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# Efficiency in the Public and Private French Water Utilities: Prospects for Benchmarking

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# Efficiency in the Public & Private French Water Utilities: Prospects for Benchmarking*

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**Abstract**

This paper uses a Data Envelopment Analysis (DEA) and a Stochastic Frontier Analysis (SFA) to assess the relative technical efficiency of 177 decision making units in the water supply sector in France in 2009. Water utilities can be directly managed by the local authorities or contracted out and then managed by a private operator. The use of a three-stage model mixing DEA and SFA enables us to dissociate managerial inefficiencies from the structural inefficiencies and statistical noise. Our results show that private managers face more difficult environments. However, after having taken into account the environmental variables, we find that private management remains on average slightly less efficient than public management. An explanation to this performance gap can be different resource management.

JEL Codes: D24, L95. Keywords: water utilities, technical efficiency, data envelopment analysis, stochastic frontier analysis, public management.

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# 1 Introduction

In industries such as energy, electricity, water and wired phone service, which are candidate for natural monopoly and where price schedules can have strong economic distortions, there is a long-time debate on the issues of utility ownership, regulation and technical efficiency. Fabrizio et al. [2007] for example evaluate the long-term impact on the industrial efficiency of privatization in electric utilities in the United States and find a significant positive impact of privatization on cost efficiency. Davis and Muehlegger [2010] discuss ownership as a determinant of price-efficiency - defined as marginal cost pricing - in the United States natural gas industry. Water supply industry exemplifies these issues. In industrialized countries, local authorities are responsible for water provision on behalf of their citizens. The service can be managed in-house or be outsourced to a private operator using a public-private arrangement. Whatever the management system, the local authorities set the objectives - such as an uninterrupted service, resource conservation and affordable prices - and have to enforce them.

Debates about the relative technical efficiency of private and public management frequently arise. In France for example, in 2009, a year after the municipal elections, the left-winger mayor of Paris decided not to renew the city's water provision contract with two private operators and to directly manage the public service. The municipality is now in charge of providing water for the 2 million inhabitants of the city. In the beginning of 2011, after a year of direct public management, the mayor announced that good performances will lead to a decrease by 8% of the drinking water price in Paris from july 2011 on. Consequently, other French public authorities decided to directly provide water to their users without contracting out with private operators arguing that public management is more efficient for public services. In other countries, we find the same debate about public and private efficiency[1].

In France, where there is no national regulator for water, water distribution is increasingly coming under scrutiny by operators, policymakers, and researchers. Benchmarking is a tool that is widely used in various countries and sectors to provide information and incentives to utilities (see for instance Shleifer [1985]). While early applications of benchmarking techniques have been practiced in the UK, most comparative studies between public and private management in the French water sector such as Carpentier et al. [2006] and Chong et al. [2006] use econometric methods. This is partly due to missing data on costs, revenues and performance or quality indicators. Since the 2007 decree and the implementation of the *French National Agency of Water and Aquatic Environments* (ONEMA) the same year, the idea of a benchmarking of water services in France got more popular[2]. Finding the regulating tools that will reduce the information asymmetry between local authorities and water companies and promote the performance objectives

[1] See for example Bhattacharyya et al. [1995] on the USA, Estache and Rossi [2002] on Asia and Kirkpatrick et al. [2006] on Africa, Garcia-Sanchez [2006] on Spain, Saal and Parker [2000] on Wales and England, Zschille and Walter [2012] on Germany.

[2] The *Fédération Nationale des Communes Concédantes et Régies* (FNCCR), an association of municipally elected persons who manage public services, has already financed two benchmarking studies on 31 voluntary French water provision services using 2008 and 2009 datasets. By the same token, the *Professional Association for Water Companies* (FP2E for *Fédération Professionnelle des Entreprises de l'Eau*), a group of private firms operating in the water and sewage sector, also collects data and fund studies (Boston Consulting Group [2007]) on the relative performances of direct and delegated management.

in the water industry has become a broadly shared goal. Assessing relative performances can become a valuable regulatory instrument and begins to gain popularity in France.

This paper addresses the relative technical efficiency of 177 public and private water suppliers in France by computing the best practice frontier of our sample. To identify managerial efficiencies, we evaluate the ability of water producers to minimize their revenues in the provision of a set of outputs, relative to the performance of other producers in our comparison set. This intuition follows a standard result in the regulation of public utilities (Coase [1946]) emphasizing that efficiency requires revenues covering operational and capital costs with downsized margins in order to limit distortions such as the deadweight loss. However, efficiency depends also on the characteristics of the environment in which production is carried out. Moreover, hazards such as "luck" must be unbundled from managerial efficiencies. These effects are taken into account by considering a set of environmental variables that can impact technical efficiencies.

Our empirical approach is different from previous studies on French data. To control for hazards and structural differences, we mix a non-parametric approach (Data Envelopment Analysis, DEA) with a stochastic model (Stochastic Frontier Analysis, SFA) in a three-stage approach introduced by Fried et al. [2002]. The three-stage model is the following. In the first-stage, a conventional input-oriented DEA using only inputs and outputs is applied to obtain initial measures of producer performance.[3] In the second-stage, we regress the slacks of the first-stage against the environmental variables and an error term using a Stochastic Frontier Analysis (SFA). This method allows us to purge the managerial inefficiencies from the possible environmental effects and statistical noise. Finally, the third-stage re-evaluates producer performance and provides improved measures of managerial efficiency, since the data have been purged of both environmental effects and statistical noise. Decision making units (DMU) are then ranked according to their efficiency scores that ranges between 0 and 1. Mixing different benchmarking models lead to a robust evaluation of the relative performance of utilities. Consistent results will improve the relevance of benchmarking tools, the reliability of performance rankings and finally, it will limit enforcement difficulties of the benchmarking.

Our results show that utilities under private management are on average more complex to manage. Accounting for environmental variables increase efficiency by 0.1 under private management while it only lifts up efficiency by 0.059 for public management. However, even after having taken into account environment variables and statistical noise, private management remains on average less efficient than public management. Public management has an efficiency score of 0.883 against 0.823 for private management. As a summary, even if the technical efficiency gap is narrowing after correcting for structural differences, it remains significantly positive. This gap partly results from a widespread technical efficiency of DMUs under private management.

This paper contributes to the literature on resource management and conservation. In addition to traditional measures of technical efficiency, a measure of resource management is considered to assess the performance of DMUs. As an output, the capacity of utilities to

[3] As noted by Berg and Lin [2008], an input-oriented DEA model is more realistic in the case of water companies, because those utilities are supposed to meet demand (the output is exogenous). Therefore, input quantities appear to be the primary decision variables related to firm efficiency.

ensure water conservation is important because it usually warrants civil society, especially as water is a scarce resource. Sustainable use of the resource is an important feature of the public service as water shortage can be severe in some regions. The performance in terms of water conservation is thus an important point to account for as a high level of costs can be linked to a high performance in reducing leaks. Such a performance indicator should be considered as an output as it has a direct impact on the cost structure of the utility.

The outline of the paper is the following. Section 2 reviews relevant literature with respect to the applied methodologies. Section 3 provides a general description of the regulatory regime and the institutional framework for the French water industry. The model specification is set out in section 4. Section 5 focuses on variables along with the arguments that support their choice. Empirical results are presented and discussed in section 6. A brief conclusion follows.

# 2 Related Literature

A large number of studies uses a benchmarking method to evaluate the efficiency of water utilities in industrialized and developing countries. Alongside the empirical research into the measurement of efficiency, an equal amount of attention has been directed to the factors that can influence efficiency. One of the key purposes of studies on efficiency has been to examine the role of ownership.

In industrialized countries, Bhattacharyya et al. [1995] using a translog variable cost function on 221 US water utilities, find that US publicly owned water utilities are more efficient. Garcia-Sanchez [2006] uses a four-stage approach to estimate technical and efficiency of 24 Spanish municipal water supply agencies. Running three best-discriminating DEA models with nearly identical efficiency scores, they find that only population density - not ownership - has a statistical significant impact on inefficiencies. Using case studies in various countries, Hall and Lobina [2004] show that private management often leads to higher prices than public management. However, the authors do not give clear-cut justifications to the price-gap between public and private management. The same impact of private management on price is found by Carpentier et al. [2006] and Chong et al. [2006] in France. Carpentier et al. [2006] used treatment effects on 3,782 municipalities in 2008 and found that private management is associated with higher prices because of more complex water utilities. Studying 5,000 French municipalities in 2001, Chong et al. [2006] find that private management is associated with a premium of 11 euros for a standard bill.

