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Technical Efficiency of Rural Water Utilities

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Technical efficiency of rural water utilities is determined using frontier production functions. An indirect production function is developed to model the two-step production process of a local government-controlled firm. Data from 26 rural Nevada water utilities are used to estimate inefficiency in terms of firm-specific variables. A multistep estimation procedure is used instead of single-step maximum likelihood estimation. Model selection tests are used to choose the best model. Privately owned utilities are most efficient; self-governing water districts are the least efficient. Municipal governments operate the most and least efficient utilities.

Key words: half-normal, indirect production function, model selection test, normal-exponential, rural water utilities, stochastic frontier, technical efficiency, truncated-normal

Introduction

Many rural citizens cling to principles of Jeffersonian democracy, desiring provision and control of community services at the local or small jurisdictional level. However, Chicoine, Deller, and Waltzer argue that small-scale operations provided by local jurisdictions, particularly rural, are inherently inefficient and costly. Some studies indicate that structural and managerial limitations, in addition to federal and state government mandates, have hampered both the effectiveness and efficiency of small rural governments (Sokolow; Seroka; Deller 1995).

Not only does small staff size make monitoring and evaluating public-service provision difficult, but often the distance separating these communities makes jointly providing public services impractical (Cigler). Given local budget constraints and federal mandates, efficiency in providing public utility services and commodities, such as water, is imperative. However, little empirical research has examined the technical (production) efficiency of small rural governments (Deller 1992). This study attempts to determine the technical efficiency of rural water utilities and to identify the most influential factors.

Small rural government effectiveness can be evaluated with Inman's two-step decision-making process, where the first step corresponds to provisionary decisions and the second step refers to production-related decisions. The provisionary effectiveness addresses the local officials' ability to develop policies to raise and allocate necessary revenue for the production of various services. The production decisions refer to the purely technical process of transforming inputs into public goods and services. The second step of the process is not

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independent of the first. Provisionary decisions, especially budget constraints, affect production decisions. Earlier studies mainly look at production efficiency, independent of the provision decision (Deller and Halstead; Deller and Nelson; Deller 1992). This article integrates *both* production and provision restrictions to address production inefficiency of rural water-supply systems.

Since the 1977 publication of Aigner, Lovell, and Schmidt, the use of frontier functions in estimating firm-level technical inefficiency has gained momentum. The error term of a frontier production function has two components: one that allows for random error around the frontier, the stochastic element of the frontier, and the other for one-sided error, the inefficiency effect. The random error results from factors beyond the firm's control, for example, weather, strikes, and damaged products. The one-sided error term measures deviation of the observed production from the frontier production, which is under the control of a firm. Therefore, the technical inefficiency under a frontier specification can be explained in terms of firm differences. We not only quantify the deviation of the observed production from the frontier production, but we also explain the deviation in terms of firm-specific variables.

Estimating a frontier specification requires decomposing residuals of the estimated production function into white noise and technical inefficiency effects. For this, the distribution of the one-sided error term must be specified. Four different distributional assumptions have been used in the frontier literature to specify the one-sided error term. These are (a) truncated-normal, (b) exponential, (c) half-normal, and (d) gamma. The shape or position of the estimated frontier may be affected by the choice of distribution (Stevenson). However, few studies have attempted to statistically determine which particular distributional assumption most closely follows the data-generating-process (DGP).¹ In this article, model selection tests are used to select the distributional form for the one-sided error term, closest to the DGP.

Specifying and estimating standard frontier models relies on strong distributional assumptions about the error terms and their interrelationships. We use a two-step estimation procedure to minimize the need for strong distributional assumptions (Kumbhakar and Hjalmarsson; Heshmati and Kumbhakar). Since technical inefficiency is under the firm's control, it is likely that a model that explains technical efficiency in terms of firm-specific variables would have higher explanatory power. In this study, the likelihood dominance test (Pollak and Wales) is used to determine whether such a model has better explanatory power than a standard stochastic frontier model. If selected, such a model can directly address policy issues because the factors influencing the firm's level of efficiency can also be identified.

