CENTRUM Católica's Working Paper Series

No. 2015-11-0020 / November 2015

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Regulatory Design and Technical Efficiency: Public Transport in France

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Abstract

Public transport systems are often subject to a close regulatory oversight because of their economic and social impacts. In the case of France, this has led to an institutional design that has involved the participation of private firms in the service provision, and the use of incentive contracts to regulate them, among other characteristics. We study the effect of these institutional features on the efficiency of the firms in the sector. For this, we use nonparametric Data Envelopment Analysis (DEA) techniques to estimate the input usage efficiency, and explore a few potential institutional and regulatory determinants. We apply a conditional DEA approach and fixed effects second stage regressions to control for potentially observed and unobserved sources of heterogeneity across different environments in which the firms operate. Our results point to a differential effect of private and mixed public-private companies. In particular, having the performance of public operators as the benchmark, efficiency is relatively higher for private firms, but lower when the service is delegated to a mixed public-private firm. Furthermore, the effects seem to diverge greatly by contract type when the firm is mixed so that, when the contract is of the cost reimbursement type, performance is lower than the public firm benchmark, while for other contract types there are no statistically significant differences.

Keywords: Data Envelopment Analysis (DEA); Conditional efficiency measures; Two-stage efficiency analysis; Regulation; Public transport

JEL Classification: C14; L32; L51; L91

1 Introduction

Cities are centers of diverse activities, which require efficient public transportation of people and goods to allow people to carry out the various activities that make up daily life, such as, accessing business activities, workplaces, education, and educational opportunities. One can say that urban public transport is a characteristic of the quality of life that is offered to citizens by the public bodies, in their attempt to improve social welfare (Vuchic, 1999). However, because the operation of such services has a significant impact on the local budget, there is an increasing concern about the efficiency of the public transport system. It has become of critical importance to monitor the resources used by these systems, as well as their levels of service provision, to be able to facilitate operational improvement and strategic decisions.

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In this line, in this paper we study potential regulatory determinants of the efficiency of public transportation firms, in the case of French urban areas. We focus on two interesting features of the regulatory design in place: the firms' ownership regimes (they can be public, private, or a mixture), and the type of contract that mediates their relations with the corresponding regulatory agencies (i.e., local urban area governments). There are reasons to expect these features to have different influences, given their different mechanics of operation. When the service is operated by a public firm linked with the local government, incentives for efficient operation are provided internally in the joint organization (i.e., the managers are public officers). On the other hand, when the service is operated by a private firm, incentives are provided via the contract design that mediates the relation between the regulator and the firm. The type of contract, in this case, is likely to affect the firm's incentives to perform efficiently.

The two aspects are significant from a policy perspective. If regulating a private firm is costly, one would want to have clear evidence this kind of service delegation produce concrete efficiency gains.[1] In this case, additionally, the regulator would want to know if there is a type of contract that further enhances the efficiency gains. The multiplicity of contractual arrangements observed in different countries (and, specifically, within the French case) already suggests a non-trivial answer. In the case of our application, in particular, it has been observed a clear tendency toward using *incentive regulation* contracts as well as toward choosing private operators for the service. These trends reflect the increased concerns for efficiency in an industry that has seen a marked increase in costs.

Such questions have been asked in the transportation and economic regulation literatures. De Borger et al. (2002) surveyed the extensive efficiency and productivity literature in the transportation sector, within the frontier tradition. Regarding ownership, the authors concluded that in general the evidence is positive in favor of private firms. However, they observed that "none of these studies control for the degree of competition and the nature of government regulation in the sector (...) it is often argued that for strongly regulated markets (in terms of entry and exit, pricing, etc.) like urban transit, ownership is of little relevance on its own, though the market structure and the nature of competition is" (p. 33). In the case of the industry at hand, Kerstens (1996) reached similar conclusions. It also documented a different level of performance according to the contract type when the service is delegated to a private firm, with the firms subject to incentive regulatory contracts exhibiting better performance.

We study the case of the French public transport industry, between 1995 and 2010. To add to the previous literature, our study proposes to examine in more detail the mixed public-private ownership - or semi-public, as is (Gagnepain et al., 2013), an intermediate type of ownership, between the extremes of fully private and public companies. In the French case, the mixed companies are characterized by having at least a 51% and at most an 82% of participation of the local government, with private partners "rarely own more than 30% of the equity" (Roy, 2005). Additionally, we also aim to show the potential influence of the type of the contract between the regulator and the firm on the effects of ownership.

It is not straightforward to theoretically conjecture how incentives for efficiency can be transmitted under the mixed ownership type. By having a significant private participation it is likely that this type of firms keep, to some degree, the incentives for efficiency that are expected in private firms. At the same time, one would expect that the public participation to affect the objectives of the firm and reduce the informational disadvantage of the regulator regarding the firm's operating decisions. The problem is even more complex when one considers that incentive regulatory contracts are often designed with profit-maximizing firms in mind.

[1] Choosing a private or mixed firm as the service operator is considered as a delegation of the service, given that the regulator distances itself from the operating decisions (to a lower degree in the case of mixed firms). On the other hand, this activity is likely to generate costs, given that the regulator must incur in activities to monitor the firm, and design incentives schemes.

In line with the expected complexities, our empirical results provide evidence of a differential performance of the mixed-ownership firms, according to the type of contract in place between the regulator and the firm.

Another contribution of our study is the application of methodological advances to improve the identification of the effects of interest. The first is related to the frontier approach. Based on the suggestions of Daraio and Simar (2005) we implement a *conditional* DEA frontier approach to estimate technical efficiency. This method takes into account the different contexts in which the firms operate, and is, therefore, useful to separate the effects of a variable of interest on the efficiency performance from its possible effect on the production function.

To illustrate this, let us consider, for example, the case of the population density. If higher population density makes it possible to reduce input usage for a given output target (i.e., it positively affects the production set), then there would be a positive correlation between the population density and the usual input-oriented DEA scores, even if the population density does not affect the efficiency performance of the city operators. A similar situation would arise if, for example, a particular contract type is correlated with population density (there would be a positive correlation between the contract type and the DEA efficiency score, even if the contract type has no effect on efficiency). Neither of these spurious relations would occur with the conditional DEA estimator because it is based on the comparison of cities with similar levels of population density.

Previous attempts to control for the different contexts of production were based on adding "environmental variables" as additional, non-discretional, inputs of the production process. These approaches, however, assume free-disposability and that the production set is convex in the environmental variables (Ruggiero, 1998), assumptions which are unlikely to hold in our application, and which are, furthermore, not required for the conditional DEA approach.

Our study also highlights the role of *unobserved* heterogeneity. If unobservable factors affect simultaneously both the efficiency and the prevalence of particular ownership regime or contracting types, a simple correlation analysis could be misleading. For example, cities with geographical features that reduce the productivity of inputs might be the most interested in delegating the service to private firms, or using certain type of contracts. Then, we could observe a negative relation between these ownership regimes or contract types and the estimated input efficiency, even if the former have no actual effect on efficiency.