In developing countries, some studies find a slight positive impact of private ownership on company efficiency. Kirkpatrick et al. [2006] use DEA and SFA to determine the impact of ownership structure on efficiency performance of 110 water utilities in African countries. Higher relative efficiency is shown for privately owned utilities, when using a DEA method, whereas no statistically significant results for the impact of ownership is found with SFA. Estache and Kouassi [2002] estimate a Cobb-Douglas production function for 21 African water utilities for the period 1995 and 1997. In a second-stage, they use a Tobit model to relate resulting inefficiency scores to governance and ownership variables. Their results indicate that private ownership significantly decreases inefficiency. However, their dataset contains only three privatized firms while corruption and governance seem far more important in explaining efficiency differences between firms than the ownership variable. No significant differences between efficiency under public and private ownership are observed by Estache and Rossi [2002], who estimate a stochastic cost frontier modeling on data from 50 water utilities in developing and transition countries in the Asian and Pacific region.

Instead of comparing public and private water utilities operating at the same point of time, another body of work focuses on the impact of privatization on the efficiency and productivity of the sector, mostly in the UK. Saal and Parker [2000, 2001] study the privatization of water utilities in England and Wales in 1989. They expect privatization to improve efficiency on the premise that it removes soft-budget constraints, eliminates any political or special interest group interference associated with public ownership, exposes utilities to the market for corporate control, and incentivises management and employees with performance pay structures and the market for managerial talent. Using cost function and Total Factor Productivity (TFP) analyses to a panel of ten UK private companies, the authors conclude that there is no statistically significant reduction in the trend growth rate of total costs following privatization using cost function and no changes in productivity after privatization using TFP.

One challenge with those studies is the appropriate recognition of the differences in public and private strategies. While there is a clear similarity in the specification of inputs and outputs, one might argue that private and public managers do not serve the same goals. As noted by a recent paper using a DEA methodology by Zschille and Walter [2012], private managers can be tempted by excessive pricing, leading to distortions (such price distortions in regulated utilities are also discussed in Davis and Muehlegger [2010] and Porcher [2012] for example) between producers and consumers, but also on connected markets (here sanitation for example). While cost-based analyses focus on management inefficiencies, we argue here that using revenues leads to a broader analyses coupling the benchmarking of managerial inefficiencies and pricing strategies.

# 3 The Water Sector in France

## 3.1 The provision of water in France

In France, municipalities must provide local public services that have public good characteristics. This provision can be made by the municipality alone or by a group of municipalities that collectively engage to provide one or several public services. As there is no national regulator for these services, local public authorities define the general principles governing those services on behalf of their citizens: they monitor prices, control entry and exit of firms into the market, organize competition and ensure uninterrupted service. Regulation has thus been replaced by a contract in the case of a private operator or a decision of the municipality board in the case of public operation. In the case of delegated management, public authorities face the classic regulatory problem: they are in an information asymmetry position and have few tools to carry out their essential tasks. Water supply is one of these public services. Water supply is a broad subject implying four public services. On the one hand, water provision refers to the production and the distribution of water; on the other hand, sewerage implies wastewater collection and treatment. Due to potential scope economies, water provision and sewerage can be run by the same operator[4] but through two separated contracts.

Furthermore, rules have been defined to ensure that standards are respected during the operation to limit the potential opportunistic behavior of operators. These rules support water quality, duration of contracts and information about management and provision quality. In the case of water quality, a precise definition of more than 60 verifiable quality parameters has been set by the 1992 water act to ensure that water services, would they be private or public, respect quality standards. Consequently, water quality is respected and is rarely below a 95% score of conformity to the standards of the microbiological analysis. Moreover, limits on duration have been implemented and management and provision information is now required to be publicly reported. To ensure that competition between operators arises, the "*Barnier Law*"(1995) gives a clear limitation to the duration of contracts and includes an automatic renegotiation of the contract every five years. To struggle against information asymmetries, the executive power passed a decree in 2007 that forces municipalities and communities to provide 14 performance indicators in the mayor's *Annual Report on Prices and Service Quality* (RPQS in French). These performance indicators and other data about water and sewerage services are collected by the *French National Agency of Water and Aquatic Environments* (ONEMA in French) to provide data in order to inform users and citizens about their water services.

## 3.2 The institutional framework of water industry in France

In France, each local public authority may choose a particular contractual form from the differentiated set of alternatives. Although some municipalities manage production through a *direct public management* and undertake all operations and investments needed for the provision of the service, the hiring of a private operator, independent of the local government, to manage the service and operate facilities is common.

In the latter case, the local public authority may choose to involve an outside firm in the operation of the service choosing a *delegated management* contract.[5] There are two types of contracts. These contracts are characterized by shared investments with the public authority to maintain the network and financial compensation directly through customer receipts. These contracts give companies incentives to reduce costs, and companies share risk in exchange for greater decision rights and claims on revenues.

The institutional framework to select the private partner is the following. Since the "*Sapin law*" (1993), if the public authority chooses a lease or a concession contract, it selects its partners in two steps. First, the public authority launches a classical invitation to tender that is open to all interested private water companies. Second, there is a negotiation phase between the public authority and potential entrants that it shortlisted. At the end of the negotiation, the public authority chooses its final partner for the duration of the contract. The selection of the private company follows the *intuitu personae* principle according to which the municipality or the community sets a list of criteria to select the

[4] An official report by Dexia, a French financial intermediary, states that 63% of French medium-sized cities contract out the services of drinkable water treatment and distribution and 58% also contract out their sewerage services. It is however difficult to have a precise estimation of how many municipalities and communities have contracted out both services with the same operator.

[5] Our sample has only *delegated management contracts*.

firm that is considered as the best partner.

# 4 Model Specifications

## 4.1 Methodology

In 1957, Farrell introduced a data envelopment methodology[6] for the measurement of economic efficiency. From an input-oriented perspective[7], technical efficiency is associated with the ability to produce on the efficiency boundary of the production possibility set given a predetermined quantity of output. DEA is useful because the researcher does not need to make any assumption about the functional link existing between inputs and outputs.

The basic DEA model described evaluates economic efficiency using traditional input and output variables but it does not consider the potential impact that environmental factors may have on producers' performance measurement. Several models have been developed in order to incorporate environmental effects into a DEA-based performance evaluation.[8]. One possible approach is to include the environmental variables directly into the linear programming formulation either as non-discretionary inputs, outputs or neutral variables, according to the circumstances (Ferrier and Lovell [1990]) This requires that further linear programming constraints be included. As a consequence, only few environmental variables can simultaneously be taken into account to avoid excessive restriction of the reference set. Contrary to the DEA approach, the stochastic frontier analysis (SFA) accounts for statistical noise and environmental variables in measuring efficiency. However, this type of analysis demands important datasets on inputs costs such as labor costs, capital costs or energy costs.

A possible approach to better evaluate producer performance is to adopt a multi-stage DEA analysis. This ensures that the comparison is made among units which operate under similar environmental conditions, thus eliminating the environmental effects from the single company's performance assessment. Another group of models is based on two-stage mixed approaches which imply a regression-based second stage. These models involve solving a DEA problem in a first stage using traditional input and output variables in order to calculate initial efficiency measures. The efficiency scores are then regressed using ordinary least squares (OLS) upon a set of environmental variables in a second stage, the objective being to determine the signs, as well as the significance of the coefficients of the environmental variables (see for instance Bhattacharyya et al. [1997]) by adjusting the first stage efficiency scores.

For their part, Fried et al. [1999] introduced a three-stage approach where the initial DEA efficiency scores based exclusively on output and input are then regressed in the

[6]For a comprehensive description of DEA models, see Charnes et al. [1978], Thanassoulis [2000a,b], Charnes et al. [1994] and Cooper et al. [2004].

[7]In principle, economic efficiency may be measured using an input or an output-oriented approach. In the first case, the input use is minimized given a certain amount of output, while in the second the output is maximized for a given level of inputs. Generally, the adoption of an input-oriented framework is preferred for public utilities as demand may be seen as exogenous.