Following Averch and Johnson, researchers have attempted to determine ownership effects on the efficiency of privately and publicly owned utilities, which face different rate-of-return regulations. It is often argued that private utilities overinvest in capital (capital padding) to justify high rate of return or prices. Therefore, in this study, private and public utilities are treated differently.

¹Cowing, Reifschneider, and Stevenson and Reifschneider and Stevenson have examined and estimated inefficiency under different distributional assumptions. Their results indicate a wide variation in the expected value of the inefficiency disturbances under different distributional assumptions. However, no statistical test has been performed to compare the alternative models. Recently, Bhattacharyya, Bhattacharyya, and Kumbhakar have used model selection tests to compare alternative models.

Although extensive research has been done to examine and compare the performance of public and private utilities, little research investigates the possible differences in efficiency levels among publicly owned utilities, their varying regulations and responsibilities, and their differing administrative structures and mode of operations. This study examines these possible differences. At least three types of public ownership can be found among rural water utilities: municipal, county, and special district-operated water systems. Given that municipalities and counties offer an array (or package) of public services, competition among public service providers may increase efficiency and gain in economies of scope. On the contrary, the special district water purveyors, specialized units with the primary goal of supplying water, lack economies of scope resulting from administering an array of public services. This study explicitly introduces alternative ownership effects into the empirical models.

Model

As explained earlier, the supply of local public goods is assumed to follow a two-step process: what services to provide and how to provide them cost-efficiently. The local government's provisional decision (first step) is assumed to set the maximum expenditure for production of the sth public good or services, that is, water supply system in this study. In the second step, the utility or the production unit maximizes output, y , subject to the expenditure constraint.

The optimization problem in the second step, therefore, is

$$\begin{aligned} (1) \quad & \max y = \Theta(X, Z), \\ (2) \quad & \text{s.t.: } C - W'X \geq 0, \\ (3) \quad & X \geq 0_n, \end{aligned}$$

where $y \in \mathfrak{R}_+^1$ is total output; $W \in \mathfrak{R}_{++}^n$ is the price vector of variable factors; $X \in \mathfrak{R}_+^n$; $Z \in \mathfrak{R}_+^m$ is the vector of quasi-fixed inputs and control variables; 0_n is a null vector of dimension n ; and C is expenditure. The production technology of a utility is represented by $y = \Theta(\cdot)$. All constraints in the above problem are written in inequality form to allow for the following possibilities: (a) the budget constraint may not be satisfied with equality, and (b) the quantity of variable inputs is nonnegative. Based on the above criteria, local officials select the optimal level of inputs given the vector of variable factor prices (W) and quasi-fixed factors and control variables (Z). Solving the first-order conditions yields the following optimum values of the endogenous variables: $X = X(W, C, Z)$, $\lambda = \Lambda(W, C, Z)$, and $\Gamma = G(W, C, Z)$, where λ and Γ are the Lagrangian multipliers of constraints (2) and (3), respectively.² Substituting the solution of X into (1), the optimal value of the objective function is obtained as:

$$(4) \quad y = \mathfrak{Y}(W, C, Z).$$

²At the solution point, one or more of the Lagrange multipliers, λ and Γ , could be zero indicating that the associated constraint is not binding. However, we assume that the Lagrange multipliers are nonzero.

Equation (4) is an *indirect production function* (IPF). With an IPF output is a function of exogenous variables—prices of variable inputs (W), expenditure (C), and quasi-fixed inputs (Z). The advantages of such an IPF specification are (a) it defines the production function of a water utility conditional on the provisional decision taken by the organization in step one of the decision-making process; (b) the classic problem of simultaneity bias involved in estimating a single-equation production function is avoided; and (c) the impact of change in budget on production can be directly examined.

