Nonparametric Benchmarking of Japanese Water Utilities: Institutional and Environmental Factors Affecting Efficiency

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Abstract: Although the Japanese water sector is economically and socially important, few empirical studies are available to help analysts and policy-makers understand the performance patterns in the industry. This study applies data envelopment analysis to 5,538 observations of 1,144 utilities that supplied drinking water between 2004 and 2007. With a comprehensive census of utilities, the present study controls for many factors affecting efficiency: region, prefecture, ownership/governance, water source, vertical integration (purchased or produced alone), water or integrated system, production, treatment, transport and distribution of water), peak factor, per capita consumption, customer density, water losses, monthly water charge, outsourcing, subsidies, gross prefecture product, and time. Thus, this study derives comprehensive conclusions regarding efficiency patterns in Japan. The analysis finds that the average level of inefficiency (weighted by volume) is 57% in the constant return to scale model, but only 24% for the (more flexible) variable return to scale model. Improving sector efficiency and transferring funds to more innovative sectors rather than using scarce funds to subsidize water distribution would benefit citizens. Thus, the application of advanced quantitative techniques to Japanese water utilities improves the understanding of efficiency patterns and underscores the importance of in-depth studies of the individual factors examined in this study. **DOI: 10.1061/(ASCE)WR.1943-5452.0000366.**

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Introduction

The Japanese residential water sector is economically and socially important; however, few empirical studies are available to help analysts and policy-makers understand the performance patterns in the industry. The purpose of this study is to examine the determinants of utility performance and to evaluate the impacts of key variables. The application of advanced quantitative techniques illustrates how powerful technical tools can help the analyst identify concerns that warrant greater attention. The metric benchmark comparisons presented here do not help managers identify particular production processes that need to be improved at particular stages of production: that is the task of process benchmarking. Rather, data envelopment analysis (DEA) identifies areas warranting further attention and provides analysts with a tool that sorts utilities into various categories of performance.

The global literature on quantitative studies of water utilities is significant: Berg and Marques (2011) identified 190 articles published between 1969 and 2009, including six studies of cost or production functions for Japan. Those published in English that use parametric techniques are by Mizutani and Urakami (2001) and Urakami (2007). If the sample is expanded to include nonparametric techniques, there are eight studies that use DEA to examine Japanese water utilities between 1997 and 2009, although only one is in English: Aida et al. (1998). The present paper uses more recent data, but builds on this earlier research on Japan; furthermore, it utilizes robust nonparametric methods to explain performance patterns in the industry.

The study by Aida et al. (1998) used billed water volume and operating revenues as the two output variables, with inputs of staff, net plant and equipment, operational expenditures (OPEX) before depreciation, network length, and total population. Their sample from 1993 consisted of 108 city-owned suppliers in the Kanto region (omitting Tokyo Metropolitan as a potential outlier). In contrast, this study has three inputs (annualized capital expenses, staff expenses, and other operating outlays) and two outputs (volume of water billed and number of customers). The sample consists of 5,538 observations on 1,144 utilities that supplied drinking water between 2004 and 2007. This number includes approximately 86.5% of the total utilities and is not constant over time because of a lack of data or because of some mergers that took place during this period. Other utilities were not included because of a lack of credible or available data.

Another contribution of the present paper is making research on Japan data available to a wider research community. Nakayama (2000, 2002a, b, 2008) presented a series of articles (in Japanese) that used single-input models to examine fundamental features of the industry. However, the sample sizes and methodologies used in these studies limited the types of issues that could be addressed. With a comprehensive census of utilities covering more years, the present study controls for more factors: region, prefecture, owner, water source, vertical integration (purchased water or integrated), peak factor, consumption per capita; customer density, water losses, monthly water charge, outsourcing, subsidies, gross

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domestic product, and time. Thus, this study derives more comprehensive conclusions regarding the factors affecting efficiency.

This paper contributes to the literature by applying nonparametric methods of DEA to a large sample of Japanese water utilities, consisting of almost the entire sector from 2004 through 2007. This study represents the most detailed performance benchmarking study conducted to date for the Japanese water sector. The study investigates the influence of exogenous variables (institutional and operational environment) on the performance of Japanese utilities by using a recently developed, robust technique. Controlling for the impacts of such variables is crucial for conducting performance benchmarking analyses (Witte and Marques 2010a).

Public investments currently contribute to the financial sustainability of the Japanese water utility industry: there are national subsidies for capacity improvements and for operations. In addition, most water services in Japan are supplied by municipalities, although the types of utility ownership and governance arrangements differ: utilities can be owned by villages, towns, cities, prefectures, or cooperatives. Previous studies have indicated that there are probably too many small utilities—one concern that is investigated here [examples are provided by Mizutani and Urakami (2001) or Urakami (2007)]. For example, in 2007, half of the 1,325 water suppliers (end-product distributors without investments in bulk supply) had fewer than 30,000 customers. Although each utility is supposed to be self-supporting (in terms of cost recovery) and to operate in an efficient manner under the water laws, suppliers are actually self-regulated and (as already noted) receive both operating and capital expenditure subsidies. Thus, the impact of subsidies is another issue examined here. In addition, this study considers the impacts of other factors on efficiency: region, prefecture, ownership/governance, water source, vertical integration (purchased water or integrated), peak factor, consumption per capita, customer density, water losses, monthly water charge, outsourcing, subsidies (totaling ¥42 billion in 2008), and gross prefecture product.

This study measures the efficiency of Japanese water utilities and evaluates the influence of exogenous variables (institutional and operational) on performance. The next section briefly describes the nonparametric techniques applied and the methodology followed to adjust for environmental factors. The third section presents and analyzes the sample and the results. The next section examines the impacts of exogenous variables. The final section presents some concluding observations. The bottom line is that although data regarding Japanese utilities are available on the web, the system of regulatory governance is not transparent. The rationales behind specific subsidies are unclear, and the process that might promote consolidation involves few incentives for cost containment. Quantitative analyses can identify sources of higher costs (some of which can legitimately be labeled as inefficiencies), but stakeholders (customers, operators, and the government) must identify strategies for improving sector performance. The present study establishes a framework for taking the next step: bringing together consumer groups, managers, and government officials to determine how the present system of self-regulation may be modified to meet national objectives in a more cost-effective manner. However, first, the techniques utilized in this study are described.