[8]See Coelli et al. [1998] for details on these models.

second stage using a Tobit upon a vector of environmental factors. Predicted values of the impact of the environmental effects can then be computed. In the third stage, the original data are adjusted to account for the effect of environmental variables and DEA is re-run in order to obtain new DEA scores unaffected by environmental characteristics. We should underline that Tobit regressors using efficiency scores as dependent variable can give biased results for at least two reasons. The first one is that the dependent variable - the inefficiency remaining from the first stage - is purely constructed. The second reason is linked to the first one. As technical efficiency scores are bounded by 0 and 1 by construction, the variable does not capture all the variance of the existing inputs.

Both OLS and Tobit are however unable to account for the role of statistical noise on efficiency. However, as noted by Erbetta and Cave [2007], both these approaches are deterministic and so they fail to take into consideration the effects of statistical noise on efficiency performance. In order to embody the action of both environmental variables and statistical noise upon efficiency, we adopt, like Erbetta and Cave [2007] a three-stage approach proposed by Fried et al. [2002]. This mixed approach which combines DEA and SFA makes it possible to obtain a measure of the intrinsic managerial performance, separately both from the impacts of the environmental characteristics in which production takes place and from random noise. As SFA is regression-based, it can isolate managerial inefficiencies from environment effects and statistical noise in the second stage. In the last stage, producers' inputs are adjusted to account for the environmental effects and statistical noise identified in stage two and DEA is run again to re-evaluate producer performance.

## 4.2 Model set-up

The initial producer performance evaluation is conducted using a conventional input-oriented DEA analysis, using input quantity data and output quantity data only. The basic DEA model can be expressed as the following linear programming problem:

$$\begin{cases} \min_{\theta,\lambda} & \theta \\ \text{s.c} & -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \\ & e^T\lambda = 1 \end{cases} \tag{1}$$

with $y > 0$ is a producer's $i$ $M \times 1$ vector of output; $x > 0$ is a producer's $N \times 1$ vector inputs used by the DMU $i$ ; $Y = [y_1, ..., y_I]$ is a producer's $M \times I$ matrix of outputs of the $I$ DMUs in the comparison set; $X = [x_1, ..., x_I]$ is an $N \times I$ matrix of inputs used by the $I$ DMUs of the sample; $\lambda = [\lambda_1, ..., \lambda_I]$ is an $I \times 1$ vector of intensity variables; $e = [1, ..., 1]$ is an $I \times 1$ vector for the $I$ DMUs of the sample; $0 \leq \theta \leq 1$ is an efficiency score measure.

The first step thus consists in solving program (1). However, actual technical efficiencies are likely to be attributable to some combination of managerial inefficiencies, environmental effects, and statistical noise, e.g. "bad luck" or a biased error term, and it is desirable to isolate the three effects.

In a second step, the total excess (radial plus non-radial) of inputs (*slacks*) computed in the first stage (noted $S_{ni} = x_{ni} - X_n\lambda \geq 0$) are regressed against the environmental variables adding an error term, using the SFA method. $S_{ni}$ is thus the excess of inputs resulting from the usage of input $n$ by the DMU $i$. $X_n$ is the $n^{th}$ column of $X$ and $X_n\lambda$ represents the optimal projection $x_{ni}$, i.e. the value that the input should reach so that the DMU is considered to be efficient. The belief from the DEA first-stage is that total slacks reflect initial managerial inefficiency. However, we interpret these slacks more broadly, as being composed of three effects: environmental influences, managerial inefficiencies, and statistical noise arising from measurement errors in input and output data used to generate the first stage slacks. The main advantage of using SFA rather than a standard econometric method such as Tobit or OLS in the second-stage is that its error term is asymmetric. Consequently, it allows to dissociate the environmental variables (here the regressors) from managerial inefficiencies (the one-sided error component) and from statistical noise (the symmetric error component). Independent variables are $K$ environmental variables : $z_i = [z_{1i}, ..., z_{Ki}], i = 1, ...I$. The $N$ regressions (one for each *input* excess) are written as follows, with $n = 1, ...N$ and $i = 1, ...I$ :

$$S_{ni} = f^n(z_i; \beta^n) + \nu_{ni} + u_{ni} \tag{2}$$

$f^n(z_i; \beta^n)$ represents the frontier of inputs slacks. The $\beta^n$ are the estimated parameters by the software. $\nu_{ni}$ measures the statistical noise whereas $u_{ni} \geq 0$ stands for the managerial inefficiencies of the DMU. The stochastic frontier is measured by $S_{ni} = f^n(z_i; \beta^n) + \nu_{ni}$. As $u_{ni} \geq 0$, this stochastic frontier represents the minimum *slacks* that can be reached by the DMUs. All inputs slacks above this frontier will be considered as managerial inefficiencies of DMUs. The idiosyncratic error term $v_{ni}$ is independently and identically distributed $v_{ni} \sim N(0, \sigma^2_{vn})$, while $u_{ni} \sim iid\ N^+(\mu^n, \sigma^2_{un})$ (zero-truncated normal law). $v_{ni}$ and $u_{ni}$ are indenpendently distributed between them and regarding regressors. The $N$ regressions (2) are estimated using a maximum likelihood. For each regression, parameters to be estimated are $(\beta^n; \mu^n; \sigma^2_{vn}; \sigma^2_{un})$. As noted by Fried et al. [2002], there are at least two virtues of using SFA in the second-stage. First, it is not necessary to assume the direction of the impact of any environmental variable on producer performance prior to the analysis. Second, the framework permits the environmental variables, statistical noise and managerial inefficiency each to exert different impacts across inputs.

We now consider how to use the results from the second-stage to adjust producers' inputs for the variable impacts of different operating environments and random statistical noise. The essence of the adjustment lies in the fact that producers operating in relatively unfavorable environments, and producers experiencing relatively bad luck, are disadvantaged in the first-stage DEA performance evaluation that does not take these factors into account. One way to level the playing field is to adjust upward the inputs of producers who have been advantaged by their relatively favorable operating environments or by their relatively good luck. Producers' adjusted inputs are constructed from the results of the second-stage SFA regressions by means of:

$$x^A_{ni} = x_{ni} + \left[max_i \left\{z_i\widehat{\beta}^n\right\} - z_i\widehat{\beta}^n\right] + \left[max_i \left\{\widehat{\nu}_{ni}\right\} - \widehat{\nu}_{ni}\right] \tag{3}$$

with $n = 1, ...N$ and $i = 1, ...I$. $x^A_{ni}$ is the adjusted input ; $x_{ni}$ is the observed input in the dataset. $\left[max_i \left\{z_i\widehat{\beta}^n\right\} - z_i\widehat{\beta}^n\right]$ put all DMUs in the same operational environment. $\left[max_i \left\{\widehat{\nu}_{ni}\right\} - \widehat{\nu}_{ni}\right]$ put all DMUs in the unluckiest environment. Corrections differ across utilities and the considered input.

Therefore, from the $\widehat{E}\left[\nu_{ni}/\nu_{ni}+u_{ni}\right]$, we derive the statistical noise:

$$\widehat{E}\left[\nu_{ni}/\nu_{ni}+u_{ni}\right]=s_{ni}-z_i\widehat{\beta}^n-\widehat{E}\left[u_{ni}/\nu_{ni}+u_{ni}\right] \tag{4}$$

with $n = 1,...N$ and $i = 1,...I$. This equation gives the conditional estimators for the $\nu_{ni}$ included in equation (3). $\widehat{\beta}^n$ is useful to estimate the contribution of each environmental variable observable for the *slacks*, while parameters $(\mu^n;\sigma^2_{vn};\sigma^2_{un})$ allows us to separately estimate managerial inefficiencies and statistical noise *slacks*. When $\gamma^n=\sigma^2_{un}/(\sigma^2_{\nu n}+\sigma^2_{un})\rightarrow 1$, managerial inefficiencies have a stronger effect than statistical noise, while it is the contrary when $\gamma^n \rightarrow 0$.

In the third-stage, we repeat stage 1 with the adjusted inputs that take into account the observable environmental variables and statistical noise. The output of stage 3 is a DEA-based evaluation of producer performance couched solely in terms of managerial efficiency, purged of the effects of the operating environment and statistical noise.

## 4.3 Outliers' detection

In DEA models, the efficiency of a DMU is evaluated relatively to a reference set comprised of all sample observations, including itself. As most efficient DMUs drive the efficiency frontier, it is sometimes necessary to peel off a fraction of the observations to obtain more reliable production frontier estimates. Some of the DMUs might be considered as outliers as they drive upward the efficiency frontier and thus drive downward the average score. DEA is thus sensitive to outliers or extreme observations in the data and a profound validation of the data is necessary.