A natural measure of technical inefficiency of a production unit is the Farrell's measure, defined as deviation of the observed output from the "frontier" output level. A two-component error term, defined as $\varepsilon = v - \tau$, is appended to (4). The error component τ captures technical inefficiency of the representative water utility defined as deviation of the observed output from the frontier output, and v is a random error term. The term τ is nonnegative, that is, $\tau \geq 0$. If $\tau = 0$, the firm attains its production frontier which is stochastic due to the presence of the white noise term v . The more realized production falls short of the stochastic frontier, the greater is the level of technical inefficiency. The stochastic frontier IPF is

$$(4.1) \quad y = \mathfrak{F}(W, C, Z) \exp(\varepsilon).$$

To impose a priori minimum restrictions on the underlying technology and to allow for Farrell's measure of technical inefficiency, a short-run IPF for a typical water utility is approximated by a translog functional form as:

$$(5) \quad \ln y = \alpha_0 + \sum_{i=1}^n \alpha_i \ln W_i + \sum_{j=1}^m \alpha_j \ln Z_j + \alpha_c \ln C + \frac{1}{2} \left\{ \sum_{i=1}^n \sum_{l=1}^n \alpha_{il} \ln W_i \ln W_l \right. \\ \left. + \sum_{j=1}^m \sum_{q=1}^m \alpha_{jq} \ln Z_j \ln Z_q + \alpha_{cc} \{\ln C\}^2 \right\} + \sum_{i=1}^n \sum_{j=1}^m \alpha_{ij} \ln W_i \ln Z_j \\ + \sum_{i=1}^n \alpha_{ic} \ln W_i \ln C + \sum_{j=1}^m \alpha_{jc} \ln Z_j \ln C + \varepsilon.$$

Symmetry and the homogeneity of degree zero in input prices are imposed on the IPF. The symmetry condition requires

$$\alpha_{il} = \alpha_{li}, \quad \alpha_{jq} = \alpha_{qj}, \quad \alpha_{ij} = \alpha_{ji}, \quad \alpha_{ic} = \alpha_{ci}, \quad \text{and} \quad \alpha_{jc} = \alpha_{cj}.$$

The homogeneity condition requires

$$\sum_{i=1}^n \alpha_i + \alpha_c = 0, \quad \sum_{l=1}^n \alpha_{il} + \alpha_{ic} = 0 \quad \forall i = 1, \dots, n, \\ \sum_{i=1}^n \alpha_{ic} + \alpha_{cc} = 0, \quad \sum_{j=1}^m \alpha_{ij} + \alpha_{jc} = 0 \quad \forall j = 1, \dots, m.$$

The specification of (5) with the imposed conditions captures technical inefficiency of a water utility. The constant expenditure input demand function for the i th input can be derived

from the IPF using Roy's identity, that is, $X_i = -((\partial y / \partial W_i) / (\partial y / \partial C))$. This enables the share of the i th input in total variable cost to be determined as:

$$(6) \quad S_i = -\frac{\partial \ln y / \partial \ln W_i}{\partial \ln y / \partial \ln C} = -\frac{\alpha_i + \sum_{l=1}^n \alpha_{il} \ln W_l + \sum_{j=1}^m \alpha_{ij} \ln Z_j + \alpha_{ic} \ln C}{\alpha_c + \alpha_{cc} \ln C + \sum_{i=1}^n \alpha_{ic} \ln W_i + \sum_{j=1}^m \alpha_{jc} \ln Z_j} + \xi_i,$$

where $S_i = W_i X_i / C$, and ξ_i is an additive error term. The numerator of α_i is the elasticity of output with respect to the price of the i th variable factor, and the denominator is the elasticity of output with respect to the producer's budget.

Equations (5) and (6), with symmetry and homogeneity conditions imposed, define a complete system of equations. The input price vector is defined as $W = [W_E, W_L, W_M]'$, where the subscripts, E, L , and M denote three variable factors: energy, labor, and materials, respectively, that is, $X = [X_E, X_L, X_M]'$. The vector Z is defined as $Z = [Z_K, Z_P, Z_D]'$, where the elements of Z are capital (K), input-water (P), and density of population (D), respectively. The budgeted expenditure is defined as $C = \sum_i W_i X_i$.

Rural water utilities face different sets of regulations depending on their organizational form. This difference in ownership forms may affect the decision-making process of these water utilities, and these effects can be captured by adding another additive term to the error component of the stochastic translog IPF and the share equations. Since it is reasonable to assume that the ownership effects are fixed across firms with similar ownership structure, these error components are introduced as dummy variables for each ownership group in the IPF. These ownership attributes are assumed known to the firm but are not observed by an econometrician.