Performance Evaluation by Nonparametric Techniques

Overview

The use of nonparametric techniques is increasing as analysts compare performance across decision units and identify determinants of outcomes (Emrouznejad et al. 2008). As previously discussed, Berg and Marques (2011) found that the water sector alone featured 190 papers (articles and reports) through 2009, with approximately 35% of these applying nonparametric models based on DEA or free disposal hull (FDH) techniques. The high proportion of parametric studies may reflect the perceived drawbacks of DEA and other nonparametric techniques [details are provided by Fried et al. (2008)].

DEA is a technique based on mathematical programming; it is used to evaluate the productive efficiency of comparable (homogeneous) enterprises (Charnes et al. 1978). DEA builds the nonparametric frontier formed by the union of a group of linear segments (piecewise surface) that includes the best practice observations.

The DEA model assumes free disposability and convexity for the production set, Ψ, (Charnes et al. 1978):

$$\hat{\Psi}_{DEA} = \left\{(x,y) \in \Re_{+}^{p+q} | y \leq \sum_{i=1}^{n} \gamma_i y_i ; x \geq \sum_{i=1}^{n} \gamma_i x_i ; \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n \right\} \quad (1)$$

where $x \in \Re_{+}^{p}$ = input vector used by the observation to produce the output vector, $y \in \Re_{+}^{q}$. The efficiency score for a given unit (x,y) is estimated in relation to the frontier of $\hat{\Psi}_{DEA}$ and is defined as

$$\hat{\theta}_{DEA}(x,y) = \inf\{\theta | (\theta x, y) \in \hat{\Psi}_{DEA}\} \quad (2)$$

The efficient observations that present scores of 1 are located on the frontier. The observations located below the frontier are inefficient and have scores less than 1. Eq. (1) presents a frontier with variable returns to scale (VRS), but if the constraint $\sum_{i=1}^{n} \gamma_i = 1$ is removed, relative to the restrictive hyperplanes, defining the envelopment surface to go through the origin, the constant return to scale (CRS) frontier is obtained. The CRS DEA model assumes that all observations of the production set operate at an optimal scale and the VRS DEA model assumes that the observations operate at a similar scale to decision-making units in the production set. By computing and relating the efficiency for both models, the scale efficiency is obtained, which measures the degree of inefficiency attributable to a nonoptimal scale operation (which may be beyond the control of a utility manager).

The nonparametric techniques have some advantages over other quantitative methods: they let the data speak for themselves (Stolp 1990). These empirical techniques do not prescribe an underlying functional form for an efficient frontier and they do not define specific values for the weight, given decision units identified as inside the frontier (Fried et al. 2008).

The downside is that the DEA nonparametric technique is deterministic in nature: the methodology assumes that there is no noise or atypical observations in the sample (Daraio and Simar 2007). Therefore, the results are very sensitive to the presence of outliers, and very demanding with regard to the information required to conduct a comprehensive quantitative analysis (Witte and Marques 2010b). In addition, the standard techniques do not incorporate errors in variables, nor do they allow for statistically testing the significance of the results or indicating the explanatory power of the specified models. For the DEA technique, adjusting for environmental variables is more complex because of the imposition of separability conditions, and depends on the correlation between the inputs and outputs and the exogenous features of the external environment (Cazals et al. 2002).

From the operational perspective, the (historical) inability to make statistical inferences has reduced the usefulness of

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nonparametric methods. It would be very hard for a regulator (or government ministry), for example, to base a decision on some performance target on DEA scores when the agency is unable to statistically test the models that were utilized in the regulatory process (Tadeo et al. 2009). Similarly, they would be unable to empirically determine the full impact of exogenous variables. For water utilities, the operational environment is a major determinant of production and cost outcomes (Carvalho and Marques 2011). Banker (1996) and Simar and Wilson (1998, 2000) have incorporated statistical properties into DEA analyses, introducing statistical inference into these analyses. Only recently, with the appearance of the partial frontier methods and probabilistic approaches (Cazals et al. 2002; Daraio and Simar 2005) has the importance of robustness in nonparametric studies been highlighted [detailed analyses and discussions are provided by Daraio and Simar (2007) and Simar and Wilson 2008].

Efficiency Computation and Adjusting for Environment

As mentioned, it is possible to allow for the inclusion of exogenous (or environmental) variables in efficiency calculations. This characteristic is very important because, in most situations, the environmental variables strongly influence the production process; not considering these variables in an efficiency analysis can lead to biased efficiency estimates (Daraio and Simar 2005). If the estimated inefficiency scores are used by policy-makers for rewarding or punishing utilities, analysts must control for elements beyond managerial control.

The partial frontier methods (e.g., order-m) originated in the probabilistic formulation of the production process proposed by Cazals et al. (2002). According to these authors, the production process can be defined by the joint distribution function of inputs and outputs [Eq. (1)], and the efficiencies can be obtained from a conditional distribution function resulting from the decomposition of that joint distribution function:

$$H_{XY}(x,y) = \text{Prob}(X \le x|Y \ge y)\text{Prob}(Y \ge y) = F_{X|Y}(x|y)S_Y(y) \tag{3}$$

where $F_{X|Y}(x|y)$ = conditional distribution function of X and $S_Y(y)$ = survivor function of Y.

Therefore, the input efficiency scores for a given point (x,y) and in a given context of input orientation can be defined in terms of the support of these probabilities and calculated by the following estimator:

$$\hat{\theta}_{m,n}(x,y) = \int_0^\infty [1 - \hat{F}_{X|Y,n}(ux|y)]^m du \tag{4}$$

where $\hat{F}_{X|Y,n}(ux|y) = \sum_{i=1}^n I(X_i \le ux, Y_i \ge y)/\sum_{i=1}^n I(Y_i \ge y)$ and $I(k)$ = indicator function that takes the value of $I(k) = 1$ if k is true or $I(k) = 0$ if otherwise.