In order to correct for this, we take advantage of the panel structure of our data, incorporating fixed effects at the city level. We also contribute to the literature (to the studies based on two-stage analysis of efficiency, in particular) by applying a semiparametric method in the second stage. The semiparametric method, proposed by Honore (1992), estimates the parameters of a censored variable model without assuming a parametric distribution for the unobservables in the model. To the best of our knowledge, this method has not been applied before in this literature.

Our results highlight the importance of our finer definition of ownership type, as well as the controlling for the observed and unobserved heterogeneity to evaluate efficient performance, corroborating, therefore, our modelling choices. More specifically, we find a differential effect of private and mixed public-private companies on input efficiency:[2] having the performance of public operators as the benchmark, efficiency is relatively *higher* for fully private firms, but *lower* when the service is delegated to a mixed public-private firm. Additionally, the effects seem to diverge greatly by contract type when the firm is mixed. Finally, controlling for both types of heterogeneity has a relevant influence on the estimated effects.

[2]We efficiency in the input orientation because in our application the input mix partially depends on the regulators' decisions, who own the ample majority of the capital - around 95% of the rolling stock. Therefore, cost efficiency not only depends on the incentives provided to the service operators, but also on regulatory decisions generally outside their control.

The remainder of the paper is organized as follows: Section 2 summarizes the previous literature on the subject, Section 3 describes the main features of the industry, Section 4 describes the methods used, Section 5 presents the results, and Section 6 concludes.

2 Literature Review

Data envelopment analysis (DEA) is, without doubt, a typical benchmarking analysis, used to assess the efficiency of decision-making units (DMUs) in a wide range of areas, such as health, finance, education, Internet and communications technology, etc. It is therefore not surprising, that it has been also used to assess the efficiency and performance benchmarking of all the major transport modes.

Some of the studies focused on port efficiency, such as the study of Roll and Hayuth (1993), who employed DEA to analyze the efficiency of 20 virtual container ports. Martinez-Budria et al. (1999) then evaluated the efficiency of 26 container ports in relation to the evolution of the efficiency of a single port in Spain through a DEA-BCC model. Tongzon (2001) used DEA to measure the efficiency of four Australian and twelve international container ports. Valentine and Gray (2001) examined the efficiency of 31 container ports, while Park and De (2004) evaluated the efficiency of 11 Korean container ports. Furthermore, Park (2005) performed a four-stage DEA analysis on 11 Korean container terminals and Song and Sin (2012) evaluated the efficiency of 53 international major container ports. The literature has, furthermore, been enhanced with the studies by Cullinane and Wang (2006) who employed DEA to measure the efficiency of 69 container terminals in Europe, Pjevḑeviü and Vukadinoviü (2010) who measured the efficiency of bulk cargo handling at river port, and Schøyen and Odeck (2013) who evaluated the efficiency of 24 container ports from Norway, all the Nordic countries and the United Kingdom. Munisamy and Danxia (2013) employed a smoothed homogenous bootstrapped frontier approach within the DEA framework to obtain efficiency estimates in order to rank Asian container ports. Moreover, Gutiérrez et al. (2014) applied DEA using a bias-corrected efficiency estimator to evaluate the efficiency of top international container shipping lines. Finally, in a more recent study, Bray et al. (2014) employed a fuzzy DEA model to assess the efficiency of container ports on the Mediterranean Sea.

Other DEA studies focused on airport efficiency. Banker and Johnston (1994), for example, developed measures of cost efficiency and revenue-generating efficiency based on DEA measures of technical efficiency, which were, furthermore, applied to the U.S. domestic airline industry. Tofallis (1997) used a modified DEA approach, namely, input efficiency profiling, to study the performance of 14 major international passenger carriers. Adler and Golany (2001) employed DEA to select the most efficient networks configurations in the deregulated European Union airline market, while Adler and Berechman (2001) measured airport quality. Lin and Hong (2006) used DEA to evaluate the operational performance of 20 major airports around the world. Merkert and Hensher (2011) evaluated the main determinants of the efficiency of 58 passenger airlines using a two-stage DEA approach with partially bootstrapped random effects Tobit regressions in the second stage. Zhu (2011) also measured the performance of 21 airlines by means of applying the centralized efficiency DEA model of Liang et al. (2008). Finally, Curi et al. (2008) measured the efficiency of Italian airports following the privatization of the sector.

In the light of the above discussion, it is important to highlight the existence of many studies carried out in various countries, such as Canada, Croatia, France, Italy, Japan, Norway, Spain, Taiwan, United Kingdom, and USA, studies which employed both the non-parametric and parametric approaches to assess efficiency, and whose results clearly favored the application of the DEA technique. For more information, the reader is referred to Tone and Sawada (1990), Chang and Kao (1992), Chu et al. (1992), Thiry and Tulkens (1992), Obeng et al. (1997), Dervaux et al. (1998), Viton (1998), Cowie and Asenova (1999), Nakanishi and Norsworthy

(2000), Boile (2001), Odeck and Alkadi (2001), Pina and Torres (2001), Nolan et al. (2002), Boame (2004), Afonso and Scaglioni (2005), and Yu (2008).

Further, applications of DEA can also be found in relation to the efficiency of road transportation. Chu et al. (1992) used DEA to measure the efficiency of selected bus transit systems in the U.S. Levaggi (1994) adopted parametric and non-parametric approaches to analyze the efficiency of urban transport in Italy. Boile (2001) used a CCR and BCC-based DEA approach to measure the efficiency of 23 bus transit systems. Karlaftis (2004) then used DEA to evaluate the efficiency and effectiveness of 256 U.S. urban transit systems over a five-year period. Hermans et al. (2009) identified the positive and negative aspects of road safety in each country analyzed, while Shen et al. (2012) used DEA to assess a country's road safety. Álvarez and Blázquez (2014) used DEA in order to estimate the production frontier and the efficiency levels of the road network in Spain. Fancello et al. (2014) compared the performance of different urban networks using DEA in order to assist policy makers in their decision-making process of improving the efficiency of transport networks. Finally, regarding the application of DEA to the management of urban transport, Fancello et al. (2013a) and Fancello et al. (2013b) adopted DEA to compare urban road systems in different cities and assess their performance.

There are also several studies which have attempted to measure the environmental efficiency of a country's transportation sector or have focused on measuring environmental performance in general within a DEA framework, most of which, however, used the traditional DEA models by data transition method or treating the undesirable outputs as inputs or outputs with a radial approach (Fare et al., 1989; Lovell et al., 1995; Seiford and Zhu, 2002; Zhou et al., 2007, see). Zhou et al. (2006), on the other hand, proposed a slacks-based measurement DEA with a non-radial approach in environmental efficiency to measure CO2 emissions of 30 OECD countries, and Chang et al. (2013) presented a non-radial and no input/output-oriented DEA model based on the slacks-based measure (SBM) to analyze environmental efficiency of China's transportation system. Also, Margari et al. (2007) analyzed the environmental effects on public transit efficiency using a mixed DEA-SFA approach. More recently, Lee et al. (2014) employed a slacks-based data envelopment analysis model to assess the environmental efficiency of port cities.