The ownership-specific dummy variables are introduced in the IPF in (5) as follows. Since the input-share equations are derived from a translog IPF, interactive variable $DUM_{ot} \times \ln W_i$ is introduced into the production function, where DUM_{ot} is a vector of the ownership dummies, and $t = 1, \dots, T$ indexes various ownership forms. Such a specification imposes cross-equation restrictions on the fixed-effect parameters between the production function and the share equations. By doing so, the unobserved organizational characteristics are introduced not only in the IPF but also in the share equations. The term $\sum_i^n \alpha_i \ln W_i$ of the production function in (5), therefore, is replaced by $\sum_i^n (\tilde{\alpha}_i + \sum_{t=1}^{T-1} \alpha_{oit} DUM_{ot}) \ln W_i$, and the parameter α_i in the share equation (6) is replaced by the term $(\tilde{\alpha}_i + \sum_{t=1}^{T-1} \alpha_{oit} DUM_{ot})$. Given this specification, appropriate adding-up constraints must also be imposed on the fixed-effect parameters as $\alpha_{om} = -\sum_{i=1}^{n-1} \alpha_{oi}$. So whether structural differences exist among the water utilities regarding hiring of variable factors due to the differences in ownership forms can be examined by testing the significance of α_{oit} parameters individually and/or jointly.

The primary goal of frontier methods is to identify inefficiency. A question of interest is whether inefficiency occurs randomly across firms or whether some firms have predictably higher inefficiency than others. If the occurrence of inefficiency is not totally random, then it should be possible to identify factors that contribute to inefficiency. Factors causing

deviation from the production frontier are under the control of the firm. The level of inefficiency would likely be better explained in terms of firm-specific factors. These factors are incorporated directly in the model by specifying the inefficiency parameters in terms of firm-specific variables.³ Instead of assuming that $E(\tau)$ and $V(\tau)$ are invariant across firms, as in the standard frontier specification, they become firm-specific which allows estimating inefficiency and explaining inefficiency in terms of firm differences.

Let τ be a function of a vector of firm-specific variables, $Q \in \mathfrak{R}_+^g$, as:

$$(7) \quad \tau_f = \psi(Q_f)u_f,$$

where $f = 1, \dots, F$ indexes firms, u_f is a nonnegative random variable which captures part of inefficiency, and Q includes the firm-specific variables that explain the extent to which the observed production level falls short of the corresponding stochastic frontier production level. Detailed discussion of the specification of Q vector is provided later in equation (12) and in the data section. Both u_f and v_f are assumed to have means and variances that are invariant across firms, that is, $E(\tau_f) = \psi(\cdot)E(u_f) \equiv \psi(\cdot)\mathbf{A}$ and $V(\tau_f) = \psi(\cdot)^2 V(u_f) \equiv \psi(\cdot)^2 \mathbf{B}$. Thus, $\psi(\cdot)$ is firm-specific and \mathbf{A} and \mathbf{B} are constants. If $\psi(\cdot)$ is a constant, the model reduces to a regular stochastic frontier (composed error) model. Therefore, we can statistically test both hypotheses with this specification.

Estimation

Since the number of parameters to be estimated is greater than the number of available data points, a simultaneous-equation estimation technique is used rather than a single-equation estimation method. This increases the number of effective data points by the factor of the number of additional equations. The system of equations can be estimated using the maximum likelihood (ML) method, and for that a set of assumptions regarding distribution of the error terms γ , τ , and v and their interrelationships are required. Without loss of generality, these models can be estimated in two steps (Kumbhakar and Hjalmarsson; Heshmati and Kumbhakar; Bhattacharyya, Kumbhakar, and Bhattacharyya). First, the parameters of the IPF and its share equations are estimated simultaneously. Second, the parameters associated with technical inefficiency are estimated conditional on the parameters of the production function. Given all estimated parameters, firm-specific technical inefficiency can be calculated as proposed by Jondrow et al. The advantage of this two-step estimation method lies in its independence from a set of strong distributional assumptions regarding the error terms and their interrelationships.⁴

Since $E(\tau_f) = \psi(\cdot)\mathbf{A}$, the production function in (5) is extended by adding $\psi(\cdot)$ to it. Failure to include $\psi_f(Q; \beta)$ in the production function leads to biased and inconsistent parameter estimates, especially if the variables in the $\psi_f(Q; \beta)$ function are not orthogonal to those on the right-hand side of the production function. The resulting production function is

³See Battese and Coelli for the advantage of such a specification, relative to that of running a separate regression of the predicted inefficiency estimates on some firm-specific variables.