The inclusion of environmental variables in efficiency estimation is very simple, and is enough to constrain the production process to a given value of the exogenous variable (usually referred to as Z), that is:

$$\begin{aligned} H_{XY}(x,y) &= \text{Prob}(X \le x|Y \ge y, Z = z)\text{Prob}(Y \ge y|Z = z) \\ &= F_{X|Y,Z}(x|y,z)S_{Y|Z}(y|z) \end{aligned} \tag{5}$$

Obtaining conditional efficiencies involves the estimation of a nonstandard conditional distribution function, which requires the use of smoothing techniques for the exogenous variables. Such smoothing techniques still require the choice of a kernel function and the determination of a bandwidth. This research used the Gaussian kernel function and the likelihood cross validation based on the k-nearest neighbor (k-NN) method to obtain the optimal bandwidths. Thus, following Daraio and Simar (2005), the conditional efficiencies of the order-m (input oriented) approach, for a given value of $Z = z$, can be determined as

$$\hat{\theta}_m(x,y|z) = \int_0^\infty [1 - \hat{F}_{X|Y,Z,n}(ux|y,z)]^m du \tag{6}$$

where $\hat{F}_{X|Y,Z,n}(ux|y,z) = \sum_{i=1}^n I(X_i \le ux, Y_i \ge y)K[(Z - Z_i)/h]/\sum_{i=1}^n I(Y_i \ge y)K[(Z - Z_i)/h]$; $I(k)$ = indicator function that takes the value of $I(k) = 1$ if k is true or $I(k) = 0$ otherwise; $K(\cdot)$ = kernel function for continuous variables; and h = appropriate bandwidth.

Kernel density estimation (KDE) is a nonparametric way to estimate the probability density function of a random variable with an unknown density, f. Its kernel density estimator is

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^n K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^n K_h\left(\frac{x - x_i}{h}\right)$$

where $K(\bullet)$ = kernel [for example, Gaussiankernel: $K(u) = 1/\sqrt{2\pi e^{-\frac{1}{2}u^2}}$] and $h > 0$ = smoothingparameter (bandwidth).

On the other hand, for qualitative or categorical exogenous variables, a discrete univariate kernel function $K[(z - Z_i)/h]$ is used for unordered categorical data (Aitchison and Aitken 1976):

$$K(Z_i, z, \lambda) = \begin{cases} 1 - \lambda & \text{if } Z_i = z \\ \lambda/(c_s - 1) & \text{if } Z_i \ne z \end{cases} \tag{7}$$

To obtain the optimal bandwidths, the likelihood cross validation was used, based on a k-NN method [examples are provided by Li and Racine (2008)]. This method consists of evaluating the leave-one-out kernel density estimate of Z [$\hat{f}_k^{(-i)}(Z_i)$] for a set of values of k and finding the value of k that maximizes the function

$$CV(k) = n^{-1}\sum_{i=1}^n \log[\hat{f}_k^{(-i)}(Z_i)]$$

where $\hat{f}_k^{(-i)}(Z_i) = 1/[\lambda(n-1)]\sum_{j=1,j\ne i}^n K(Z_j, Z_i, \lambda)$ and λ = local bandwidth, and chosen such that there exist k points Z_j observing $|Z_j - Z_i| < \lambda$ (Daraio and Simar 2005).

The influence of exogenous variables on the production process is assessed through a smoothed nonparametric regression between the ratio of conditional and unconditional efficiencies (Daraio and Simar 2005). That is, in an input orientation context, when the nonparametric regression has a positive slope, the exogenous variable is unfavorable to efficiency; if the regression has a negative slope, the exogenous variable is favorable to efficiency. In addition to the previously emphasized benefits of this methodology, the nonparametric regression does not suffer from the endogeneity problem (Phillips and Su 2011).

Determining the Efficiency of Japanese Water Utilities

Data and Model Specification

This section describes the data and model specification. The current study used a sample of 1,144 utilities (5,538 observations) that supplied drinking water between 2004 and 2007 in Japan. The model considered three inputs and two outputs. All monetary variables are expressed in 2007 prices by using the consumer price index (CPI). The inputs included capital cost, staff cost, and other operational

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Table 1. Summary of Statistics for the Data Set

	CAPCOST (¥)	Inputs: Other OPEX (¥)	Inputs: Staff cost (¥)	Outputs: Customers (n)	Outputs: Billed water volume (10^3 m^3)
Average	750,519	669,051	442,213	87,781	10,324
SD	3,222,736	3,646,928	2,443,920	399,865	49,107
Minimum	6,455	4,763	5,968	723	161
Maximum	99,756,811	124,435,860	75,448,946	12,494,467	1,529,784
Median	248,652	165,331	104,855	26,585	3,051

expenditures. Some studies use kilometers of network pipe as a proxy for capital costs. However, annual capital expense (CAPCOST) was computed for this study by summing depreciation, amortization, and interest payments and other financial charges paid. Staff cost was determined by the sum of labor cost and outsourcing expenses. Other operational costs included energy, chemicals, and the other (operational) costs. All inputs were measured in monetary units. For outputs, the volume of water billed (in thousands of cubic meters) and the number of customers were adopted. Earlier quantitative studies published in Japanese utilized similar input and output variables, usually for much smaller samples.

Table 1 presents the summary statistics of the sample used here, covering 2004–2007. An input orientation was adopted for the model specification, which is usual in the water sector (because there is a demand side management policy in this sector and all customers must be supplied).

All data except for deflators were taken from the *Year Book of Local Public Corporations* for fiscal year (FY) 2004–2007, published online by the Ministry of Internal Affairs and Communications (MIC 2007). The wide range of utility sizes (reflected in the number of customers and billed water volumes) may present potential heteroscedasticity problems for parametric studies, but the frontier (comparison) utilities have similar sizes when DEA methodology is utilized.

Results

Table 2 presents the results of applying standard DEA to Japanese water utilities.

Table 2 shows the average efficiency for utilities in the sample. When each utility is given the same weight, there are substantial levels of inefficiency (52.3% in the CRS model and 44.1% in the VRS model). It can be concluded that most water utilities are operating under decreasing return to scale (DRS) and a small number are operating under increasing return to scale (IRS). Indeed, current levels of output in Japan (relative to producing when average cost is minimized) are responsible for approximately 15% of the observed inefficiency. Because the VRS model is less constraining than the CRS model, the measured inefficiency is slightly lower for the former.