More closely related to the present work, Kerstens (1996, 1999) studied technical efficiency through DEA techniques in the same context of urban transportation companies in France, but only for the year 1990. The author found impacts from ownership (private firms are more efficient), contract type (incentive regulation contracts are related to more efficiency), and the local tax rate earmarked for transportation (the higher the tax rate, the higher the efficiency). Roy and Yvrande-Billon (2007), on the other hand, studied the same industry for a longer time scale, from 1995-2002, but by using stochastic frontier methods, and found similar results regarding ownership and contract type.

3 The Background

The urban transport services are almost universally under close regulatory oversight. This means that generally the output levels are contractually predetermined and the firms have, to some degree, limited influence over them. This is particularly the case of this application, where the local regulators impose such output targets contractually. Therefore, we study input usage efficiency.

In this section, we discuss the theoretical reasons of why and how some features of the French regulatory environment could affect the input usage efficiency of the firms. Before that, we provide a brief description of the sector. For more comprehensive descriptions, see Kerstens (1996), Gagnepain and Ivaldi (2002), and CERTU (2003).

3.1 The French Public Transport Sector

In France, the responsibility for the service provision is decentralized at the city level. Each commune or, more frequently, group of communes, is responsible for: (i) setting the parameters of the service (target public, frequency and hour amplitude for each line, choice of operator, contract, and prices), and (ii) defining the modes of funding and functioning of the investments and exploitation of the network.

The operator can be broadly defined as being of three types, based on the degree of participation of the local government on the firm's board: fully public firms, fully private firms, and mixed public-private firms (also called "mixed economy societies"). More precisely, when the operator is mixed, the operator is a limited liability company owned in at least 51%, and at most 82% by the regulator - also, in these cases, the private co-owners "rarely own more than 30% of the equity" (Roy, 2005).

Given the different degrees of direct influence of the regulator on the firm's operating decisions and management, when the service is operated by mixed or private firms, it is said that the service is "delegated". Clearly, when the operator is public, the regulator can more directly influence the performance efficiency of the firm, i.e. any incentives to the decision-making agents is provided "internally" (within the local government administration). The situation is different when the service is delegated, and the regulator is farther away from the firm's operating decisions and management. In this case, incentives are provided indirectly, through the contractual design. In particular, we focus on the influence of the mechanism for setting subsidies stated in the contracts that are in place when the service is delegated to fully private or mixed public-private firms.[3]

Subsidies are an important share of the revenues of the firms in the sector. These are almost always required given that commercial revenues rarely cover costs (on average, they cover 45% of the operating costs), as consumer prices are generally set at low levels to make the service affordable.

One can distinguish three broad contract types, according to their mechanisms to set subsidies:

- **Management contract.** This is a cost reimbursement rule: the subsidies are set to cover the difference between the firm's revenues and the realized operating costs.
- **Net cost contract.** The regulator provides a fixed subsidy before the operating costs are realized. This subsidy is neither updated nor complemented *ex post*.
- **Gross cost contract.** The regulator provides a subsidy before the operating costs are realized, but this can be updated if the service demand deviates sensibly from previous expectations. On the other hand, the subsidy is not updated if operating costs deviate from the expected values.

The subsidies are funded by the regulators' own budgets. Besides direct revenues and contributions from the central government, an important share of the local regulators budgets is covered by a local transportation tax. This represents, on average, around 40% of the total budget, and collects a fixed percentage of the total payroll costs of the firms operating in the local area. The tax rates range from 0% to up to 2%, and are chosen by the local government, within certain boundaries imposed by the central government. These boundaries

[3] In principle, the regulator could also provide incentives by manipulating the service rates, given that commercial revenues are still an important part of the total firms' revenues. However, in practice, the regulator has limited degrees of freedom to modify prices, because the rate of change is constrained by the central government. This is reflected in the data, where the service rates are generally very stable, much more than the subsidies transferred to the operators.

differ according to the size of the urban area (measured by its population) and whether there is a system of dedicated lines for public transportation in the commune (bigger cities can set the tax at a higher level, as well as the cities with dedicated lines).

Besides the payment, the contracts also specify technical and quality requirements for the service (routes, stops locations, vehicles to use, hours and frequencies of operation), including, as previously mentioned, the amount of service to be supplied. When the operation is delegated to a private firm, the operator is selected through a bidding procedure (usually complemented with a negotiation stage) every few years (six, on average). The bigger share of cities with private or mixed public-private operators is concentrated in the hands of a few economic groups that operate in multiple cities. For example, in 2002, the share (in terms of cities) were divided mainly between Connex (25%), Keolis (20%), and Transdev (19%).[4] The remaining 36% was divided between AGIR and other small operators and local governments (Gagnepain et al., 2013).

3.2 Determinants of Input Usage Efficiency

We study some elements of the institutional design that might impact the performance of the firms. The economic theory relates the incentives for efficiency with the external pressures faced by the firm, such as competition (Nickell, 1996). In monopolistic industries, such as the case under study, the incentives can be provided by the regulator via contract design, when the service is delegated (Laffont and Tirole, 1986). On the other hand, when the service is operated directly by the local government (the operator is fully public), the efficiency objectives are likely to be traded off with others that are important to the local government administration. Therefore, the effects of both ownership and contracts can become even more complicated in firms that have mixed public-private ownership.

Figure 1 shows the evolution of the ownership and contract types. The solid line is the share of cities where the operator is fully public ("Publicly Operated"), the dotted line is the share of cities where the service is delegated to a firm of mixed public-private ownership ("Mixed Public-Private"), and the dashed line is the share of cities with a "fixed price" contract[5] (only cities that delegate the service can have these type of contracts). As shown in the graph, there is a clear tendency toward using incentive contracts as well as toward delegating the service to a private firm. These trends reflect the increased concerns for efficiency in an industry that has seen a marked increase in costs.

The main reference regarding the effects of these variables on the efficiency of this sector is Kerstens (1996). The author studied a cross-sectional sample of French cities for the year 1990, and found a positive influence of the contract types (the net and gross cost contracts), private ownership of the service operator, the contract duration, and the transportation tax rate in the city on the firms' productive efficiencies. We aim to verify whether these effects are robust to controlling for unobserved heterogeneity in the second-stage regression, as well as to taking into account the context of production in the first stage. Another important difference between the present study and Kersten's work is the time range analyzed, given that in our case we study 16 years of operation of the industry.

[4] This is a corporation specialized inthe mixed public-private operators.

[5] We include in this category the net and gross cost contracts described in the previous section, as discussed previously.

