline{\varepsilon}_{mt}
\end{aligned} \tag{5}$$

where β_m is a fixed county effect[6]. In can easily be seen that if the number of companies in each county is large the last term will tend to zero. Thus controlling for the county specific effects, the residuals are consistent estimates of the county specific time varying inefficiencies.

Notice that we have obtained time varying inefficiencies for each county in a very flexible way, without making any parametric assumption as to the dynamic evolution of these measures. In addition, we are not assuming that the county average efficiencies are not correlated with input choice only that within a county this effect is similar for all firms. We overcome the correlation of input choice and efficiencies by differencing within each county each period.

In effect what we do is to change the focus of attention from the individual firm efficiencies to county average efficiencies for each period and to see how these are affected by different regulatory contracts. In the present context this seems a reasonable approach. All firms within a county face the same type of regulation. Other environmental factors are also expected to affect each firm within a county in similar way.

There is an interesting empirical consequence of the approach taken. If one were to be consistent with the stochastic frontier literature, then $\overline{\mu}_{mt}$ should all be positive. The residuals however, need not be positive since there are other terms in equation (5). However, we should expect the residuals to be positively skewed, something which we can test in the empirical application below.

4.2 Second stage: modelling contract type choice

In order to control for the possible endogeneity of the contract variable, we model the probability of a county introducing a particular type of contract as a first order Markov process. This implies that we need to model the transition probabilities of going from one type of contract to another. The full matrix of transition probabilities is:

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[6] There is also a term reflecting the fact that the β_1 used to obtain the residuals is an estimate. However, under the assumptions made and the large number of observations in the data this term should be close to zero. Including it

$$\begin{pmatrix} P_{in|in} & P_{sc|in} & P_{pc|in} \\ P_{in|sc} & P_{sc|sc} & P_{pc|sc} \\ P_{in|pc} & P_{sc|pc} & P_{pc|pc} \end{pmatrix}$$

where P_{ij} is the probability that a firm with contract j in period t-1 will implement contract i in period t.

From Table 1 it is immediately clear that some of the above probabilities are already determined or at least with the data available it is not possible to estimate. In particular, no county that adopted the standard cost approach returned to the individually negotiated contract. In addition, once adopted, no county changed the subsidy-cap regime. Therefore, the transition probability matrix is:

$$\begin{pmatrix} P_{in|in} & P_{sc|in} & P_{pc|in} \\ 0 & P_{sc|sc} & P_{pc|sc} \\ 0 & 0 & 1 \end{pmatrix}$$

Therefore, we need to model the first row and second row of the matrix in order to obtain the conditional probabilities. The choice of which contract to go to from an individually negotiated status quo (the first row of the matrix) can be modelled using a multinomial logit regression. The decision of which contract to adopt once the standard cost approach is being used (the second row of the matrix) can be modelled using a simple logistic regression of the choice of staying with the current contract or implementing the subsidy-cap[7].

In the above multinomial logit or logistic regression, the past inefficiency of the county is used as an explanatory variable (among others). We can then test whether past inefficiencies affected the decision to adopt a particular type of contract. In addition, the models can then be

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in what follows would not change anything in the analysis.

[7] An alternative modelling strategy would be to split the data into two samples, before 1992 and after. The reason is that the subsidy-cap may not have been an alternative before that 1992. However, the results do not change at all if this second approach is used. Because of the small number of observations from which to study the contract choice issue, the results we present below include the full sample.

used to instrumentalize the dummy contract variables in the final regression where we examine the impact on efficiency of these contracts.