Table 2. DEA Efficiency Statistics

	CRS[a]	VRS[a]	CRS[b]	VRS[b]
Average efficiency	0.477	0.559	0.430	0.760
SD	0.147	0.178	0.130	0.295
Minimum	0.134	0.153		
Maximum	1.000	1.000		
Median	0.453	0.528	0.390	0.460
Efficient observations (n)	39 (1%)	128 (2%)	39 (1%)	128 (2%)
Observations with CRS (n)		728 (13%)		
Observations with IRS		1,296 (23%)		
Observations with DRS		3,514 (63%)		

[a]Arithmetic average.
[b]Weighted by the volume of water delivered.

However, a better indication of overall national efficiency would take into account the sizes of the different utility systems instead of weighting them equally, regardless of size. When the computed levels of efficiency are weighted by delivered volume of water, the weighted average level of inefficiency increases to 57% in the CRS model, but decreases to 24% for the (more flexible) VRS model. This point is clearer in Fig. 1, which depicts the efficiency scores of Japanese water utilities for the CRS and VRS models (in descending order of efficiencies for the CRS).

Fig. 2 contrasts the scores for the CRS and VRS models in terms of the relative sizes of the utilities, in which the amount of water delivered is reflected in the area of the circle for each utility. If the DEA is constrained to the CRS technology, the largest cities (Tokyo, Yokohama, and Osaka) have efficiency scores lower than 0.4. However, with the VRS, these large cities move to the frontier: measured inefficiency dramatically decreases. This result underscores the importance of recognizing the role of variable returns to scale in measuring performance.

Next, a more comprehensive approach to efficiency analysis will be discussed that incorporates corrections for institutional and environmental factors.

Adjusting for Environment

Methodology

As stated earlier, it is possible to allow for the inclusion of exogenous (or environmental) variables in efficiency calculations. This characteristic is very important because, in most situations, the environmental variables strongly influence the production process; not considering them in an efficiency analysis can lead to biased efficiency estimates (Daraio and Simar 2005). If the estimated inefficiency scores are used by policy-makers for rewarding or punishing utilities, analysts must control for elements beyond managerial control.

The inclusion of environmental variables is accomplished here by constraining the production process to a given value of the exogenous variable (usually called Z). The technique allows the analyst to obtain the efficiency scores a posteriori, taking into account the impacts of exogenous variables.

Obtaining the conditional efficiencies involves the estimation of a nonstandard conditional distribution function (Daraio and Simar 2005), which requires the use of smoothing techniques for the exogenous variables. These smoothing techniques require the adoption of a kernel function and the determination of a bandwidth. In this research, in the case of continuous exogenous variables, the Gaussian kernel function and the likelihood cross validation were obtained to obtain optimal bandwidths (Daraio and Simar 2007). On the other hand, for qualitative or categorical exogenous variables, a discrete univariate kernel function was used for unordered categorical data (Aitchison and Aitken 1976).

Therefore, a nonparametric regression using an input-oriented context was adopted. In this case, if the smoothed nonparametric

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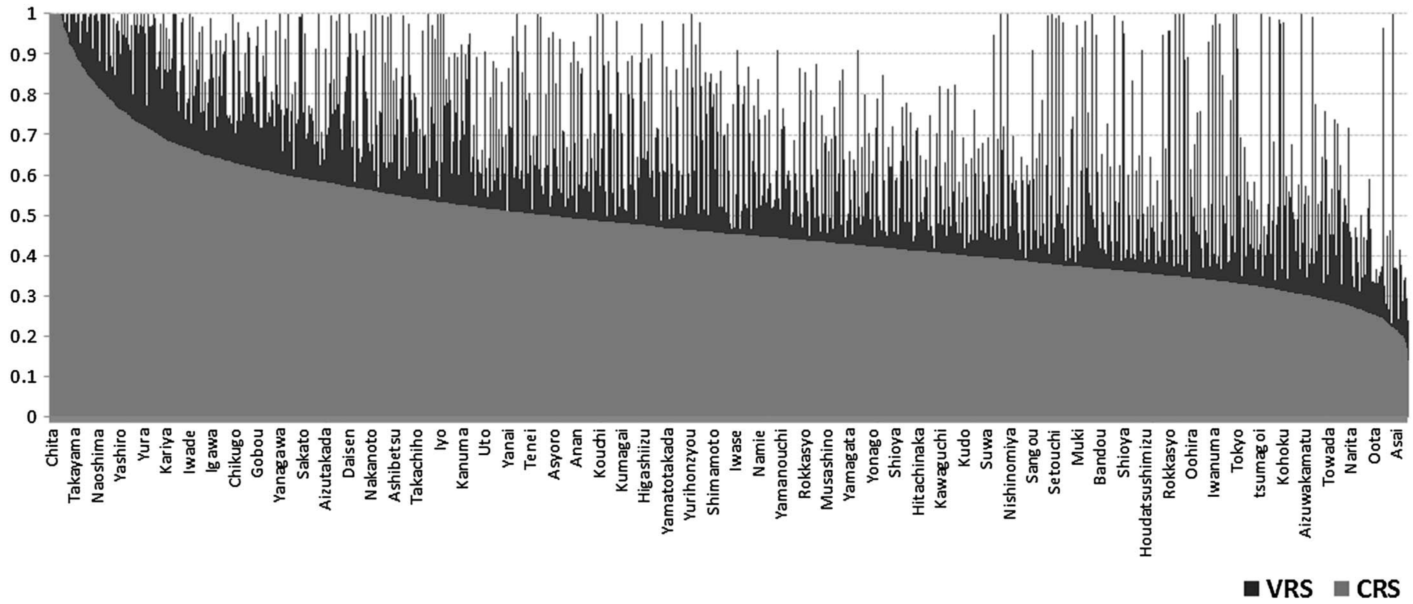

Fig. 1. Efficiency scores of Japanese water utilities for the CRS and VRS models (in descending order of efficient CRS)

regression increases, it means that Z is unfavorable to efficiency (Daraio and Simar 2005). This is because the effect of Z increases the conditional efficiency for large Z values more than the unconditional efficiency for small values of Z. Consequently, the ratio of conditional efficiency to unconditional efficiency will increase, on average, with Z. In contrast, when the smoothed nonparametric regression decreases, it indicates that Z is favorable to efficiency (Daraio and Simar 2007).