⁴At the first step of the two-step estimation process, no distributional assumption other than zero mean and constant variance is needed on the error terms of the IPF and the share equations. The error terms across equations are allowed to be correlated. Distributional assumptions on the one-sided error term and the random error term are needed in the second step for estimation of the inefficiency parameters. In the case of a single-step ML estimation, a set of strong assumptions are needed not only to

$$(8) \quad \ln y_f = y_f(W, Z, C, DUM_{ot}; \alpha, \tilde{\alpha}, \alpha_o) + \psi_f(Q; \beta) + \varepsilon_f,$$

where $y_f(\cdot)$ is the right-hand side of the translog IPF in (5) with homogeneity and symmetry conditions imposed and ownership-specific dummy variables included.

The error vector $(\varepsilon_f, \xi_{if})$ is assumed to have zero mean and constant variance-covariance matrix and is independent across utilities. Since there are $(n-1)$ independent input share equations, one of them is dropped to avoid singularity of the variance-covariance matrix of the share equations. Thus, we have a system of nonlinear seemingly unrelated regression (NLSUR) equations, where the error terms are correlated across equations. The multivariate normality assumption on the error vector is not made. Because of heteroskedastic error terms, parameter estimates, except α_o , are consistent but not asymptotically efficient. Heteroskedasticity-consistent standard errors are obtained using White's correction (White).⁵

Next, the predicted residuals, \hat{B}_f , of the production function are obtained using the consistent parameter estimates, $\hat{\alpha}$ and $\tilde{\alpha}$, that is, excluding α_o and setting $\hat{\beta} = 0$. \hat{B}_f , therefore, contains all inefficiency factors and white noise errors as:

$$(9) \quad B_f = \alpha_o + \varepsilon_f = \alpha_o - \psi_f(\cdot)\iota_f + v_f.$$

At this step, distributional assumptions regarding ι_f and v_f are needed to develop the required log-likelihood function to obtain consistent estimates of the rest of the parameters.

Four different distributional assumptions have been used in the literature for specifying the one-sided error term, ι_f : (a) truncated-normal, (b) half-normal, (c) exponential, and (d) gamma. In this study, instead of assuming any particular distributional structure as a candidate for inefficiency specification, the first three distributional assumptions are tested to determine which particular one follows the DGP most closely.⁶ Model selection procedures for nonnested models, as proposed by Vuong, are used to determine the appropriate distribution for specifying the one-sided error term of the translog IPF. However, for all three distributional specifications, the random error part (v_f) of the composed error is assumed distributed normally with zero mean and constant variance, that is, $v_f \sim i.i.d. N(0, \sigma_v^2)$.

The most commonly used distributional assumption in the literature for the one-sided error term ι_f is the half-normal, that is, ι_f is independently distributed, such that is ι_f obtained by truncation at zero of the normal distribution with mean zero and variance σ_ι^2 . Under a half-normal specification with normally distributed v_f , the log-likelihood function for utility f , following Aigner, Lovell, and Schmidt, can be expressed as:

$$(10.1) \quad \ln L_{HNf} = \Delta - \frac{1}{2} \ln \sigma_f^2 - \frac{1}{2\sigma_f^2} \varepsilon_f^2 + \ln \Phi \left[\frac{\varepsilon_f \delta_f}{\sigma_f} \right],$$

where $\sigma_f^2 = \sigma_v^2 + \psi_f(\cdot)^2 \sigma_\iota^2$, $\delta_f = \psi_f(\cdot) \sigma_\iota / \sigma_v$, $\varepsilon_f = v_f - \tau_f = B_f - \alpha_o$, $\Phi(\cdot)$ is the cumula-

⁵With heteroskedasticity the estimated variance-covariance matrix is not consistent. The White correction (1980) does not alter the estimated parameters but provides a consistent estimate of the variance-covariance matrix of the estimated parameters.