4.3 Third stage: estimating the impact of each type of contract

Finally, using the above results we estimate the impacts of the contract variables on the average cost of each county. An equation analogous to equation (2') above is estimated. The efficiency measures are first differentiated in order to remove the county specific effects and then regressed on a vector of indicator variables for each type of contract.

$$\hat{\mu}_{mt} - \hat{\mu}_{mt-1} = \alpha_0 + \alpha_1 I_{mt} + \eta_{mt} \qquad (6)$$

The predicted conditional probabilities from the second stage can be used in order to control for any endogeneity problems related to the contract variables. Notice that because we have taken the first difference in equation (6), the indicator variables will be one for the first year a standard cost or a subsidy-cap contract is introduced given that an individually negotiated contract was used before. We also define an indicator variable that takes a value of one if the given contract was the same as the year before. Thus, we are justified in using the above transition probabilities to model these variables.

Another estimation strategy might be to model the unconditional probabilities of having a particular type of contract using a multinomial logistic regression. However, this alternative would not take into account that there are probably quite substantial amounts of persistence in the type of contract used. That is, the probability of having the standard cost contract is different depending on whether that type of contract was used last period or not.

5. Data

The data used in this study was collected by the Central Bureau of Statistics in Norway. It is based on annual reports presented by bus companies. In certain parts of Norway there is a large number of very small bus companies, often with only one or two employees. As these companies produce a very narrow set of services and at very small scale, they are excluded

from the dataset. Furthermore, companies with incomplete reports of either costs or output are excluded. In some cases, incomplete data was a consequence of the decision by the Bureau of Statistics to store only aggregated county summaries rather than company level information.

In all, information was available for 142 companies over the 11 year period from 1987 to 1997. Not all companies had complete information for all years. Therefore, an unbalanced panel with 1127 company/year observations was obtained[8].

The two outputs used in this study were the number of vehicle kilometers in the regulated transport sector (urban) and the unregulated transport sector (inter city services). Labor costs are reported separately for drivers and administrative personnel. Wages for these two inputs were derived from reported labor costs and hours. The fuel price was derived from reported fuel-costs and quantity used. Capital is measured by the total number of seats of the rolling stock per driver hour.

A set of indexes, constructed by the Central Bureau of Statistics, is used to control for systematic differences between counties. These are the density, centrality, and the industry index. Their values are associated with the region in which the major part of the companies' production takes place. The density index measures population density (low values are associated with more scattered populated areas) and the centrality index measures the average distance to different types of city centers (a low value is associated with areas having longer travelling distances to city centers). Finally, the industry index shows the average type of industry in the region (low values are associated with more weight on agricultural production).

Another aspect of our data set are variations in company ownership. Most companies have been privately owned throughout the sample period. Since 1993, however, the state-owned Norwegian railway company (NSB) has been responsible for around 20-25 takeovers (Carlquist, 1998). Before 1993, the bus division of NSB was already one of the major companies in Norwegian bus transport.

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[8] The results are not sensitive to the unbalanced nature of the data. Estimation using a balanced sub-panel did not affect the general results presented below.

6. Results

Table 2 shows the results of a translog cost function specification. In order to maximize the use of the available information, the cost function was estimated along with two of the cost share equations (driver wages and administrative wages) with cross equation restrictions imposed[9].

The input price variables are driver hourly wages, administrative hourly wages and fuel price. Homogeneity of the cost function was imposed by deflating costs and the first two price variables for each observation by the fuel price. The output variables included regulated and unregulated output, and the rolling stock (number of seats). Dummy variables were included for each category of the industry, density and centrality variables. Finally, in order to estimate the model using the difference between each observation and the county average for each time period, dummy variables for each (year*county) were included[10].

In order to facilitate the interpretation of the results, the data was normalized to the average firm of the data set prior to estimation. Table 2 shows that except for some interaction terms, all variables are strongly significant and have the expected sign. The results imply that there are strong economies of scale in unregulated output for the average firm but for higher outputs there are diseconomies of scale. For regulated output, economies of scale are not as strong for the average firm as for unregulated output, and there are also decreasing returns for higher outputs. The parameter for the regulated and unregulated interaction variable is negative, indicating economies of scope between these two output types.