Impacts of Exogenous Variables

The potential explanatory factors are selected, taking into account the features of the water sector, the available Japanese data, and the extant literature (190 studies) by Berg and Marques (2011). Therefore, 14 exogenous variables were considered that will be described briefly while the expected impact on efficiency will be highlighted along with the results obtained. Some factors are not completely exogenous for the management of water utilities, at least in the long run, but in the short run the capacity of the managers is limited (for example, water losses are difficult to reduce, because the effect of investments takes time). Similarly, outsourcing frequently involves complicated contracts that should be fulfilled over time.

The influence of the following variables on the efficiency of Japanese water utilities is analyzed: (1) region; (2) prefecture; (3) owner; (4) water source; (5) vertical integration (purchased water or vertically integrated); (6) peak factor; (7) consumption per capita; (8) customer density; (9) water losses; (10) monthly

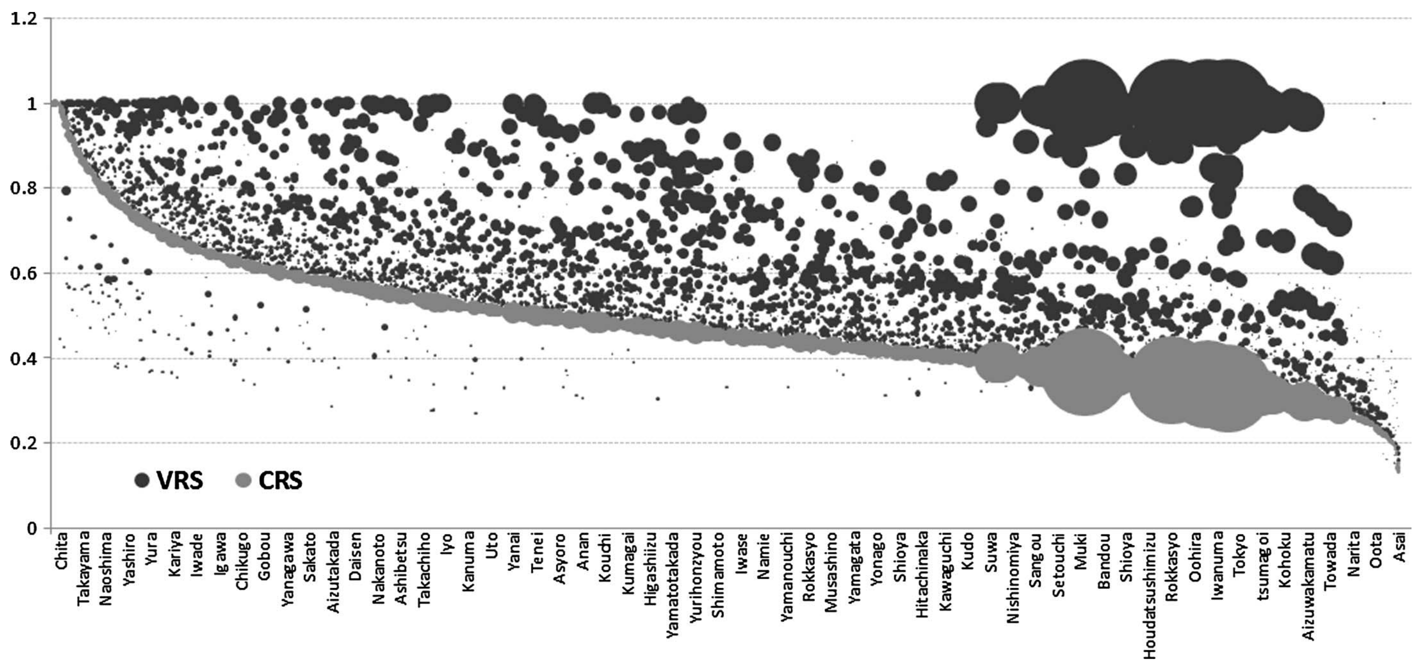

Fig. 2. Efficiency scores of Japanese water utilities for the CRS and VRS models (observations are weighted by delivered water)

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water charge; (11) outsourcing; (12) subsidies; (13) gross domestic product (GDP); and (14) time. Customer mix, although important (Renzetti and Dupont 2009), was not investigated because these utilities primarily supply residential customers: unlike other utility industries in Japan, customer mix is not a relevant variable (Matsukawa et al. 1993). The results are presented in Fig. 3. Some of these variables are categorical and the plot of the figures represents the different influences on efficiency when moving from one option to the other. All nonparametric regressions are associated with bandwidths and *p*-values, which indicate the significance of adjusting for the environment captured by the variable under study. They are presented in Table 3.

Japan is divided into several regions that group some prefectures together. This study uses 13 regions: Hokkaido, North Tohoku, South Tohoku, North Kanto, South Kanto, Hokuriku, Tokai, Kinki, Chugoku, Shikoku, North Kyushu, South Kyushu, and Okinawa. Because the northernmost and southernmost regions, Hokkaido and Okinawa, are prefectures themselves, this classification is relatively detailed. It was expected that extreme weather conditions in the north would require more inputs to produce the same levels of output. For example, in 2008, the mean temperature varied from 6.7°C in Hokkaido to 22°C in Okinawa. In addition, some regions have a greater length of coastline or extreme topologic and geographic features, thus contributing to different production conditions. However, despite some differences in average scores, no strong, statistically significant impacts of regions on efficiency were found. Fig. 3(a) depicts the results, in which region is a categorical variable taking the value from 1 to 13 corresponding to the 13 regions; there is a lack of overall statistical significance. Nevertheless, based on the nonparametric regression, there seem to be some efficiency advantages in particular regions (Regions 3, 7, 8, 11, and 12) and some disadvantages in Regions 1, 4, 9, 10, and 13, although they are only significant at a 79% confidence level. Japan is divided into 47 prefectures, allowing a jurisdictional refinement of the regional categorical variable. The inclusion of these prefectures in the analysis allowed those prefectures that had favorable conditions to be identified [Fig. 3(b)]; future research will focus on the characteristics associated with favorable conditions. Certainly, different operating conditions associated with particular geographic areas need to be controlled to determine whether one is deriving policy implications from performance rankings.