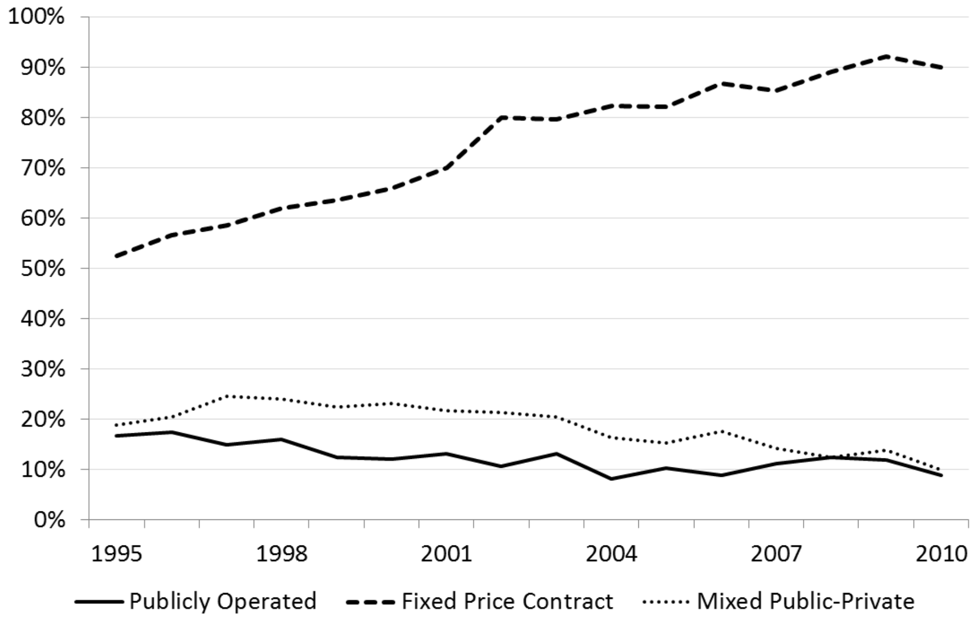

Fig. 1. Share of Cities Directly Operated and with Incentive Contracts

Kersten's findings are consistent with the theoretical economics literature about privatization and procurement, and their effects on efficiency. For example, Hart et al. (1997) suggested that delegating a public service to a private operator might promote investments in efficiency - although, it could also affect negatively the quality of the service. The reason is that under private operation, the manager has more incentives to invest in noncontractible improvements if he is able to reap their benefits (given the prevalence of bonus for performance in private firms, the manager is more likely to be rewarded for improving profits, rather than the quality of the service). On the contrary, a manager of a state-owned firm would have less incentives, given that at the end his efforts are less likely to be acknowledged or compensated by the local government.

In the same vein, the economics literature points to the importance of contracts to elicit incentives. Given that consumer prices are regulated and generally well below costs, subsidies are of the utmost importance and so the way the contract types determine subsidies might generate different incentives. If subsidies guarantee a fixed rate of return, as in the case of the management contracts (denoted hereafter as "cost-plus", or CP contracts), then the firms might not have incentives for cost reduction.[6] In contrast, if the subsidy is fixed in advance and is not adjusted *ex post* after costs are realized, then the firm could have incentives to actually reduce costs. This is the case of the net and gross cost contracts ("fixed price", or FP contracts).

Another feature which can affect the firms' efficiency in the sector, linked with dynamic incentives, is the duration of the contracts. Longer term contracts can be used to provide incentives for the firms to carry on non-contractible investments that increase efficiency in future periods (Williamson, 1976). Longer term contracts are a commitment tool for the regulator in order to not adjust the subsidies too frequently, which could diminish the incentives to invest in cost reduction activities. For example, the firms could invest in training for the drivers in order to reduce the depreciation rate of the buses, and, therefore, future costs. However, after observing the lower operation costs, the regulator might be tempted to reduce the subsidies in

[6] Given that the fixed rate of return would produce higher profits when applied to a higher share, incentives for over investment could actually exist instead. This is the so-called Averch-Johnson effect. This, however, is less likely to be present in our application, given that the local regulators own the vast majority of the rolling stock (about 95%), which is the main component of capital for these firms.

the future. If the firms anticipate this, they might lose the incentives to carry on the investments in the first place. A fixed, less-frequent review of the subsidies rule can re-instate the incentives.

The last feature we study is related to the regulators' enforcement (or general) capabilities. We propose the transportation tax rate as a measure of this, because it is a major contributor to the regulators' budgets. Also, as suggested by Kerstens (1996), "higher tax rates increase the monitoring effort of citizens and, indirectly, regulators", from which we further conjecture that a higher tax rate might increase the regulators' monitoring abilities. All this is likely to impact the performance of the operators.

4 Methods

We propose a probabilistic formulation for the production set, as outlined in Daraio and Simar (2005).

4.1 Production Frontier

Consider a vector of inputs, $X \in \mathbb{R}^p$, used to produce a vector of outputs, $Y \in \mathbb{R}^q$. Then, the production set is defined as:

$$\Psi \equiv \{(x, y)|F(x|y) > 0\}$$

where the small caps denote realizations of the random vectors, and $F(x|y) = \Pr(X \leq x|Y \geq y)$. In this context, the Farrell's radial input efficiency measure for a DMU using input vector x to produce output y can be defined as:

$$\begin{aligned} \theta(x, y) &\equiv \inf\{\theta|(\theta x, y) \in \Psi\} \\ &= \inf\{\theta|F(\theta x|y) > 0\} \end{aligned}$$

Now consider a city i operating during year t, or DMU it, which is an observation from a sample of J cities during T years. Assuming free disposability and convexity of the production set Ψ, we can use DEA to consistently estimate the previously defined efficiency measure for DMU it. We can write this estimator as:

$$\hat{\theta}_{DEA}(x_{it}, y_{it}) = \inf\{\theta|(\theta x_{it}, y_{it}) \in \hat{\Psi}_{DEA}\}$$

where

$$\begin{aligned} \hat{\Psi}_{DEA} = \{(x, y) \in \mathbb{R}_+^{M+P}|\ x \leq \sum_{j\in J}\sum_{t\in T}\lambda_{jt}x_{jt},\ y \geq \sum_{j\in J}\sum_{t\in T}\lambda_{jt}y_{jt}, \\ \sum_{j\in J}\sum_{t\in T}\lambda_{jt} = 1,\ \lambda_{jt} \geq 0,\ \forall j \in J,\ \forall t \in T\} \end{aligned}$$

Two issues are worth considering regarding this estimator. First, as suggested in the literature, this estimator may be susceptible to "extreme values, noise or outliers" (Cazals et al, 2002, p.3). Therefore, alternative estimators have been suggested that are intended to be more robust to these phenomena, such as the m-frontiers (Cazals et al, 2002) and the α-frontiers (Daouaia and Simar, 2005). These estimators avoid estimating the envelopment of all the observed input-output combinations, instead, they estimate an interior frontier. In the case of the α-frontier, for example, the idea is to estimate the α-quantile of the distribution of output conditional on the inputs. These procedures, however, are susceptible to another potential problem, which is the endogeneity of the inefficiencies with respect to the inputs. That is, if the realized efficiency levels are noisy, and its distribution is not independent of the input levels, then the efficiency estimators based on interior frontiers would be biased (Cazals et al, 2015). Even if we assume at this point that efficiency is independent of the inputs, as it is common practice, it might be problematic to keep the assumption once we add environmental variables to our analysis (see next subsection). On the other hand, DEA only requires the independence of the maximum border of the distribution of inefficiencies in order to achieve consistency.