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[9] It may seem odd to estimate a translog cost function with share equations and cross equation restrictions imposed when this assumes cost minimization by firms, thus contradicting somewhat our assumption that there are productive inefficiencies. This would be a correct approach only if the inefficiencies affect (shift) the cost function in a neutral way with respect to input use. We also estimated the cost function in a more flexible way, without the share equations. The final results did not differ at all from the ones presented below. Results are available from the authors upon request.

[10] Including (year*county) specific dummies is identical to estimating the model using each variable minus the county average for each time period as in equation (4).

Table 2: Translog cost model results

Variable	Cost equation		Administrative cost share equation		Driver cost share equation	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Constant	-0.3771	-6.33	0.0892	9.95	0.7504	73.49
Seats	0.1000	5.31	0.0055	1.81	-0.0009	-0.30
$(Seats/2)^2$	0.0567	3.75	-------	-----	-------	-----
Adm. Wage	0.0892	9.95	0.0143	6.23	-0.0105	-4.50
$((Adm. Wage)/2)^2$	0.0143	6.23	-------	-----	-------	-----
Driver wage	0.7504	73.49	-0.0105	-4.50	0.0332	10.39
$((Driver wage)/2)^2$	0.0332	10.39	-------	-----	-------	-----
Q unregulated	0.1017	12.32	-0.0070	-4.67	-0.0002	-0.16
Q regulated	0.8200	49.43	-0.0051	-2.08	0.0075	3.07
Qunreg*Qreg	-0.1403	-14.37	-------	-----	-------	-----
$((Q unregulated)/2)^2$	0.1005	12.12	-------	-----	-------	-----
$((Q regulated/2))^2$	0.2124	10.77	-------	-----	-------	-----
(Adm. Wage)*(Driver wage)	-0.0105	-4.50	-------	-----	-------	-----
(Driver wage)*(Q regulated)	0.0075	3.07	-------	-----	-------	-----
(Adm. Wage)*(Q regulated)	-0.0051	-2.08	-------	-----	-------	-----
(Driver wage)*(Q unregulated)	-0.0002	-0.16	-------	-----	-------	-----
(Adm. Wage)*(Q unregulated)	-0.0070	-4.67	-------	-----	-------	-----
(Driver wage)*(Seats)	-0.0009	-0.30	-------	-----	-------	-----
(Adm. Wage)*(Seats)	0.0055	1.81	-------	-----	-------	-----
(Seats)*(Q regulated)	-0.0702	-4.35	-------	-----	-------	-----
(Seats)*(Q unregulated)	0.0391	3.00	-------	-----	-------	-----
Nsb	-0.0389	-2.45	-------	-----	-------	-----
Observations	1127		1127		1127	
Parameters	220		204		204	
R^2	0.9914		0.4840		0.5107	

Note: All continuous variables are in natural logarithm. Results for the industry, density, centrality and county time categorical dummy variables not shown (available upon request from the authors).

Table 3: Elasticities of substitution and own price

Substitution elasticities	Administrative labor	Driver labor	Fuel
Administrative labor	-5.4133		
Driver labor	0.8988	-0.2894	
Fuel	0.7713	0.7433	-5.5263
Own price elasticities	-0.7578	-0.2144	-0.6586

The input price elasticities are shown in Table 3. All own price elasticities are negative, which is in accordance with the concavity requirement of the cost function. The cross price elasticities show that all three inputs are substitutes of each other.

The NSB variable indicates that publicly owned companies have a cost advantage of nearly 4% over similar privately owned firms. There are several possible interpretations for this

result. First, since *Nsb* operates a substantial number of services, the lower costs of these firms could be an indication of strong economies of scale or scope in the industry. These economies may explain the increasing numbers of mergers and takeovers observed among private operators. Another interpretation is that there are economies of scope between road transport and the provision of railway services. In general, the *Nsb* owned companies are used as an extension of rail services to those areas where there is no rail infrastructure. These routes may be more long-distance and less congested than the average bus routes and therefore costs are lower. It could also be the case that the cost advantage arises from the ability of the rail company to coordinate schedules between its train operations and its bus operations. Third, the results may be showing that this public firm is intrinsically more efficient than private operators[11].