A first attempt for identifying outliers has been made by Timmer [1971] who suggests discarding a certain percentage of efficient observations from the sample and re-estimating the production frontier using the remaining observations. All the difficulty lies in the capacity to correctly select the outliers. Banker and Gifford [1988] use another procedure based on contamination of efficiency scores by super-efficient outliers. For each observation $i$, the idea of the super-efficiency approach is to solve the linear program given in equation 1 by only using all observations $k = (1,...,K)$ other than $i$, i.e. $k \neq i$ as possible peer units. The observation $i$ is not included in the reference set and can have a score greater than 1, i.e. considered as super-efficient, as it can not be a reference for itself. This method is useful to detect outliers that do not stand at the frontier. The drawback is that it needs to repeat *I-1* DEA linear programming which is inappropriate for large samples.

In this paper, we use a simple method to detect outliers (see Tran et al. [2010]). We compute for each observation two simple indicators. First, we consider the number of times that an observation is used as a reference[9]. Second, we compute the cumulative weight of efficient DMUs across all constructed efficient sets. As we use a variable returns to scale (VRS)[10], the frontier consists in a convex combination of inputs and outputs of the most efficient DMUs. An easy way to detect outliers is then to use a graphical

[9]Indeed, the DEA method gives for each inefficient DMU the DMUs that are used as references to compute its technical efficiency. Efficient DMUs, i.e. those which determine the efficiency frontier, can thus be quoted as references for inefficient DMUs.

[10]See Banker et al. [1984] for a detailed explanation. The VRS hypothesis is the less restrictive hypothesis on

representation of the number of times that a DMU is used as a reference and the cumulative weight of the observation across the efficient sets. We then drop outliers and re-run the first-stage until the results are stable. Using this simple method, five observations are dropped (one under public management and four under private management) after having repeated the process three times.

Figure 1 in the appendix depicts the link between the number of times a DMU is used as a reference and the sum of weights for the first round of outliers detection. All efficient DMUs are represented in this graph. As one can see, two outliers are easily detected. As there are no clear rules for defining what is an outlier, we decided to graphically select outliers and not to drop more than two variables at each stage. In this case, DMUs A and B are identified as outliers and are then removed from the dataset. In the following section, we present the dataset.

# 5 Data

A data collection has been launched to get the 325 biggest French water services 2009 *Annual Reports on Prices and Service Quality* (*RPQS*). When we could not access the Annual *RPQS*, we used the 2009 *Delegate Annual Reports*, a confidential compulsory annual report made by the firm for the municipality. Like other studies, we focus only on the water service and we do not consider the sewerage one for two reasons. First, a benchmarking on sewerage activities would be constrained by a lack of comparators. Second, we lack data on sewerage services that are sometimes managed by another operator or under another organizational form. We managed to get 297 reports.

One problem that arose during data collection is that reports do not systematically present data in the same way. For example, performance indicators can be computed at city-level, at contract-level or at territory-level. In the latter case, we have information for a bunch of contracts covering several neighbor cities and managed by the same firm. The main criterion to distinguish producers is the contract-level approach. However, sometimes we only have data for the main city of the contract or for the bunch of connected contracts of a single firm. More complicated is the scenario when we have data for the territory with different firms and organizational forms to manage the local utilities. In this case, we considered the utility as public (private) if a majority of connections are managed by a public (private) operator. Because of missing data, our unique sample for this study - OSEA - is made of 177 observations before outliers' detection. In the following subsections, we present the selected variables and their construction when necessary.

returns to scale. The use of the constant returns to scale (CRS) specification when not all DMUs are operating at the optimal scale will result in measures of relative efficiency which are confounded with scale efficiencies. The use of the VRS specification enables to measure relative efficiencies devoid of these scale efficiencies effects.

## 5.1 Dependent variables

We use revenues as a proxy for costs.[11] By including the utility's revenues as an input, we first assume that revenues reflect operating and capital costs plus a mark-up. From the regulator point of view, tariffs should cover the monopoly's costs and to avoid market distortions resulting from excessive margins. Excessive revenues can reveal managerial inefficiencies if they are not used to cover costs. Moreover, using revenues is meaningful as the price of water must cover the production costs, the so-called "water pays water" principle: under private management, the price is jointly set by the municipality and the firm, following operator costs; under direct management the price is decided by the municipality following its costs. Following the European water framework directive (Directive 2000/60/EC, article 9), revenues must cover all material costs, depreciation and labor costs. Therefore, a water provision unit will be more efficient the lower the revenues for a given level of outputs. The advantage of such a revenue yardstick approach is that there is no need to measure operational and capital costs. Such an exercise can be hazardous with data coming from publicly and privately managed utilities as accounting rules differ. For example, depreciation rules are not the same under public and private accounting rules which makes impossible the comparison between costs in public and private management. Furthermore, documents used for the coding usually report detailed revenues but rarely write costs. Considering revenues as thus two advantages: first, revenues are comparable from an utility to another; second, it is a good proxy for costs as by construction, revenues must cover costs and can include a mark-up for the operator.

Utilities' revenues mainly depend on the volumetric charge and the fixed-fees paid by consumers but it also includes other products and revenues from works on the networks and other products. In France, the price of water is divided between a fixed-fee and a variable part depending on the consumption pattern of the user. A part of the profit coming from water sales can be paid back to the community or to the municipality in accordance with the contractual design. The final price paid by consumers also includes several taxes transfered to the public water agencies and to the State. As the extra-revenues from works on the networks and other products, these taxes do not reflect the service's performance. We thus use as an input revenues of the water service coming from the billing of consumers excluding revenues coming from other products, works on the networks, product of public taxes and exports to other municipalities. The remaining part represents the revenues from the water sales that are shared between the private water company and the public authority. These "net" revenues cover costs and include a margin captured by the private firm when the management is private and by the public authority when the management is public.

## 5.2 Physical outputs

In order to compare water provision units' performances, three traditional physical outputs used in the literature are considered: billed water in cubic meters, number of customers and the pipes' length in kilometers. These three variables actually represent the three professions of water operators: producing and distributing water, managing customers'

[11] Most of benchmarking studies in the water industry use operating costs as the dependent variable (see for instance Thanassoulis [2000a,b] in the case of water companies in England and Wales, Corton [2003] for water companies in Peru and Corton and Berg [2009] for Central American water utilities). A recent study by Zschille and Walter [2012] uses revenues as a proxy for price to apply a consumer perspective in regulation.

service and managing pipe maintenance. They are thus proxies for the amounts of operational costs and capital costs.

Billed water is a conventional measure of the water production activity and is represented, in our database, by the total volume of water delivered and billed to households and non-households customers. We do not take into account exports neither in billed water nor in revenues. The number of customers is also a commonly used output (see for instance Saal and Parker [2000]). The number of customers in our database represents the number of properties connected for water supply. In French urban areas, a connection can represent a whole building or a part of the building. Several studies underline the relevance of combining both the volume of water billed and the number of customers (Saal and Parker [2006], Thanassoulis [2000a]). For instance, Saal and Parker [2006] justify this specification by the fact that the two tasks have different characteristics and heterogeneous marginal costs. Moreover, previous researches (see for instance Garcia and Thomas [2001]) have suggested that because of the cost of maintaining network connections, the number of customers is an important determinant of water industry costs and revenues. According to Erbetta and Cave [2007], this specification is a proxy for the scale of the distribution activity. For Thanassoulis [2000a], combining billed units and the number of connections is recommended to better account for utilities with numerous but rather low-consumption customers.

Furthermore, water suppliers may have different revenues depending on the length of mains (Corton and Berg [2009]). Therefore, as regards the outputs commonly used in benchmarking studies and following for example Thanassoulis [2000a,b]) and Garcia-Sanchez [2006], we add the length of mains as an output. Note that the Ofwat[12] also uses this variable as an output to determine the relative efficiency of water and sewerage companies. Thanassoulis [2000a,b] argued the length of mains reflects the geographical dispersion of connections. For Berg and Lin [2008], this variable is an indicator of capital.[13] These explanatory variables are positively correlated with the revenues.

## 5.3 Quality output

In addition to traditional measures of technical efficiency, service quality is a performance indicator that warrants attention, since one important characteristic of water companies is that they must comply with quality standards. To measure performance, we use a variable that gives us information about environmental performance and network quality. This quality indicator is an important outcome as private operators usually justify their higher prices by higher quality standards and a better consideration for water conservation policies.