Owners of water utilities in Japan are divided into five types [prefecture-owned utilities (0.3%), city*-owned utilities (1.3%), city-owned utilities (52.4%), town or village-owned utilities (42.3%), and 49 wide-ranged cooperative-owned utilities (3.7%)]. Current computations provide evidence of the positive influence of the town and village category compared with the ownership/governance structure of the cities [Fig. 3(c)]. This may be attributable to the ability of elected officials in smaller towns to monitor the utility performance of less complicated (smaller) operators. In addition, they have different laws and organization (corporate) regimes, which influence their performance.

In Japan, customer density (computed by the number of customers per kilometer of pipe length) is very high (averaging 148 customers per km for 2007); the nation has very few rural utilities. A priori, one may expect a positive impact from this high density of customers, at least up to a point (beyond which the complexity of the network may increase such that efficiency falls). In the Japanese water utilities, this limit might be exceeded, so the influence of density is unclear. In this study, customer density was not a significant determinant of efficiency [Fig. 3(d)].

The sources of water supply in Japan are primarily surface water (72%) and ground water (25%). According to the nonparametric regression, the water source has no influence on water utility efficiency [Fig. 3(e)]. Based on earlier studies (Aubert and Reynaud 2005), it was expected that water utilities using ground water would be more efficient. In addition, as shown in Fig. 3(f), there is a slight positive influence of vertical integration (at a confidence level of 90%).

The peak factor (computed as the ratio between the maximum daily consumption in the year and the average consumption per day) in Japanese water utilities varies substantially. It was found that the peak factor has a positive influence on the efficiency of water utilities in global terms [Fig. 3(g)]. This result is rather surprising because it implies that a steady, level load on the system is more expensive than a load that is peaked [in contrast to previous studies (Woodbury and Dollery 2004; Tadeo et al. 2009)]. One explanation may be that these utilities supply seasonal and tourist areas, which normally have high per capita income: the higher cash flows may enable the utility to invest more in the assets and technology, and thus, to become more productive. In addition, a steady load may require less storage capacity for the utility. Also, the results are not statistically significant and there are some intervals (1.32 and 1.4) in which the influence is negative.

According to the current sample, Japanese water utility customers consume an average of 323.7 L per day (water billed). On average, increased consumption per capita has a positive influence on efficiency (suggesting that running more water through a given distribution system is not costly). The level of significance of this result is approximately 93% [Fig. 3(h)]. Consumption per capita is closely connected with the concept of economy of density; previous research has tended to find economy to density for water utilities (Carvalho et al. 2012).

As Fig. 3(i) indicates, leakage has no influence on efficiency. This may be because the leakage level is so small (an average of 7.5%) and relatively comparable across companies. High values of this variable normally correspond to high values of inefficiency (Bhattacharyya et al. 1995; Corton and Berg 2009).

As shown in Fig. 3(j), a positive influence was found of gross prefecture product up to ¥25,000 (10^3) of prefecture GDP and a negative influence after that (at a 90% confidence level). These results might be attributable to reduced efficiency stemming from DRS associated with major cities, which also have higher GDP. Normally, water utilities in areas with high GDP are more efficient because cash flows are available for low cost planning that lead to system upgrades and operating efficiencies (Simões et al. 2010). Furthermore, staff are likely to be more productive (although also more expensive).

In Japan, variations in consumer charges are substantial, involving a tenfold difference in customer bills between the most and the least expensive utilities. One might expect that where consumer charges are quite high, the water utilities are more efficient, because citizens would force managers to address inefficiencies. However, this would only be the case if citizens were fully informed about the performance of their local utility relative to those in comparable situations. In addition, the higher bills may reflect costly operating conditions beyond managerial control. The results in Fig. 3(k) indicate that there is no statistically significant positive or negative impact of consumer charges on the efficiency of Japanese water utilities. This issue warrants further investigation.

It was examined whether water utilities that make greater use of outsourcing are more (or less) efficient than otherwise. The average percentage of outsourcing costs in Japan is 5.9%. As shown in Fig. 3(l), the ratio of outsourcing to total operating expenses seems to have a negative influence on the efficiency, primarily near the 10% range; this ratio has a positive influence as it tends to 0% and for values greater than 10%. Although there is no consensus in the literature, scholars have highlighted the positive effect of