Table 4: Summary statistics of estimated efficiency measures

Statistic	Value
Mean	-0.3988
Median	-0.4086
Standard Deviation	0.0738
Maximum	-0.2208
Minimum	-0.6030
Skewness	0.1085
Kurtosis	2.5907
Normality test (joint skewness and kurtosis test)	2.94
P(x>X) for a Chi-squared distribution (df=2)	0.23

Note: normality test result shown was undertaken using the number of firms in each county as weights for the inverse of the variance of each observation. The test results do not change if observations are not weighted.

Using the estimation results, county time varying efficiency measures were estimated as described earlier. Table 4 presents the descriptive statistics of these efficiency measures. It must be borne in mind that they contain county specific fixed effects in addition to some random variation. Thus, it is perfectly possible to have negative efficiency measures as shown in Table 4. This implies that compared to the omitted county and year (first year), most other county-years had lower costs. As noted above, we expect the residuals to be positively skewed, which is confirmed by the results. However, a formal test cannot reject the

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[11] Another possibility is that there is some accounting cross subsidy between the railway company and its affiliated bus companies. However, this is unlikely. First, we are estimating operating costs and it would be difficult to directly subsidise the fuel or wage bill as compared, for example, to maintenance expenditure where it may be possible for the bus companies to use some of the staff and infrastructure of the railway company.

hypothesis that the residuals are normally distributed. Therefore, although the residuals are slightly skewed, it is not strong enough to be statistically significant.

Table 5 shows the results (log odds ratios) of the multinomial logit model for the transition probabilities of adopting a standard cost or subsidy-cap contract, conditional on having an individually negotiated contract the year before. As explanatory variables we used the population size of each county, the number of firms being regulated, the year and the lagged efficiency measure. Since each county efficiency measures includes some unobservable county fixed effects, we also experimented using an adjusted lagged efficiency measure consisting of the original measure minus the county average over all years:

$$\mu_{mt}^{*} = \hat{\mu}_{mt} - \sum_{y=1}^{Y} \hat{\mu}_{my}$$

However, the results were unchanged and we prefer the specification shown in Table 5 since by taking the county average form each observation we may be introducing some confounding correlation between the efficiency measure and the contract variable[12].

We also experimented using efficiency-year interactions, two-year lags and the difference between efficiency measures in year *t-1* and *t-2*. This last variable was used to test whether a sudden change in efficiency might have prompted a regulatory reform. However, in all cases the results were not qualitatively different from those presented in Table 5, our preferred model[13].

Second, the bus company is operated autonomously as a daughter-company, owned by *Nsb*. Therefore, there is an arms length relationship between both types of actives in the railway company.

[12] This arises from the fact that the average efficiency for each county is calculated using the measures from all years. Thus, the efficiency measure for years after the contract was implemented would be included in the adjusted variable.

[13] All results are available from the authors upon request.

Table 5: Log-odds ratio estimated for the adoption of each type of contract given that the individually negotiated contract was used in t-1

	Log-odds ratio	z-value
Standard Cost contract		
Population	0.9999	-1.98
Number of firms	1.5437	5.31
Year	1.4549	1.62
μ_{t-1}	1.88e+07	1.09
Subsidy-cap contract		
Population	1.0000	-0.56
Number of firms	1.4171	1.70
Year	1.7284	2.43
μ_{t-1}	2.13e-07	-1.11
Number of observations	74	
Pseudo R^2	0,28	
Log likelihood	-23,8923	

Note: the comparison outcome is the individually negotiated contract. Standard errors were adjusted for clustering by county.

The results show that the lagged efficiency measure does not seem to determine the move from an individually negotiated contract to a subsidy-cap or standard cost regime. For the standard cost, the population and the number of firms seems to be the main determinants of a county adopting this regulatory scheme. That is, counties with more population and firms tended to adopt the standard-cost contract. For the subsidy-cap, it seems that the only significant influence on the adoption of this contract is time. That is, the probability of adopting this contract increased later in the decade, which is obvious from an examination of Table 1. The important point to note is that the average relative efficiency of each county did not seem to influence this decision.