To measure the quality of resource management, we use network performance measured as the ratio between billed water and the sum of billed water and water losses. Some

[12] The Office of Water (Ofwat) is the regulatory institution in charge of the water and sewerage sector in England and Wales.

[13] The length of mains is often considered to be an output in benchmarking studies. However, in some studies, this variable is considered as a proxy for the cost of capital, being therefore included as an input variable. For our part, we consider as being more realistic to include this variable as a physical output, since otherwise, the model will recommend the water services to minimize the length of mains used, which is not applicable in facts.

studies use water losses to take account for deficiencies in either operational or commercial practices. Indeed, as argued by Corton and Berg [2009], water losses may reflect a cost trade-off between increasing water production and repairing network leaks to keep up with water demand. Hence, the idea is that, to satisfy demand, managers may find it more costly to repair leaks and to control water losses than to increase water production. For Garcia and Thomas [2001], water network losses are considered as a non-desirable output produced jointly with the service of water delivery. For their part, Coelli et al. [2003] regard water losses as an indicator of the technical quality of service. Network performance is a good quality indicator for at least two reasons. First, dealing with leaks implies very costly in human capital investments as pipes are mostly are repaired using human workforce. Second, water conservation has been at the center of the European water policies in the last twenty years.

One might argue that we could use some other variables to measure quality such as water quality or consumers' satisfaction for example. In some developing countries, service coverage, service continuity or the percentage of water receiving chemical treatment are adequate variables to measure water quality (see for instance Berg and Lin [2008] in the case of Peru or Corton and Berg [2009] for the Central American water utilities). In contrast, in developed countries where water services cover nearly all the population, alternative measures of quality are required (see for instance Saal and Parker [2000, 2001]) and should focus on water conservation policies.

Regarding drinking water quality, we could have retained compliance with microbiological standards measured as the percentage of successful tests (see for instance Saal and Parker [2000]). It is sometimes considered as an "environmental" advantage for the supplier, since the drinking quality is often regarded as being closely linked to the production of drinking water from groundwater as the source is less polluted. However, a higher quality of drinking water may also come from DMUs' efforts to achieve the qualitative criteria. In this case, a positive impact on revenues is expected. In our sample, the drinking water quality never exceeds the 5% of non-compliance and variance is less than 1% for the full-sample. Because of this low variance, we prefer to consider network performance rather than microbiological quality. In our opinion, it is a far stronger indicator to better understand differences in performance. In order to take into account the need for good water quality and its costs, we controled for some characteristics of water in the environmental variables.

## 5.4 Environmental Variables

The efficiency of a firm could be affected by exogenous conditions that are not under the direct control of managers. Environmental variables have been included because they may influence the technology under which water utilities operate and may account for exogenous differences in operating environments experienced by each firm (see Bhattacharyya et al. [1995], Garcia and Thomas [2001] and Filippini et al. [2008] among others). These variables account for the different characteristics of networks and areas, thus controlling for heterogeneity among DMUs. The environmental variables used are consistent with many of the empirical studies mentioned.

We use five environmental variables that are common to the literature (see Erbetta

Table 1: Descriptive Statistics: Public vs. Private Management

| | **Public Management** | | | | **Private Management** | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Standard deviation | Min | Max | Mean | Standard deviation | Min | Max |
| **Dependant variable** | | | | | | | | |
| *Revenues (in thousands)* | 6,183.944 | 7,407.255 | 773.149 | 37,220.44 | 9,027.477 | 37,624.75 | 889 | 407,840.4 |
| **Physical outputs** | | | | | | | | |
| *Volume billed (in thousands)* | 5,095.302 | 5,982.645 | 830.6 | 29,556.4 | 5,999.989 | 22,928.11 | 681.358 | 248,223 |
| *Length of mains* | 476.1578 | 511.4282 | 65.89 | 3,094 | 559.546 | 1,541.276 | 29.64 | 14,157 |
| *Customers* | 25,980.1 | 28,100.24 | 3,378 | 176,500 | 26,475.63 | 61,359.26 | 1,409 | 547,938 |
| **Quality Output** | | | | | | | | |
| *Network Performance* | 0.751 | 0.094 | 0.506 | 0.923 | 0.778 | 0.093 | 0.345 | 0.939 |
| **Environmental variables** | | | | | | | | |
| *Population density* | 196.9848 | 114.6751 | 67.8112 | 791.667 | 218.1504 | 128.4048 | 31.725 | 717.329 |
| *Touristic Area* | 0.157 | 0.367 | 0 | 1 | 0.091 | 0.289 | 0 | 1 |
| *Ground Water* | 0.294 | 0.460 | 0 | 1 | 0.248 | 0.433 | 0 | 1 |
| *Interconnected* | 0.412 | 0.497 | 0 | 1 | 0.430 | 0.497 | 0 | 1 |
| *Mixed Treatment* | 0.353 | 0.483 | 0 | 1 | 0.306 | 0.463 | 0 | 1 |
| *Complex Treatment* | 0.392 | 0.493 | 0 | 1 | 0.570 | 0.497 | 0 | 1 |

and Cave [2007] for instance). The source of water is a proxy not only for the complexity of service provision, but also the level of specific investments needed to operate the service, an important variable from a transaction cost perspective (Williamson [1999]). Indeed, as noted before, a better quality of drinking water may be due to a higher share of groundwater sources for an operator. The source of water determines the type of treatment as the quality of underground water is generally more stable over time, reducing uncertainty about the evolution of the kind of treatment over the life of the contracts.

Moreover, we use two variables referring to water treatments. A dummy equals 1 if water treatment is complex and 0 either. A complex treatment is, according to the Health ministry, an A3-type treatment, i.e. an advanced physical and chemical treatment and a disinfection in several steps. Non-complex treatments such as A1 and A2 only include physical and chemical treatment plus a simple disinfection. We also account for the use of multiple or mixed treatments. Indeed, some utilities have multiple sources of water and thus need mixed treatments or to invest in particular factories. We thus insert a dummy that equals 1 if the treatment is mixed and 0 otherwise.

Extensive literature has included measures of the density of operations as an important determinant of water industry costs (see for instance Bhattacharyya et al. [1995], Estache and Rossi [2002]). Therefore, the water service density or, in other words, the population density is included in our specification and is defined as the ratio between inhabitants served per kilometer of water main (i.e. the ratio between the population provided with water and the length of mains). For Erbetta and Cave [2007], providing service to a more concentrated population is, generally, cheaper than providing a dispersed population. The idea is the following: the higher the dispersion of the network, the more maintenance and energy are needed. However, the population density may have ambiguous effects on cost inefficiency for two reasons. On the one hand, it may be more expensive to supply water to dispersed customers. On the other hand, a higher density may create congestion problems.

Some water services can be subject to a high volatility of demand due to seasonal variations in the population that might necessitate overcapacity in order to satisfy peak-load demand. This is the case of touristic areas that have higher demand during national holidays. A dummy variable for the touristic nature of the service takes the value 1 if the service area is considered to be touristic according to the *French National Bureau of Statistics* (INSEE) classification and 0 otherwise.

Moreover, small towns have fewer internal resources either to produce water themselves or to pay external experts and to monitor and control private operators. At the same time, private operators have little incentive to operate in small towns. This may explain the tendency of small towns to create pools, which then provide water directly through a joint bureau of outsource. A dummy equals 1 if the municipality provides water jointly with other local authorities, 0 otherwise.

Descriptive statistics are presented in Table 1 such as to compare public and private management at the DMU-level. Table 1 is divided in two parts. The left part shows the descriptive statistics for public management and the right part shows descriptive statistics for private management. As we can see, private operators get on average higher revenues which is consistent with the fact that they have on average higher outputs, including higher network performance. The impact of the environmental performances on inefficiencies is not predetermined. However, we observe overall that private management is associated with higher density, interconnected networks and more complex treatment while public management is associated with ground water, mixed treatment and touristic areas.

## 5.5 Representativeness of the Sample

In order to ensure the validity of our results for the whole main French water utilities, we need to compare the dataset of this paper regarding the only representative dataset on French water utilities, the IFEN-SOeS dataset. IFEN-SOeS is a nationally representative dataset of water utilities in France that has been collected four times (1998, 2001, 2004 and 2008) and contains a range of information on water demand and supply. As IFEN-SOeS stops in 2008 while OSEA is collected for 2009, the comparison will especially be on the efficiency difference between the two organizational choices. Table 5 in appendix shows the distribution of public and private management in IFEN-SOeS and OSEA and the difference in prices for a standard bill (i.e. a bill for a household of three persons). As we have no data on revenues or costs in IFEN-SOeS, we picked prices as a proxy for revenues. Revenues are indeed highly correlated to consumption and connection to the network. OSEA over-represents directly managed utilities but gaps between public and private efficiency, measured by price, remain the same. In the two datasets, we observe a 20% gap between public and private management in terms of price. Overall, we conclude that our dataset is representative of the DMUs serving more than 15,000 inhabitants.