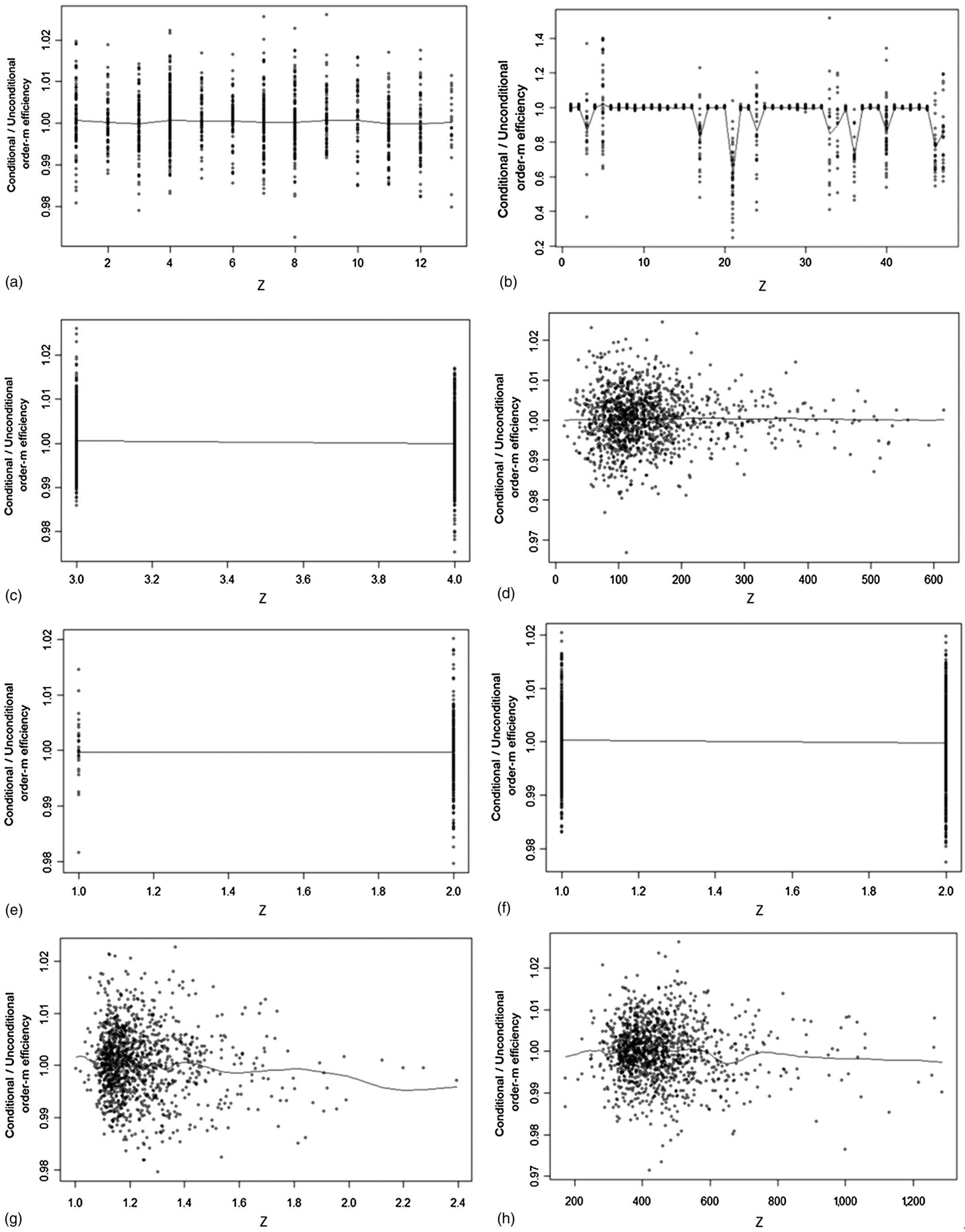

Fig. 3. Influences of exogenous variables on efficiency scores: (a) regions (b) 47 prefectures; (c) owner of water utilities; (d) density; (e) dam versus other sources; (f) integrated versus imported water; (g) peak factor; (h) per capita consumption; (i) leakage; (j) GDP; (k) consumer charges; (l) outsourcing; (m) level of subsidy; (n) time trend

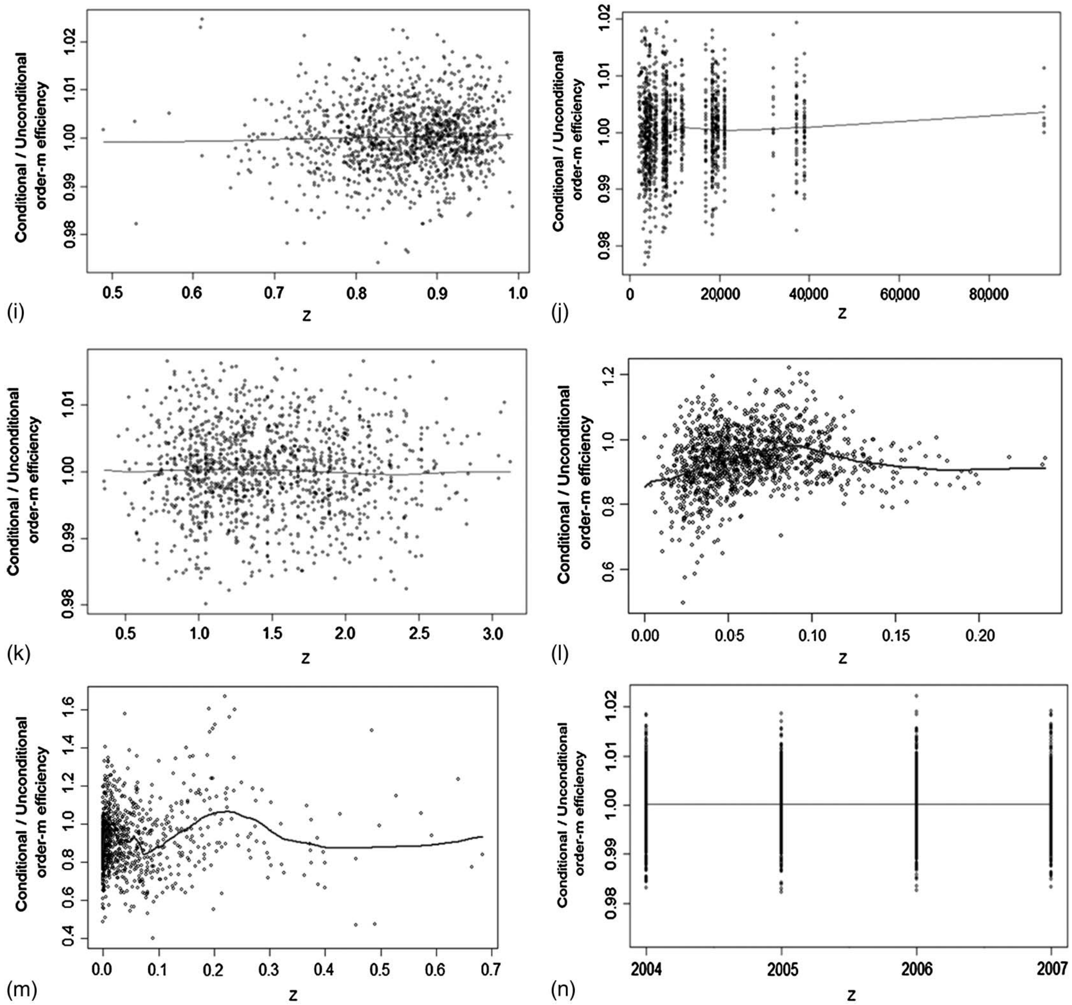

Fig. 3. (*Continued.*)

outsourcing (Bhattacharyya et al. 1995; Marques 2008). In addition, there appears to be a minimum value of outsourcing for the activity to have a positive impact (Pérard 2009; Estache and Rossi, "Relevance of reforms, institutions and basic economics for the economic efficiency of African water utilities," working paper, World Bank, Washington, DC).