Table 6: Logit estimates for the adoption of the subsidy-cap contract when the standard cost contract was used in t-1

	Log-odds ratio	z-value
Constant	-3511,81	-2.40
Number of firms	-0,4402	-1,00
Year	1,7691	2,40
μ_{t-1}	38,2342	1,19
Number of observations	54	
Pseudo R^2	0,58	
Log likelihood	-8.1995	

Table 6 shows the results of logistic model of the probability of adopting the subsidy-cap contract given that the standard cost contract was being applied in the year *t-1*. The population

variable was dropped since it created some numerical problems in the estimation. Also, with such few observations we were unable to estimate standard errors by clustering county observations.

The results from Table 6 show that, once again, the change from a standard cost to a subsidy-cap contract has more to do with a trend than with the relative efficiency of the county.

In summary, at this stage we do not find much evidence for the endogeneity of the contract variables in determining the transition probabilities. However, we test this formally below.

The first two columns of Table 7 show the results from regressing the first difference of the efficiency estimates on the contract variables (equation (6)). From equation (5) it can be seen that these errors will include a residual with a variance inversely proportional to the number of firms in each county. Therefore all regressions were weighted least squares using the number of firms as weights. The second column uses the predicted score from the second stage logistic and multinomial regressions in order to control for endogeneity. This is equivalent to a Wu-Hausman exogeneity test but in the context of limited dependent variables (Smith and Blundell, 1986). A rejection of the null hypothesis that the coefficients of these scores are zero is equivalent to rejecting the exogeneity of the contract variables. The third and fourth columns present the results from estimating the level of efficiency using lagged efficiency as a dependent variable.

The results show that none of the transition indicators are significant. That is, compared to the base case where the individually negotiated contract is used, introducing the standard cost contract does not influence the first difference in the efficiency measure[14]. Neither does introducing the subsidy-cap contract have any effect. Maintaining the contract type does not seem to affect the evolution of costs either.

What is apparent from the constant of the first two regressions shown in Table 7 is that cost decrease annually by around 1.5% to 1.7%. This cost reduction does not seem to be related to the contract type however and it could be attributed to general productivity increases.

The t-test for the score variables do not reject the hypothesis that the contract type indicators are exogenous. This is consistent with our previous results that the lagged efficiency variable does not seem to affect the contract type chosen in a given county.

Table 7: Results of efficiency regressions

Dependent variable	U_t-U_{t-1}				U_t			
Variable	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Constant	-0.0156	-2.71	-0.0173	-2.54	-0.0957	-4.85	-0.1023	-4.89
D (sc/in)	-0.0108	-0.50	-0.0493	-1.26	-0.0137	-0.66	-0.0549	-1.49
D (pc/in)	0.0256	1.06	0.0819	1.75	0.0126	0.65	-0.0260	-0.51
D (sc/sc)	0.0002	0.03	0.0040	0.15	0.0044	0.23	-0.0155	-1.62
D (pc/sc)	0.0062	0.48	0.0080	0.59	-0.0025	-0.85	-0.0091	-0.68
U_{t-1}	----	----	----	----	0.7778	14.79	-0.7445	12.43
Score sc/in	----	----	0.0464	1.07	----	----	0.0577	1.40
Score pc/in	----	----	-0.0726	-1.36	----	----	0.0454	0.79
Score sc/sc	----	----	0.0463	1.05	----	----	0.0658	1.57
Number of observations	153		153		153		153	
R^2	0,02		0,04		0,64		0.66	

7. Conclusions

In this paper a careful analysis of the evolution of transit bus performance was undertaken for a panel of Norwegian companies between 1987 and 1997. In particular, the paper examines the potential effect of different types of regulatory contracts on firm efficiency.