We also look at the representativeness of the dataset in terms of its covering rate of the national population, customers or billed water. Despite missing data concerning big French cities such as Lille, Lyon, Paris and Toulouse, our dataset covers 17.5 million inhabitants, 4.5 million customers and more than a billion of cubic meters billed. We thus have utilities that represent 30% of the population and a quarter of total water consumption in France. In the next three sections, we describe the variables used to assess efficiency.

# 6 Empirical Results

## 6.1 First-Stage Results

A summary of the first-stage results of our model is presented in Table 2. Table 2 details efficiency scores for public and private management and for the full-sample. It also reports the number and the share between parentheses of efficient DMUs. The last two lines report the mean input slacks and its standard deviation. The mean technical efficiency score equals 0.754 which indicates that the average company could become efficient by reducing its revenues by almost 25%, still producing the same amount of outputs. Public management has an efficiency score of 0.825 while private management has an efficiency score of 0.724. The minimum value is 0.373 for private management and 0.450 for public management, indicating that there are substantial differences among water services. The ranking is computed using the efficiency score, the number of times an observation appears during the construction of the DEA frontier and its cumulative weight in the construction of the frontier.[14] Even if private management is less efficient on average, it provides a larger stock of DMUs for the construction of the frontier. It has thus a larger impact in absolute value but it is relatively less performing than public management. For the full sample, 18% of DMUs are efficient but 23.53% of publicly managed utilities and 15.70% of private utilities.

We finally report the input slacks and its standard deviation. As we expect regarding the efficiency score, private managers have to endorse larger revenue cuts than public managers to be efficient. These input slacks will be used to re-adjust inputs for the final stage.

Table 2: Public vs. Private Management - 1st Stage

| | **Public Management** | **Private Management** | **Full Sample** |
|---|---|---|---|
| | Score | Score | Score |
| Mean | 0.825 | 0.724 | 0.754 |
| Standard Deviation | 0.144 | 0.188 | 0.182 |
| Min | 0.450 | 0.373 | 0.373 |
| Max | 1 | 1 | 1 |
| Best Rank | 3 | 1 | - |
| Efficient DMUs | 12 (23.53%) | 19 (15.70%) | 31(18.00%) |
| Observations | 51 | 121 | 172 |
| Input Slacks | 873.256 | 1293.377 | 1168.806 |
| Standard Deviation | 1351.338 | 1659.967 | 1582.612 |

## 6.2 Second-Stage: SFA and Input Adjustment

Table 3 summarizes the first step of the second-stage which consists in a SFA regression of inputs versus the environmental variables. Results suggest that the operating environment does exert a statistically significant influence on water supply performance. As we can see, the coefficients are all positive and mostly significant. To better understand the results, it is easier to start with an example. Ground water has a positive and significant impact on input slacks, meaning that it has a significant negative impact on efficiency. Being localized in a touristic area, complex and mixed treatments, population density and interconnected utilities all have a positive impact on inputs slacks, i.e. on inefficiencies, and thus a negative impact on efficiency.

Results in Table 3 also shed light on the contribution of statistical noise to DMUs' performance. The $\gamma$ is computed as the ratio between $\sigma_{u^2}$ and $(\sigma_{v^2} + \sigma_{u^2})$. $\gamma$ lies between 0 and 1. The closer it is to 1, the less statistical noise there is in the model. As $\gamma$ tends to 1, statistical noise is very low in our model. This suggests that the environmental variables explain virtually all of the variation in input slacks.

In a second step of this second-stage, we use the results from the SFA to adjust the input following Fried et al. [2002] described above. As a result, we will put all the DMUs

[14]For confidentiality reasons, the ranking cannot be published.

Table 3: Second Stage: Input Slacks versus Environmental Variables

| **Variables** | Input Slacks |
|---|---|
| Ground Water (=1) | 286.238*** |
| | (25.353) |
| Touristic Area (=1) | 192.449*** |
| | (42.449) |
| Mixed Treatment (=1) | 291.899*** |
| | (53.388) |
| Complex Treatment (=1) | 17.763 |
| | (65.637) |
| Population density | 1.460*** |
| | (0.068) |
| Interconnected (=1) | 233.831** |
| | (112.929) |
| Constant | -1299.06*** |
| | (104.757) |
| $\gamma$ | 0.999 |
| Log-Likelihood | -1452.255 |

Standard errors in parentheses with *** p<0.01, ** p<0.05, * p<0.1.

in the worst production environment by correcting the input upward.

## 6.3 Third-Stage Results

Table 4 summarizes the differences in performance results between public and private water companies after having adjusted the input. The table shows the results separately for public and private management. The mean technical efficiency score equals 0.841 versus 0.754 in the first-stage. The average correction is thus 0.087. This supports that some DMUs that received relatively low initial performance evaluations did indeed have a valid complaint, due to their relatively unfavorable operating environments or their relatively unfavorable extenuating circumstances. DMUs under public management are adjusted upward by 0.059 while DMUs under private management are adjusted upward by 0.100. Private management is thus not as poorly managed as the first-stage indicated. The minimum is adjusted upward also from 0.373 to 0.496. Accounting for different operational environments is thus helpful to correct for efficiency. Overall, we now have 30 efficient DMUs against 31 in the first-step. Some DMUs were unfairly considered as being efficient in the first-step while some others were unfairly considered inefficient. There is thus an efficiency gap of 6% between public and private management in the French water supply industries.

However, the Spearman correlation test of the first and the third steps equals 0.890 and is significant at the 5% threshold. The Kendall correlation test - which depends upon the number of inversions of pairs of objects which would be needed to transform one rank order into the other - is 0.700. These tests indicate that results from the first and third steps are highly correlated. It also means that DMUs that received relatively high (low) initial performance evaluations did so in relatively favorable (unfavorable) operating environments and circumstances. Accounting for contextual variables renders the results more robust but does not fundamentally change the relative DMUs' managerial performance.

Table 4: Private vs. Public management - Final Results

| | **Public Management** | **Private Management** | **Full Sample** |
|---|---|---|---|
| | Score | Score | Score |
| Mean | 0.883 | 0.823 | 0.841 |
| Standard Deviation | 0.112 | 0.132 | 0.129 |
| Min | 0.564 | 0.496 | 0.496 |
| Max | 1 | 1 | 1 |
| Best Rank | 1 | 3 | - |
| Efficient DMUs | 13 (25.49%) | 17 (14.05%) | 30(17.44%) |
| Observations | 51 | 121 | 172 |
| Average Correction | 0.059 | 0.100 | 0.087 |

Graph 2 in appendix depicts the link between billed water and technical efficiency by organizational form. As we can see, there is no clear link between the size of the market and technical efficiency, whatever the management type. For easiness in reading, we excluded utilities billing more than 40,000 thousand cubic meters in 2009 (a single utility - which was moreover efficient - has been dropped). However, we notice a greater level of dispersion of technical efficiency for private management.

The ranking follows a simple rule (see Fried et al. [2002]). DMUs are ranked regarding i) their efficiency scores, ii) the number of times they are used as references for defining the frontier and iii) the cumulative sum of their weight in defining other DMUs' scores. A lot of utilities are close to the efficiency frontier as 66 DMUs have efficiency scores larger than 0.9. While private operators are under-represented in the efficient DMUs, they are largely represented in the less efficient DMUs as we can observe in Graph 2. For example, if we only consider utilities with efficiency scores below 0.7, we find that 23 out of 26 DMUs are under private management. The average efficiency gap between public and private management results from this higher dispersion of utilities' efficiency score.

Such a dispersion in privately managed utilities can be explained by several factors. First, private operators can have differentiated strategy depending on some structural aspects of the municipality. Moreover, municipalities themselves may have different capabilities in negotiating contracts before and after the bidding process. Differences in performance can thus appear as differences in capabilities to negotiate contracts or by the fact that differences in complexity are not completely purged. Other unobserved factors - for example altitude - can have also an impact on performance.