The second issue is related to the possible presence of additional variables that affect the production set of the firms. We denote these as "contextual" or "environmental" variables. The framework proposed at this point does not take them into consideration and compares the DMUs assuming that they all share the same context or environment. This, however, might be problematic, especially in our application. For example, let us consider the case of city A with a transit network much bigger than city B. Given that our measure of output is related to the distance travelled by the buses in the network, it is much more likely for the operator in city A to appear much more efficient than the operator in city B, regardless of their actual efficiencies. This is a key issue in our application given that we consider cities with sometimes very different characteristics between themselves. Furthermore, given that we study a long panel data of cities, it might be hard to assume a constant production set across the whole set of sample years.

4.2 Production Frontier with Contextual Variables

In order to account for different contexts, we consider now, additionally, a vector of environmental factors, $Z \in \mathbb{R}^r$, that may influence the production possibilities of the firms. Given our application, this vector should include, at the very least, an indicator of the time frame period. Then, the conditional production set is defined as:

$$\Psi^z \equiv \{(x, y)|F(x|y, z) > 0\}$$

where $F(x|y, z) = \Pr(X \leq x|Y \geq y, Z = z)$. We also redefine, correspondingly our measures of efficiency, and the estimator. The Farrell's measure of input usage efficiency is now:

$$\begin{aligned}\theta(x, y) &\equiv \inf\{\theta|(\theta x, y) \in \Psi^z\} \\ &= \inf\{\theta|F(\theta x|y, z) > 0\}\end{aligned}$$

Correspondingly, the conditional DEA estimator is defined now as:

$$\hat{\theta}_{DEA}(x_{it}, y_{it}|z_{it}) = \inf\{\theta|(\theta x_{it}, y_{it}) \in \hat{\Psi}^{z_{it}}_{DEA}\}$$

where

$$\begin{aligned}\hat{\Psi}^z_{DEA} = \{(x, y) \in \mathbb{R}^{M+P}_+ |\ x \leq \sum_{j\in J}\sum_{t\in T} \lambda_{jt} x_{jt},\ y \geq \sum_{j\in J}\sum_{t\in T} \lambda_{jt} y_{jt}, \\ \sum_{j\in J}\sum_{t\in T} \lambda_{jt} = 1,\ \lambda_{jt} \geq 0,\ \forall jt \in JT \cap B(z)\}\end{aligned}$$

and where $B(z) = \{j \in J, t \in T \mid z - h \leq z_{jt} \leq z + h\}$, with h being a bandwidth parameter.

This estimator is based on Daraio and Simar (2005), who proposed the estimation of conditional efficiencies to study the effect of a set of potential explanatory variables on the efficiency performance of DMUs. The idea is that these explanatory variables could also affect the production frontier, rather than only the distance with respect to it (i.e., the efficiency) - in other words, the context of production could differ. Therefore, if one wants to investigate the effect of contextual variables on efficiency, one would need to adjust the production set to take into account these differences - otherwise, a correlation between the contextual variable and the DEA efficiency estimator could simply be capturing the effect of the contextual variable on the production set, rather than on the efficiency. The conditional DEA attempts to do this, by conditioning the production set on the set of observations with relatively similar levels of the conditioning variables (the vector z).

The approach is different from others in the existing literature. For example, Banker and Morey (1986) added the contextual variables as non-discretionary inputs in the DEA model. As shown by Ruggiero (1996), however, this model requires the assumption of free disposability and convexity of factors that are considered to be exogenous to the firm. Alternatively, the work of Ruggiero (1998, 2004) requires the assumption that the effect of the contextual variables on the production frontier to be monotonic. The approach of Daraio and Simar avoids making these assumptions.

4.3 Second Stage Analysis

Given the previously estimated conditional DEA efficiency measures, we study the effect of a set of potential determinants. As suggested in the introduction, the focus is on variables related to the institutional and regulatory environment, such as the regulatory contract type, the ownership of the firm operating the service, and the level of the transportation tax (as a measure of the regulator's budget constraint, as well as the incentives for closely monitoring the service operator).

In order to do this, we carry on a regression analysis on the estimated efficiency, which we model as a censored variable. That is, we propose the following relation between the Farrell's input usage efficiency measure and a set of explanatory variables, w_{it}, for city i at time t:

$$\theta_{it} = \min\{w_{it}\beta + \epsilon_{it}, 1\}$$

where the vector w now includes the variables used to condition the production set in the first stage (vector z) and additional covariates. To select which variables are used in both stages and which ones are used only in the second stage, we follow two considerations. The first consideration is that some variables could not affect the production set for theoretical reasons, so then their influence on the production can only come through the performance efficiency of the firms - then, they are only in the w vector. For example, although the type of the contract used to regulate the relation with the firm could affect its incentives for cost minimization, it should not affect its technological possibilities. For the remaining variables, we implement the test proposed by Daraio et al. (2010) to select those to be included in the conditioning set of the first stage. The null hypothesis of this statistical test postulates that a contextual variable does not affect the firm production set. If the null hypothesis is rejected, we include the variable in the first stage conditioning set (see Appendix B for a description of the test).

Given the above model, the object of interest is to estimate β, i.e., the effect of the covariates on the estimated efficiency below the efficient frontier. We propose up to three alternative specifications according to the strength of the assumptions that one is willing to make.

The stronger set of assumptions is that the model's error is independent and indentical normally distributed - i.e., $\epsilon_{it} \sim N(0, \sigma)$. A second alternative model introduces the possibility of correlation between the error and the covariates. For this, we decompose the error in two terms, $\epsilon_{it} = \eta_i + u_{it}$, where u_{it} is iid normal, but we don't impose assumptions on the distribution of η_i (the "fixed effect"). Another advantage of the model with fixed effects is that it can also clean up the possible bias from the first stage efficiency estimation, if this is constant by city. Finally, the last and more general model would additionally lift the assumption of normality of u_{it}.

The first model is estimated with a standard Tobit maximum likelihood estimator. The same ML estimator is used for the second model, but adding dummy variables to control for each of the cities' fixed effects, η_i.[7] Finally, for the third model we implement the semiparametric procedure proposed by Honore (1992), the trimmed least absolute deviations model. This model does not assume any distribution for the model's error, u_{it}.

5 Data and Results

5.1 Data

We have information about the firms and regulators from a survey implemented by CERTU, a public research center specialized in infrastructure and transportation. The survey is conducted on a yearly basis and collects information about the output, costs, technical characteristics, and some regulatory aspects of the networks and operators. Given that the surveys are not mandatory, there is some degree of non-response, especially for the small cities and for the earlier years of the sample, which includes the period from 1995 to 2010.