The analysis proposes a method to generate flexible time varying efficiency measures even when the input choice variables may be correlated with the efficiency effect. It also takes into account the potential endogeneity of the contract type variable.

The initial hypothesis was that presumably high-powered contracts—such as a yardstick type contract or a subsidy-cap contract—would generate empirically measurable improvements in performance. However, our results show that the contract type does not seem to affect

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[14] The same results are obtained if, instead of the whole sample, only observations in which the individually negotiated contract was used during the last year are used.

efficiency across counties. In addition, past inefficiency does not seem to have affected the contract type adopted by a particular county. The standard cost contract seems to have been adopted in larger counties, but not necessarily in those with higher than average cost inefficiency. The introduction of the subsidy-cap contract in the nineties seems to be related to a secular trend, and there is no evidence that the introduction of this contract occurred in counties with higher than average past inefficiencies.

The results of this paper contradict previous research on this subject, especially Jorgensen, Pedersen and Volden (1997) and Dalen and Gómez-Lobo (1996, 1997) who find a significant impact of the standard cost contract. However, in these studies the potential correlation between the inefficiency and input choice decisions was not taken into account. Neither did they control for the potential endogeneity of the contract type variable, although our results indicate that this endogeneity problem should not be too serious.

The interpretation of our negative results is an open question. Perhaps in practice, due to the bargaining power of firms, the power of the standard cost (yardstick) and subsidy-cap type contracts is lower than one would expect from the formal analysis of the regulations.

However, our results are consistent with one empirical phenomenon observed in Norway during the period: the constant search for new regulatory instruments. First, the standard cost contract was introduced. However, during the mid-nineties regulators began voicing their intention to tender bus routes, perhaps as a reaction to disappointing results from the standard cost contracts. This would be consistent with our results that the standard cost contract did not have an appreciable effect on cost compared to the individually negotiated contract. The introduction of the subsidy-cap contract was a political compromise between firms and regulators as an alternative to tendering. Our results would indicate that it was in the interest of firms to lobby for this type of contract, since it did not have a measurable effect on performance.

If the above interpretation is correct and if there are effectively cost inefficiencies in bus transport, as the constant reforms undertaken by regulators would seem to suggest, then further regulatory changes are to be expected in the future. Perhaps, tendering bus routes will be the next regulatory experiment in Norway.

Besides the interpretation of the empirical results, this paper shows that a careful empirical analysis is required in order to infer the effects of contract types on firm performance, Otherwise the results may be quite misleading.

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Appendix: The standard cost model

The standard-cost model is developed and maintained by a consultancy firm (ASPLAN VIAK) and is used by regional regulators to determine the level of subsidy granted to the companies. The main input to the model is a 4x5 output-vector Q that consists of the number of kilometers produced in four different types of routes by five different types of buses. q_i^j denotes the number of kilometers in route type i with bus type j. Route types differ according to average speed of traffic and bus types differ according to size. The regulator controls this output-vector.

The benchmark costs of producing the output-vector is derived from a linear model that determines the drivers, fuel, maintenance and bus capital inputs:

$$c_k = p_k \sum_i \sum_j a_i^j q_i^j ,$$

where p_k is the market price for input k and a_i^j is the input coefficient for output q_i^j. a_i^j is derived from observed cost figures from companies within several regions and applies to all companies controlled by the regulator. The number of bus companies in each region is large enough to make a_i^j almost insensitive to efficiency improvements by the individual company.

Administration costs, c_{adm}, are set proportional to $\sum_k c_k$ (excluding fuel costs, however, that tend to vary considerably over time).

The level of subsidy, S, is now determined by the difference between expected traffic revenue, given fares and kilometer produced, and standard-costs:

$$S = P \cdot y^e \cdot \sum_i \sum_j q_i^j - \sum_k c_k - c_{adm} ,$$

where y^e is the expected number of passengers per kilometer produced and P is the average fare level set by the regulator. It is important to note that S is not adjusted to the actual number of passengers per kilometer effectively transported.