Whereas a water supplier must follow the cost recovery principle according to the law, a national subsidy is given based on governmental subsidization criteria for the development of water resources, reorganization of water supply bodies, sludge treatment facilities at purification plants, and small water supply systems (JWWI 2003, p. 33). The total subsidy budget of public enterprises related to water supply is more than ¥200 billion (more than US $2.5 billion). In addition, in 2008, the total amount of subsidy from the national treasury related to capital income and expenditures for 1,316 water utilities was ¥42 billion: 5.2% of total capital income. Furthermore, on average, 4.8% of the operating costs were subsidized (although many companies receive no subsidies). It was expected that subsidized water utilities would be less efficient, in line with the findings of Urakami ("The effects of subsidies on the cost structure of Japanese water supply organizations," working paper, School of Business Administration, Kinki University, Japan), who found that subsidies had a negative effect on the efficiency of Japanese water utilities. The results depicted in Fig. 3(m) suggest that the ratio of subsidy to total operating expenses has a positive influence on the efficiency of the Japanese water utilities as it approaches 7% and a negative influence as it approaches 20%. This result warrants more detailed analysis in future research. The key question is whether (potentially politically determined) subsidies promote cost containment. In addition, the current rationales for specific subsidy allocations are not transparent: are they are based on observed patterns of efficiency and inefficiency and designed to improve efficiency?

Table 3. Bandwidths and *P*-Values

Exogenous variables	Bandwidth	*P*-values
Regions	0.5630	0.2005
Forty-seven prefectures	0.0391	$<2.22 \times 10^{-16}$[a]
Owner of water utilities	0.1134	0.0301[b]
Density	8.7407	0.1998
Dam versus other sources	0.5	0.3609
Integrated versus imported water	0.1463	0.0827[c]
Peak factor	0.0226	0.09998[c]
Per capita consumption	32.5	0.0677[c]
Leakage	0.006	0.3457
GDP	125	0.1000[c]
Consumer charges	0.0185	0.1500
Outsourcing	0.0029	$<2.22 \times 10^{-16}$[a]
Level of subsidy	0.0133	0.3459
Time	0.75	0.2988

[a]Statistically significant at the 10% level.
[b]Statistically significant at the 5% level.
[c]Statistically significant at the 1% level.

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Concerning the influence of time on efficiency between 2003 and 2007, it was expected that productivity should increase over time, but the efficiency of firms might increase or decrease, depending on other factors. For example, because the population is stable and the consumption is decreasing (and fixed inputs are not changing), output is falling. Furthermore, health and environmental regulations in this sector are stricter every year, leading to more inputs, but measured outputs are not changing. Thus, the results indicate no time trend for the efficiency of the Japanese water utilities [Fig. 3(n)].

Concluding Remarks

This research evaluates the efficiency of water utilities in Japan and provides a preliminary exploration of the influence of exogenous variables on measured efficiency. The Japanese data are comprehensive; the access researchers have to data is outstanding compared to many nations. In a sense, the data system represents transparency at its best, and has provided Japanese scholars with the raw material for numerous studies. However, the atomistic structure of the industry suggests that many small utilities may lack the managerial and engineering capabilities required for maintaining operational best practices. Furthermore, the system of governance is nontransparent and lacks incentives for cost containment. In particular, the potential causes and impacts of subsidies definitely warrant more in-depth analysis. Of course, the decision relevance of production function studies depends on whether the basic conclusions are communicated to decision-makers in a clear and authoritative manner. In particular, the development of robust performance scores is necessary if policy-makers are to target subsidies to utilities that are using resources effectively. There is no evidence that subsidy programs consider this issue at present. The Japanese economy has had relatively slow growth. Furthermore, there appears to be significant inefficiency among water utilities. Improving sector efficiency and transferring funds that now subsidize water distribution to more innovative sectors would benefit citizens.

In this DEA study, the outputs were the number of customers and the volume of billed water; the inputs were expressed in monetary terms: capital outlays (as a proxy for capital stock), staff expenses, and other OPEX. The study updates previous studies of Japan that utilized similar models, but had far fewer observations. Furthermore, this research extends the extant literature by controlling for a large number of exogenous factors, so the adjusted efficiency scores can reflect the external constraints that are beyond managerial control.

In its present form, this technical study does not purport to serve as a guide to public policy. Rather, it identifies several areas that warrant greater policy discussion: consolidation versus disaggregation, current subsidy arrangements, and the long-term financial sustainability of water networks in the absence of improved incentives for cost containment. Each of these topics deserves a comprehensive study, because the results will affect billions of dollars of transfers, in addition to how incentives may be established to ensure that current customers are receiving value for their money. Efficiency scores can be used for developing internal incentives for managers and for external incentives (for setting cost targets, prices, or subsidies). In the latter case, benchmarking reduces the information asymmetry between managers and those providing oversight (Berg 2010, p. 114).

However, in Japan, the oversight function is missing. The industry basically operates under self-regulation. Using the CRS model, average efficiency is 47.7 and 43% of utilities on the frontier for weighted and unweighted observations, respectively. This result is worrisome. If the true relationship is a VRS model, the average level of efficiency rises to 55.9% (if unweighted by water volume), but improves dramatically to 76% if weighted by water volume, suggesting that the larger cities exhibit relatively better performance. The choice between constant and variable return to scale models warrants greater attention in the future. One lesson from experiences in other nations is that citizen awareness of relative performance places pressure on managers to reduce costs and improve service quality. However, at present, despite an excellent record on data collection and access, there seems to be no advocate for efficiency in the Japanese ministerial system.

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