For homogeneity purposes, we exclude from our sample cities with less than 30,000 or more than 600,000 inhabitants, and cities where the operator manages additional modes of public transport, like tramways and metros. We end up with 126 cities, with an average of 9.1 time series observations for each one. Table 1 shows the summary statistics for our working dataset. In spite of the trimming, there is still considerable heterogeneity in the sample, as can be seen from the reported standard deviations.

Table 1: Summary Statistics

	Mean	St. Deviation	Min	Max
Output				
pko	278935.7	303247	1391	1402947
Inputs				
labor	164.0015	176.3435	2	714.2
gasoline	984.313	1051.75	3	4600
park	65.94404	60.71	3	288
Contextual Vars.				
fp	.7310469	.4436157	0	1
cp	.2111913	.4083381	0	1
private	.7202166	.4490954	0	1
mixed	.2220217	.4157933	0	1
public	.0577617	.2333977	0	1
tax	.805	.4137011	0	1.8
speed	16.40704	2.421696	8.1	30.8
duration	7.236462	2.909668	1	30
density	.7205547	.5323391	.0560873	4.061479
kmlines	212.9436	187.1659	10	1625.2
linelength	12.32292	5.584293	1	42.775
stoplength	.5733583	.3071764	.031746	2.521591

[7] This Tobit model with fixed effects is biased, given the incidental parameters problem. However, Montecarlo simulations provided by Greene (2004) show that this estimator's small sample bias is almost insignificant, especially for panels of length of $T \approx 8$ or more, which is the average duration for cities' series in our application.

To measure output, we employ the most frequently used measure in the literature, which is the number of seat-kilometers provided (Kerstens, 1996, 1999; Roy and Yvrande-Billon, 2007; Dalen and Gómez-Lobo, 2003) - the variable is named *pko*. This is the number of kilometers travelled by each vehicle in the network multiplied by their individual capacities, which are measured in number of seats. As Kerstens (1996) sustained, the number of seat-kilometers is a pure supply measure of output, given that it is not directly affected by the service demand - for example, the number of passengers would, on the other hand, be affected.

Regarding the inputs, we follow the literature on the French case (see studies referenced above). We consider: (i) the total number of full time employees in the year (*labor*), (ii) the number of vehicles in the network (*park*), and (iii) the fuel consumption (*gasoline*, measured in cubic meters).

We denominate the remaining variables as "contextual variables", because they can affect the production frontier of the firms and/or their efficiency performance. In particular, our results below will be based on conditional DEA efficiency estimates that condition the production set on the year of operation, the population density of the city (*density*, measured in inhabitants by squared kilometer), and the total length of the network (*kmlines*, measured in kilometers) - see the methodological and results sections for a description of the procedure used to select these variables and its implementation.

The remaining variables are used in the second stage analysis, to study the influence of the regulatory environment on the estimated conditional efficiency. As described previously, our focus is on the following dimensions: contract type (fp and *cp*, which are equal to one if the city has an FP or CP contract, correspondingly), contract duration (*duration*, in years), ownerwship (*public*, which is equal to one if the regulator operates the service directly; *mixed*, which is equal to one if the delegated firm is of mixed public-private ownership; *private*, which is equal to one if the delegated firm is private), and the transportation tax rate in place at the city in the corresponding year (*tax*).

The last subset of variables is used as control variables in the second stage regression, and reflect the physical features of the local transportation networks: *Speed* measures the average speed of the operator's vehicles (in kilometers per hour), *linelength* measures the average length of the lines (calculated as the total length of the lines in the network, divided by the number of lines), and *stoplength* is the average distance between stops (calculated as the total length of the lines in the network, divided by the number of stops).

5.2 Results

As discussed in the methodological section, we do not use all the contextual variables to condition the production set in the first stage of our procedure. We use both theoretical reasons and the statistical procedure described in Appendix B to select them. As a result, we decided to condition the DEA estimator on three variables: time, population density in the served area, and the total length of the network in kilometers. To condition with respect to time, we choose four equally-sized time windows, each with length of four years (1995-1998, 1999-2002, 2003-2006, and 2007-2010). For the other two variables, we select the bandwidth h following Silverman's rule of thumb for nonparametric kernel density estimation.

The Figure 2 shows the histogram of the estimated efficiencies (green bars). The estimates are compared, for reference, with an alternative set of estimates, produced by conditioning the production set only on the time (transparent bars) - using the same four-year windows as for the full conditional DEA estimates. The difference between the two histograms shows the effect of conditioning additionally on population density and network length. The size of the difference simply reflects that a big portion of the heterogeneity, which the second estimator attributes to inefficiency, can actually be explained by the different contexts in which the firms

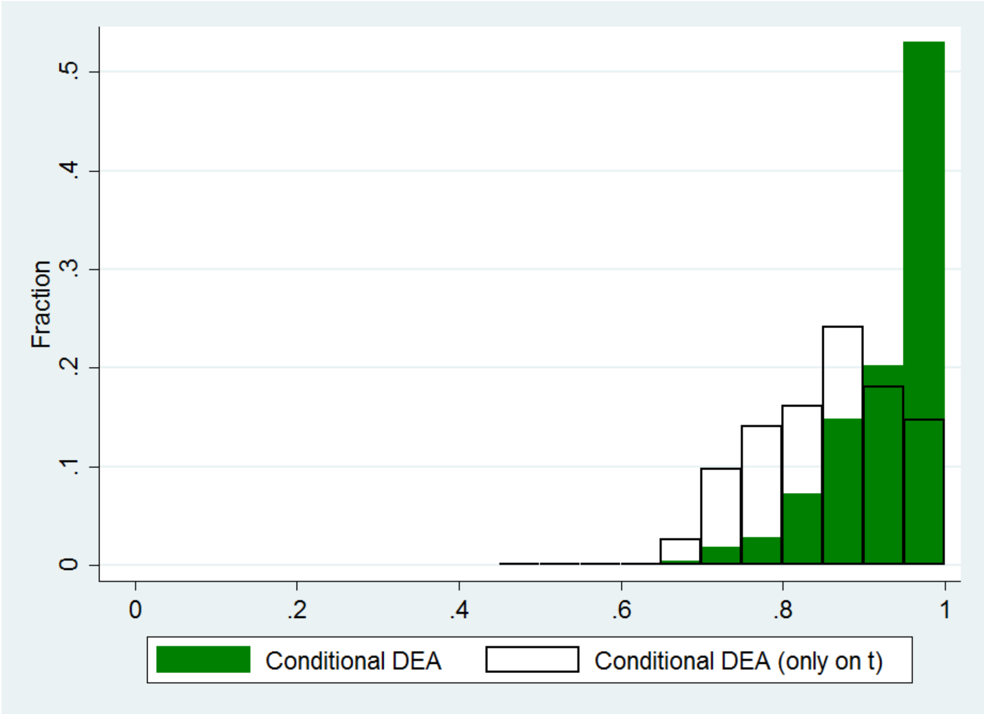

Fig. 2. Histogram of Estimated Input Efficiencies

operate.