⁶A gamma distribution has mainly been used for deterministic frontier specifications. Gamma-exponential (Greene 1990) and gamma-normal (Beckers and Hammond) models have been theoretically proposed, but empirical application of either stochastic specification greatly increases the complexity of estimation procedure (Greene 1993). Moreover, Ritter and Simar show that there are other major problems in using a normal-gamma frontier model.

tive standard normal distribution function, and Δ is a constant which can be dropped from the estimation.

Under an exponential distribution specification of the one-sided error term, v_f , with $v_f \sim i.i.d. N(0, \sigma_v^2)$, the log-likelihood function for utility f , again following Aigner, Lovell, and Schmidt, can be expressed as:

$$(10.2) \quad \ln L_{NE_f} = -\ln \bar{\sigma}_f + \frac{\sigma_v^2}{2\bar{\sigma}_f^2} - \frac{\varepsilon_f}{\bar{\sigma}_f} + \ln \Phi \left[\frac{\varepsilon_f}{\bar{\sigma}_v} - \frac{\sigma_v}{\bar{\sigma}_f} \right],$$

where $E(\tau_f) = \bar{\sigma}_f = \psi_f(\cdot)\sigma_v$, and $V(\tau_f) = \bar{\sigma}_f^2 = \psi_f(\cdot)^2\sigma_v^2$.

Stevenson has argued that the zero mean assumption in Aigner, Lovell, and Schmidt is an unnecessary restriction. Instead, the one-sided error term v_f can be taken as a variable obtained by truncating the distribution of a variable with possibly nonzero mean at zero. Under a truncated normal specification for the one-sided error term v_f with $v_f \sim i.i.d. N(0, \sigma_v^2)$, the log-likelihood function for utility f can be expressed as:

$$(10.3) \quad \ln L_{TN_f} = -\ln \sigma_s - \frac{1}{2} \frac{(\varepsilon_f - \mu)^2}{\sigma_s^2} - \ln \Phi \left(\frac{\mu}{(\sigma_f^2 \sigma_s^2)^{1/2}} \right) + \ln \Phi \left(\frac{\mu^*}{\sigma^*} \right),$$

where $\sigma_s^2 = \sigma_f^2 + \sigma_v^2$, $\mu^* = (\sigma_v^2 \mu - \sigma_f^2 \varepsilon_f) / \sigma_s^2$, and $\sigma^{*2} = (\sigma_f^2 \sigma_v^2) / (\sigma_f^2 + \sigma_v^2)$.

Maximizing each log-likelihood function (10.1–10.3), summed over all utilities, gives consistent estimates of the parameters associated with the estimation of technical inefficiency, that is, α_o , σ_f^2 , σ_v^2 , μ , and β_g . Since B_f is not observed, it is replaced by:

$$(11) \quad \hat{B}_f = \ln y - \left(\sum_{i=1}^n (\hat{\alpha}_i + \sum_{t=1}^{T-1} \hat{\alpha}_{ot} DUM_{ot}) \ln W_i + \sum_{j=1}^m \hat{\alpha}_j \ln Z_j + \hat{\alpha}_c \ln C \right. \\ \left. + \frac{1}{2} \left\{ \sum_{i=1}^n \sum_{l=1}^n \hat{\alpha}_{il} \ln W_i \ln W_l + \sum_{j=1}^m \sum_{q=1}^m \hat{\alpha}_{jq} \ln Z_j \ln Z_q + \hat{\alpha}_{cc} \{ \ln C \}^2 \right\} \right. \\ \left. + \sum_{i=1}^n \sum_{j=1}^m \hat{\alpha}_{ij} \ln W_i \ln Z_j + \sum_{i=1}^n \hat{\alpha}_{ic} \ln W_i \ln C + \sum_{j=1}^m \hat{\alpha}_{jc} \ln Z_j \ln C \right),$$

which converges in distribution to B_f asymptotically as $\hat{\alpha}$ s and $\hat{\tilde{\alpha}}$ are consistent estimators of α s (Griffiths and Anderson).