Particular attention could focus on the issue of endogeneity of the management choice in the water sector and its impact on the relative efficiency of water services. Indeed, ignoring the endogeneity of the choice between public and private management may bias the efficiency measurement of in-house and delegated services. For example, poorly performing utilities can induce citizen pressure for reform and the selection of private management. Such endogeneity problems are however not possible to control in a DEA model. Moreover, endogeneity requires good instruments that do not impact the dependent variable. Our three-stage approach allows us to include sufficient fixed-effects that can explain differences in performance and to correct for them. Our environmental variables are proxies for cost-shifting variables and should be considered as fixed-effects rather than instruments for a selection equation. Moreover, our specification does not include the management form as a dependent variable in the second-stage. Including such a variable puts all the utilities in the situation as if they were privately managed, which makes the comparison between public and private management performance impossible. A way to control for this endogeneity issue would have been to observe water public services for several years and to assess the dynamic efficiency of public and private management. Our dataset does not allow us to make such a study.

# 7 Conclusion

This article provides an efficiency analysis of 177 French water utilities for 2009. In order to dissociate managerial efficiencies from bad luck and structural differences across utilities, we employed an outliers detection and a three-stage DEA approach. While the first-stage DEA would conclude on a large advantage of public management, leveling the playing field leads to lower differences in efficiency between public and private management. The remaining differences can be divided between managerial inefficiencies, higher margins or differences in taxation. Overall, we found large differences in efficiency from a DMU to another, leaving room for potential cost savings or price decreases. The first-stage DEA gives an average technical efficiency score of 0.754 with the lowest score at 0.373. After controlling for contextual variables and statistical noise, technical efficiency scores range from 0.496 to 1 with an average of 0.841. Public management scores on average 0.883 while private management scores 0.823 in the last stage while the gap was 10% in the first-stage.

We can discuss the results regarding some missing information about public and private management. A study by the Boston Consulting Group [2007] for example shows that private management faces higher costs than public management because of differences in tax-burdens. As a matter of fact, the cost of labor is higher under private management and private DMUs have to pay several local taxes. This can lead to a 9.5% fiscal overload charged to the private DMUs. Such an overload, regarding our previous results of a 6% gap means that private firms are, everything else being equal, more cost-efficient or operate with lower margins, a result that is discussed in Porcher [2012]. Other explanations for this 6% efficiency gap can be related to different strategies towards water conservation and to differences in the water budget debt between public and private management.

Resource management and conservation is also an important issue. In the traditional consumer behavior approach, higher prices can lead to a decreasing consumption. In this perspective, managers can be tempted to increase fees or to apply progressive tariffs in order to ensure resource protection. Such an hypothesis is plausible as non-price demand management programs can be costly to implement, to monitor and to enforce. Such conservation programs based on non-price mechanisms are moreover difficult to evaluate *ex ante* and to estimate *ex post*. Our dataset does not allow us to investigate whether progressive tariffs are implemented by operators. The strategy of private operators to ensure resource management can thus be linked to progressive tariffs that foster higher revenues. As the price-elasticity of water consumption is rather low (see Porcher [2012] for a discussion), increased tariffs automatically lead to increased revenues. When costs are marked-up, a distortion arise and it is then necessary to compare the current distortion to the costs of non-conservation or the welfare effects of constrained consumption for households. Such estimates are not available in France but could be the focus of further studies.

Because of missing information, we were able to collect water budget debt for only 117 DMUs, 52 under public management and 65 under private management. However, a simple means comparison is useful to understand the technical efficiency gap between public and private management. For utilities that provide water in-house, the water budget debt is 7,211,440 euros while it is 5,812,337 euros in municipalities under private management. There are at least two reasons for this gap between public and private management. The first reason is that private managers fund a part of their investments through the price setting while public managers may directly use the municipal water debt. As a result, water budget debt is expected to be lower under private management. The second reason is that debt refunding is partly linked to the life-cycle of the contract as shared investment programs are launched for a given number of years. One can expect a municipality to engage in a faster debt refunding when the water supply is contracted out, perhaps because its refunding rates follow the duration of the investment program, itself anchored on the duration of the contract. Assume that directly managed DMUs had to converge to the level of debt of privately managed DMUs, then we could expect that directly managed utilities would increase their revenues everything else being equal. Such an increase would lead on average to lower technical efficiency of public management regarding private management. Future research could focus on the importance of public finance.

# References


Banker, R. and Gifford, J. (1988). A Relative Efficiency Model for the Evaluation of Public Health Nurse Productivity. Mellon University Mimeo, Carnegie.

Banker, R. D., Charnes, A., and Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiences in Data Envelopment Analysis. *Management Science*, 30(9):1078–1092.

Berg, S. and Lin, C. (2008). Consistency in Performance Rankings: The Peru Water Sector. *Applied Economics*, 40(6):793–805.

Bhattacharyya, A., Harris, T. R., Narayanan, R., and Raffiee, K. (1995). Specification and Estimation of the Effect of Ownership on the Economic Efficiency of the Water Utilities. *Regional Science and Urban Economics*, 25(6):759–784.

Bhattacharyya, A., Lovell, C. A. K., and Sahay, P. (1997). The Impact of Liberalization on the Productive Efficiency of Indian Commercial Banks. *European Journal of Operational Research*, 98:332–347.

Boston Consulting Group (2007). Etude economique comparative relative aux modes de gestion des services d'eau. Report, Boston Consulting Group.

Carpentier, A., Nauges, C., Reynaud, A., and Thomas, A. (2006). Effets de la délégation sur le prix de l'eau potable en france: Une analyse à partir de la littérature sur les effets de traitement. *Economie et Prévision*, 3(174):1–19.

Charnes, A., Cooper, W. W., Lewin, A. Y., and Seiford, L. M. (1994). *Data Envelopment Analysis: Theory, Methodology and Application.* Kluwer Academic Publishers, Boston.

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 2:429–444.

Chong, E., Huet, F., Saussier, S., and Steiner, F. (2006). Public-Private Partnerships and Prices: Evidence from Water Distribution in France. *Review of Industrial Organization*, 29:149–169.

Coase, R. H. (1946). The Marginal Cost Controversy. *Economica*, 13:169–182.

Coelli, T. J., Estache, A., Perelman, S., and Trujillo, L. (2003). *A Primer on Efficiency Measurement for Utilities and Transport Regulators.* The World Bank Institute, Washington.

Coelli, T. J., Rao, D. S. P., and Battese, G. E. (1998). *An Introduction to Efficiency and Productivity Analysis.* Kluwer Academic Publishers, Dordrecht.

Cooper, W. W., Seiford, L. M., and Zhu, J. (2004). *Handbook on Data Envelopment Analysis.* Kluwer Academic Publishers, Boston.

Corton, M. L. (2003). Benchmarking in the Latin American water sector: the case of Peru. *Utilities Policy*, 11(3):133–142.

Corton, M. L. and Berg, S. V. (2009). Benchmarking Central American water utilities. *Utilities Policy*, 17(3-4):267–275.

Davis, L. W. and Muehlegger, E. (2010). Do Americans Consume Too Little Natural Gas? An Empirical Test of Marginal Cost Pricing. *Rand Journal of Economics*, 41(4):791–810.

Erbetta, F. and Cave, M. (2007). Regulation and Efficiency Incentives: Evidence from the England and Wales Water and Sewerage Industry. *Review of Network Economics*, 6(4):425–452.

Estache, A. and Kouassi, E. (2002). Sector organization, governance, and the inefficiency of African water utilities. Policy Research Working Paper Series 2890, The World Bank.

Estache, A. and Rossi, M. A. (2002). How Different Is the Efficiency of Public and Private Water Companies in Asia? *World Bank Economic Review*, 16(1):139–148.

Fabrizio, K. R., Rose, N. L., and Wolfram, C. D. (2007). Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on U.S. Electric Generation Efficiency. *The American Economic Review*, 97(4):1250–1277.

Farrell, M. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, 120(3):253–290.

Ferrier, G. D. and Lovell, C. A. K. (1990). Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence. *Journal of Econometrics*, 46:229–245.

Filippini, M., Hrovatin, N., and Zoriä, J. (2008). Cost efficiency of Slovenian water distribution utilities: an application of stochastic frontier methods. *Journal of Productivity Analysis*, 29(2):169–182.

Fried, H. O., Lovell, C. A. K., Schmidt, S. S., and Yaisawarng, S. (2002). Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis. *Journal of Productivity Analysis*, 17:157–174.