We use the conditional DEA estimates for the second stage analysis. Table 2 shows the regressions' results. Also, for reference, Table 3 in Appendix A shows the results using another set of estimated efficiencies, that are conditioned only on time (these are calculated for each of the four four-year time windows).

We present the estimates of the censored models described in the methodological section (last three columns), along with the results of the linear regression models (first two columns). In all cases, we try specifications with and without fixed effects by city, as indicated. For the censored models, column 4 shows the result of the Tobit model (i.e., normal errors) with dummies by city (i.e., cities' fixed effects), and column 5 estimates the same model but with the trimmed LAD semiparametric procedure that does not assume normality (Honore, 1992). Finally, all specifications include a dummy variable for the time windows described earlier (excluding the last, 2007-2010), which cleans up any potential influence from having an unbalanced panel on the efficiency estimates.

We include the results of the linear models to compare the influence of including fixed effects. The advantage of linear models is that they are simpler to control for fixed effects, while nonlinear panel models face the incidental parameters problem. The disadvantage, of course, is that the linear model does not account for censoring, and then tends to underestimate the parameters. This effect is apparent in the results. Regarding the influence of including fixed effects, in general these affect the results of the linear and nonlinear models similarly - with a few exceptions. Considering this, and the evidence provided by the simulation exercises in Greene (2004), that showed that the small sample bias of the Tobit model with dummies is negligible for panels of similar length to the one in our application (see methodological section), we consider our results in column 4 as informative. Nevertheless, the semiparametric results in column 5 are more robust, given that they do not depend on distributional assumptions.

The focus of our study is represented by the effects of ownership and contracting, and their interactions, while the other variables are included mainly as control variables. Therefore, we interact the contract types (FP and CP) with the private and mixed ownership dummies, leaving the publicly operated firms as the baseline group.

We find that, in general, privately operated firms exhibit higher efficiency than publicly operated ones, but also, interestingly, that mixed public-private firms perform worse than both previous types. Furthermore, the effects seem to be related to the contract in place. More specifically, we find a statistically positive coefficient for private firms regulated with FP contracts, and a statistically negative coefficient for mixed firms with CP contracts.[8] Although, in general, the interaction between the identity of the operator and the contract type is not surprising (CP contracts can be seen as providing few incentives for efficient input usage), the sign of the relation for the mixed firms is harder to rationalize.

This result, however, is not entirely new: Roy and Yvrande-Billon (2007) also found that the mixed public-private firms would perform worse from a technical efficiency point of view than either the fully private or public firms (the authors used a stochastic frontier approach and did not differentiate the effects by the type of contract). They conjectured that the result was originated in "differences in managerial competences and incentives" (p. 277), in particular, because: (i) mixed companies do not face competition at the bidding stage (when the contract ends), (ii) mixed firms are likely to face governance problems (opportunistic behavior between the regulator and the firm) due to the unclear allocation of responsibilities, (iii) the mixed firm could be captured by the private operators, and (iv) because of the characteristics of the regulators (the direct operation of the service might be taken on by especially proactive regulators, which might be correlated with them being more efficient). Although our empirical exercise is not suitable to disentangle which of all of these effects might be in place, conditioning on the fixed effect by city allows us to discard the fourth conjecture.[9] Furthermore, we believe that the result could be related more directly to the identity of the operators that work with this ownership type: around half of the mixed firms are associations with small local firms, and the other half are mostly associations with one of the four big conglomerates in the sector, i.e., Transdev. If either of these groups (or both of them) is characterized by low performance, this could produce the negative correlation between mixed ownership and efficiency.

On the other hand, we find no significant effect from either the contract term (*duration*) or the transportation tax rate in place at the city (*tax*). In the last case, the effect turns non-significant once we introduce fixed effects. Although one could attribute this result to the scant time-series variation of the tax rate, the large length of the panel makes this explanation less plausible - the within variation is actually almost 40% of the total standard deviation for this variable.

Our results partially contrast with previous findings by Kerstens (1996, 1999), where the tax rate and the contract term had been positively associated with efficiency. Also, we find a negative influence for the mixed public-private firms, which was not explored there. In general, the differences seem to arise as a result of taking into consideration the different contexts in which the firms operate (conditioning the production set) as well as a result of considering the effects of unobserved heterogeneity on the second stage regressions (controlled here with city fixed effects). The long nature of our panel is also helpful in order to attribute these results to real empirical relations, rather than artificial results coming from the data sampling.

[8] Given the sample sizes and the stability of the coefficients across the Tobit specifications, the non-significance of the positive coefficient of privately operated firms under CP contracts could also be due to sampling error (consider that semiparametric estimators are estimated with less precision).

[9] We also do not find the third conjecture especially persuasive - it is unclear to us how the aforementioned capture should lead to lower efficiency.

Table 2: Regressions for Conditional DEA Efficiency Measures

	(1) OLS	(2) OLS	(3) Tobit	(4) Tobit	(5) Semipar.
private × fp	0.0168**	0.0107	0.0231***	0.0194*	0.0286**
	(0.00659)	(0.00888)	(0.00837)	(0.0108)	(0.0140)
private × cp	0.0284***	0.00734	0.0297***	0.0108	0.0245
	(0.00794)	(0.0103)	(0.0102)	(0.0124)	(0.0208)
mixed × fp	0.0165**	-0.0279**	0.0181*	-0.0174	-0.0724
	(0.00795)	(0.0140)	(0.0103)	(0.0193)	(0.0495)
mixed × cp	0.000539	-0.0312**	-0.00705	-0.0400**	-0.0684***
	(0.00944)	(0.0146)	(0.0120)	(0.0179)	(0.0175)
tax	0.0491***	0.0175*	0.0711***	0.0173	0.0147
	(0.00494)	(0.00937)	(0.00690)	(0.0131)	(0.0249)
duration	-0.000159	-0.000111	-0.000307	-0.000255	-0.00125
	(0.000453)	(0.000546)	(0.000608)	(0.000705)	(0.00130)
lspeed	0.00489	-0.00939	0.00110	-0.0261	-0.0308
	(0.0131)	(0.0168)	(0.0168)	(0.0203)	(0.0447)
density	0.0385***	0.0116*	0.0649***	0.0260***	0.0165
	(0.00372)	(0.00690)	(0.00551)	(0.00936)	(0.0279)
llinelength	0.0297***	0.0319***	0.0387***	0.0476***	0.0468***
	(0.00523)	(0.00672)	(0.00685)	(0.00821)	(0.0173)
lstoplength	0.0146***	0.0147***	0.0240***	0.0148**	0.0181
	(0.00428)	(0.00494)	(0.00566)	(0.00606)	(0.0177)
d1	0.0203***	0.0313***	0.0193***	0.0337***	0.0525***
	(0.00536)	(0.00504)	(0.00702)	(0.00622)	(0.0177)
d2	0.00993*	0.0171***	0.00817	0.0170***	0.0274*
	(0.00513)	(0.00451)	(0.00674)	(0.00558)	(0.0149)
d3	-0.0131***	-0.0109***	-0.0207***	-0.0177***	-0.0197*
	(0.00492)	(0.00396)	(0.00641)	(0.00480)	(0.0109)
_cons	0.780***	0.869***	0.756***	0.879***	
	(0.0375)	(0.0527)	(0.0483)	(0.0663)	
FE	No	City	No	City	City
N	1147	1147	1147	1147	1147

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusions

This study analyzes the way in which certain features of the urban transportation regulatory environment can affect the input use efficiency of the firms, such as ownership and contracting. Although these two topics have received increased attention in prior research studies, they have been treated separately, leaving a gap in the existing literature regarding the effect of their interaction. Furthermore, the different contexts in which the firms operate have been considered following certain assumptions of free disposability and convexity that are unlikely to hold in certain contexts.

The current study presents an application of data envelopment analysis approach, and considers the case of the French urban transport industry between 1995 and 2010.

Our research study makes several contributions: firstly, we attempt to fill the identified gap in the literature by means of studying the effects of both ownership and contracting, along with their interaction effect.

Secondly, our contribution to the literature is enhanced through the inclusion in the analysis of an intermediate type of ownership, i.e., the mixed public-private ownership; we aim, thus, to provide evidence of the impact of this type of ownership and contract type on the relative performance of the operators.

Thirdly, from a methodological perspective, the contribution brought by our study lies within the use of a conditional DEA frontier, an approach that takes into account the different contexts in which the firms operate, which can affect how the firms transform inputs into output. The superiority of this approach resides in dropping any assumptions of free disposability and convexity and in eliminating the assumption according to which the effect of the contextual variables on the production frontier is monotonic.

In the fourth place, we correct the effects of unobserved heterogeneity by means of using a panel structure of our data and incorporating fixed effects at the city level.

In the fifth place, we also add to the literature on efficiency determinants based on two-stage procedures by means of building upon recent methodological developments that are robust to possible miss-specification problems that could invalidate the results of the parametric approach.

Our results point to a differential effect of private and mixed public-private companies. In particular, having the performance of public operators as the benchmark, efficiency is relatively higher for private firms, but lower when the service is delegated to a mixed public-private firm. Additionally, the effects seem to diverge greatly by contract type when the firm is mixed. In this case, when the contract is of the cost reimbursement type, performance is lower than the public firm benchmark, while for other contract types there are no statistically significant differences.

The negative result for the mixed public-private firms suggests further avenues of inquiry into the mechanisms that cause this phenomenon. In particular, and given previous results in the literature in other sectors, we conjecture that this might be originated in the lack of competition at the bidding stage when the contracts are auctioned every few years for the mixed firms (the so-called competition *for* the market). For example, Ai and Sappington (2002) found that the effect of incentive regulation on efficiency depends greatly on the level of competition faced by the incumbent firms, coming from other firms that are seen as alternative providers by the consumers in the market (competition *in* the market).

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A Additional Tables

Table 3: Regressions for Conditional DEA Efficiency Measures (conditioning only on time)

	(1) OLS	(2) OLS	(3) Tobit	(4) Tobit	(5) Semipar.
private × fp	0.0189***	0.0179**	0.0195***	0.0161*	0.0171*
	(0.00727)	(0.00869)	(0.00747)	(0.00841)	(0.0103)
private × cp	0.0238***	0.000887	0.0239***	-0.00219	-0.000589
	(0.00876)	(0.0100)	(0.00902)	(0.00969)	(0.0109)
mixed × fp	0.00684	-0.0179	0.00708	-0.00443	-0.0000379
	(0.00877)	(0.0137)	(0.00903)	(0.0144)	(0.0164)
mixed × cp	0.00230	-0.0308**	0.00110	-0.0255*	-0.0260*
	(0.0104)	(0.0143)	(0.0107)	(0.0141)	(0.0139)
tax	0.0899***	-0.00855	0.0920***	-0.0101	-0.0125
	(0.00545)	(0.00917)	(0.00563)	(0.00894)	(0.0190)
duration	-0.00000428	-0.000619	-0.00000462	-0.000870*	-0.00106
	(0.000499)	(0.000534)	(0.000514)	(0.000526)	(0.000790)
lspeed	0.0791***	0.000814	0.0791***	-0.00261	0.000557
	(0.0145)	(0.0164)	(0.0149)	(0.0159)	(0.0377)
density	0.0173***	-0.0143**	0.0168***	-0.0148**	-0.0154
	(0.00410)	(0.00675)	(0.00421)	(0.00648)	(0.0105)
llinelength	0.0122**	0.0127*	0.0119**	0.0138**	0.0138
	(0.00576)	(0.00658)	(0.00593)	(0.00631)	(0.0108)
lstoplength	-0.00391	0.00325	-0.00353	0.00340	0.00335
	(0.00473)	(0.00483)	(0.00486)	(0.00463)	(0.00932)
d1	0.0491***	0.0425***	0.0512***	0.0440***	0.0453***
	(0.00591)	(0.00493)	(0.00609)	(0.00475)	(0.00945)
d2	0.0428***	0.0376***	0.0441***	0.0382***	0.0398***
	(0.00566)	(0.00441)	(0.00583)	(0.00426)	(0.00806)
d3	-0.0582***	-0.0629***	-0.0581***	-0.0634***	-0.0700***
	(0.00543)	(0.00388)	(0.00558)	(0.00373)	(0.00790)
_cons	0.499***	0.841***	0.498***	0.837***	
	(0.0414)	(0.0516)	(0.0425)	(0.0523)	
FE	No	City	No	City	City
N	1147	1147	1147	1147	1147

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Nonparametric Test of Separability Condition

This is a statistical test proposed by Daraio et al. (2010). The objective is to provide statistical evidence regarding whether a contextual variable affects the boundary of the production set - the authors call this the "separability condition". It is based on the comparison of the unconditional estimated efficiencies for each DMU with the estimates that are conditional on the contextual variables. If the environmental variable (z) does not affect the border of the production set, then conditioning on z should not generate, on average, different estimates of efficiency. Based on this idea, they proposed the statistic:

$$\hat{\tau}_{FDH} = \frac{1}{n} \sum_{j \in J} \hat{D}'_{FDH,j} \hat{D}_{FDH,j}$$

where $\hat{D}_{FDH,j} \equiv (x_j \hat{\theta}_{FDH}(x_j, y_j) - x_j \hat{\theta}_{FDH}(x_j, y_j | z_j))$ (these are $M \times 1$ vectors), and where $\hat{\theta}_{FDH}(x_j, y_j)$ and $\hat{\theta}_{FDH}(x_j, y_j | z_j)$ are the unconditional and conditional FDH scores, respectively. Although the statistic is asymptotically normal under the null hypothesis, the authors proposed a subsampling procedure to obtain the critical values in practice. See Daraio et al. (2010) for details.