Fried, H. O., Schmidt, S. S., and Yaisawarng, S. (1999). Incorporating the Operating Environment into a Nonparametric Measure of Technical Efficiency. *Journal of Productivity Analysis*, 12:249–267.

Garcia, S. and Thomas, A. (2001). The Structure of Municipal Water Supply Costs: Application to a Panel of French Local Communities. *Journal of Productivity Analysis*, 16(1):5–29.

Garcia-Sanchez, I. M. (2006). Efficiency Measurement in Spanish Local Government: The Case of Municipal Water Services. *Review of Policy Research*, 23(2):355–371.

Hall, D. and Lobina, E. (2004). Private and Public Interests in Water and Energy. *Natural Resources Forum*, 28:268–277.

Kirkpatrick, C., Parker, D., and Zhang, Y.-F. (2006). State versus Private Sector Provision of Water Services in Africa: An Empirical Analysis. *The World Bank Economic Review*, 20(1):143–163.

Porcher, S. (2012). Efficiency and Equity in Two-Part Tariffs: The Case of Residential Water Rates. Chaire EPPP Discussion Paper.

Saal, D. S. and Parker, D. (2000). The Impact of Privatization and Regulation on the Water and Sewerage Industry in England and Wales: a Translog Cost Function Model. *Managerial and Decision Economics*, 21(6):253–268.

Saal, D. S. and Parker, D. (2001). Productivity and Price Performance in the Privatized Water and Sewerage Companies of England and Wales. *Journal of Regulatory Economics*, 20(1):61–90.

Saal, D. S. and Parker, D. (2006). Assessing the Performance of Water Operations in the English and Welsh Water Industry: A Lesson in the Implications of Inappropriately Assuming a Common Frontier. In *In Coelli T., Lawrence D. (eds): Performance Measurement and Regulation of Network Utilities*. Edward Elgar Publishing, Cheltenham.

Shleifer, A. (1985). A Theory of Yardstick Competition. *RAND Journal of Economics*, 16(3):319–327.

Thanassoulis, E. (2000a). DEA and its use in the Regulation of Water Companies. *European Journal of Operational Research*, 127(1):1–13.

Thanassoulis, E. (2000b). The use of Data Envelopment Analysis in the Regulation of UK Water Utilities: Water Distribution. *European Journal of Operational Research*, 126(2):436–453.

Timmer, C. (1971). Using a Probabilistic Frontier Function to Measure Technical Efficiency. *The Journal of Political Economy*, 79:776–794.

Tran, N., Shively, G., and Preckel, P. (2010). A New Method for Detecting Outliers in Data Envelopment Analysis. *Applied Economics Letters*, 17(4):313–316.

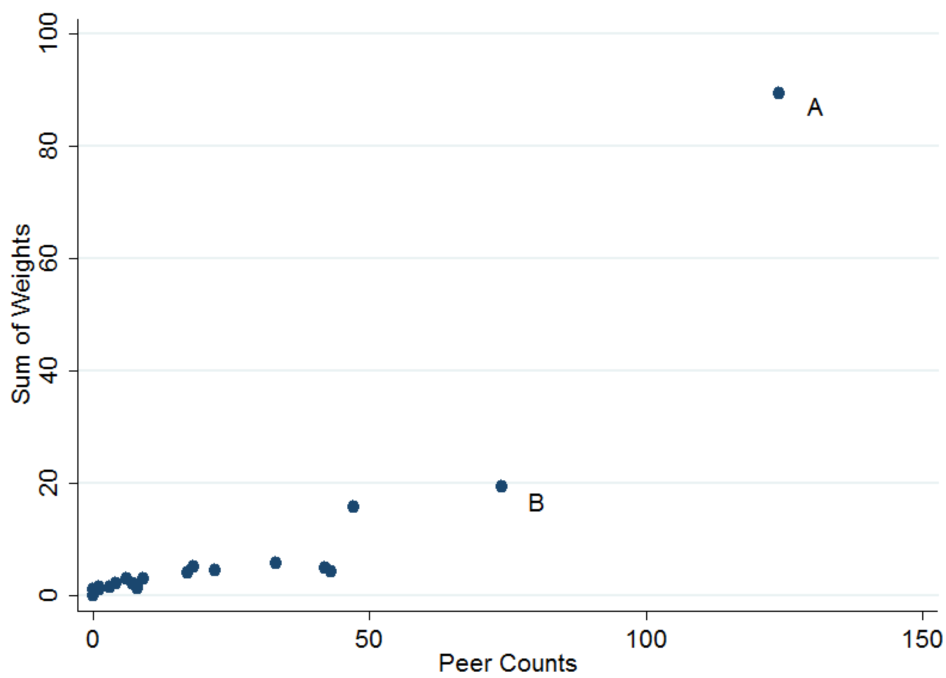
Williamson, O. E. (1999). Strategy Research: Governance and Competence Perspectives. *Strategic Management Journal*, 20:1087–1108.

Zschille, M. and Walter, M. (2012). The Performance of German Water Utilities: a (semi)-Parametric Analysis. *Applied Economics*, 44(29):3749–3764.

# Appendices

## 7.1 Graphical Analysis: Outliers Detection

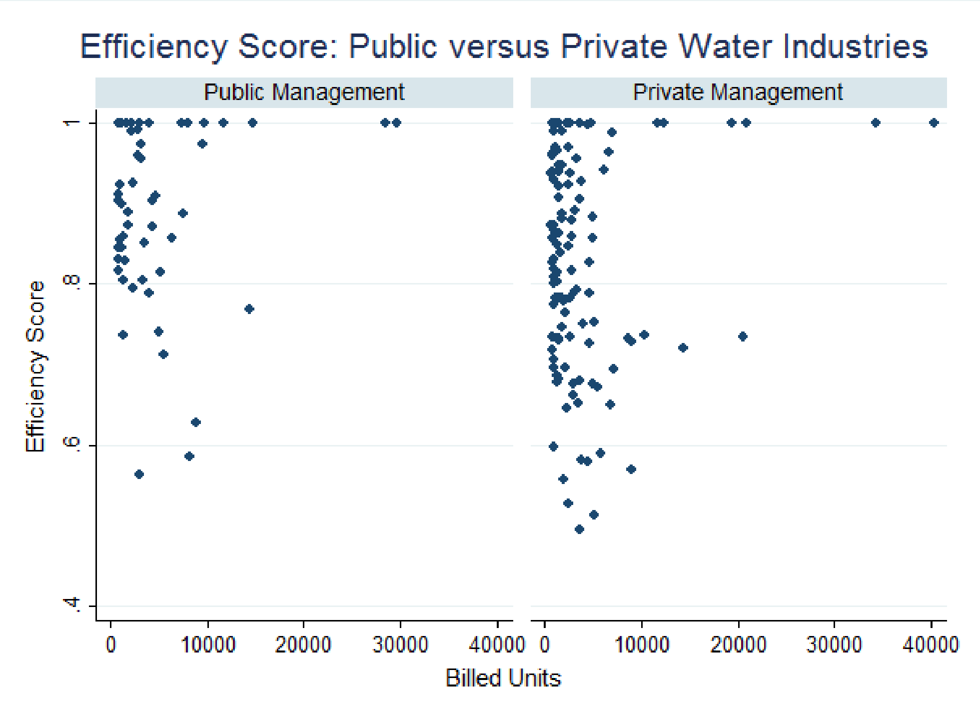
Figure 1: Outliers Detection




Note: Outliers are defined as DMUs that push up the efficiency frontier. As one can see, outliers are here A and B, not only because they are often used as peers but also because their weights are important in the definition of the frontier.

## 7.2 Graphical Analysis: Efficiency and the Size of the Market

Figure 2: Efficiency and Size of the Market



## 7.3 Comparison between the nationally representative dataset and our dataset

Table 5: Comparison of IFEN-SOeS with OSEA

| | **IFEN Dataset** | | |
|---|---|---|---|
| Variable | Public Management | Private Management | Mean |
| *Share* | 22% | 78% | - |
| *Price of the 120 cubic meters bill* | 140.88 | 176.41 | 170.29 |
| *Observations* | 137 | 479 | - |
| | **OSEA Dataset** | | |
| *Share* | 30.5% | 69.5% | - |
| *Price of the 120 cubic meters bill* | 141.83 | 174.12 | 164.21 |
| *Observations* | 54 | 123 | - |