To incorporate firm-specific effects in efficiency estimation, a linear function approximation of $\psi(Q_f)$ is used in estimation. It is

$$(12) \quad \psi_f = \beta_o + \beta_{PL} \ln PL + \beta_{SL} \ln SL + \beta_{S_1} DUM_{S_1} + \beta_{S_2} DUM_{S_2} \\ + \beta_T DUM_T + \beta_{SD} DUM_{SD} + \beta_{PMC} PMC,$$

where PL is the total mile length of distribution pipelines; SL is the system loss of water in million of gallons; DUM_{S_s} are dummy variables to capture differences in sources of water inputs; DUM_T is a dummy variable that captures whether a water utility treats water before

delivery; DUM_{SD} is a dummy variable that accounts for a utility that only supplies water or a utility that also treats sewer, and PMC is the percentage of metered connection. These variables are discussed further in the data section.

If all β parameters associated with firm-specific variables are zero and $\beta_o = 1$, then the half-normal and normal-exponential models represent the corresponding models specified by Aigner, Lovell, and Schmidt. Under similar conditions, the truncated-normal model reduces to the one specified by Stevenson.

Tests for Model Selection

Two different model selection tests are used to select the appropriate model. First, the *likelihood dominance criterion* (LDC) is used to select between models with inefficiency specification in terms of (12), that is, Model A, and the standard frontier model, that is, Model B, under each of the three distributional assumptions.⁷ Next, the Vuong test is used to select the appropriate model from the two strictly nonnested models. A sequential test process is followed to select among the competing models. That is, if the truncated-normal model (Model I) is better than the normal-exponential model (Model II), and Model II is found to be better than the half-normal model (Model III), then Model I is chosen. But in the second test, if Model III turns out to be closer to the DGP than Model II, then another test is done between Model I and Model III to select the best of the three competing models.⁸

Likelihood ratio tests to select between two competing models can be conducted by evaluating the test statistic $ST = \sqrt{[(F - 1) / F]} \times t_s$. In ST , t_s is the t -statistic of the regression of a series of one, $\{1\}$, on m_t , where m_t is the difference between the log-likelihood values of two models, for example, F_0 and G_c , evaluated at each data point and F is the total number of observations. If the estimated test statistic $ST > C$, then the null hypothesis that the two models are equivalent is rejected in favor of F_0 being better than G_c , where C is the critical value from the standard normal distribution. If, on the other hand, $ST < -C$, then one rejects the null hypothesis in favor of G_c being better than F_0 . If $|ST| \leq C$, then one cannot discriminate between the two competing models given the data.

Efficiency Estimates

Given the parameter estimates, the *i.i.d.* component of technical inefficiency can be estimated for both distributional assumptions from the conditional mean of τ_f given $\varepsilon_f(\hat{\tau}_f)$ or its mode ($\tilde{\tau}_f$). For the truncated-normal model the conditional mean is

$$(13.1) \quad E[\tau_{f_j} | \varepsilon_{f_j}] = \hat{\tau}_{f_j} = \hat{\mu}_* + \hat{\sigma}^2 \left[\frac{\phi(\hat{\mu}_* / \hat{\sigma})}{\Phi(\hat{\mu}_* / \hat{\sigma})} \right];$$

and the mode is

⁷The LDC prefers Model A over Model B if $L_B - L_A < [C(N_B + 1) - C(N_A + 1)] / 2$; and Model B is preferred over Model A if $L_B - L_A > [C(N_B - N_A + 1) - C(1)] / 2$, where L_A and L_B are the values of the log-likelihoods of Models A and B, respectively; N_A and N_B are the number of respective independent parameters in Models A and B; and $C(N)$ is the critical value of the chi-squared distribution with N degrees of freedom. If two hypotheses have the same number of parameters, the one with a larger likelihood value is preferred in that case.

⁸Two models F_0 and G_c are strictly nonnested, if and only if $F_0 \cap G_c = \phi$. Models I, II, and III are strictly nonnested because each of them follows a different distributional assumption (Vuong, p. 317).

$$(13.2) \quad M[\tau_{I_f} | \varepsilon_f] = \tilde{\tau}_{I_f} = \begin{cases} \hat{\mu}_*, & \text{if } \hat{\mu}_* \geq 0; \\ 0, & \text{otherwise,} \end{cases}$$

where $\phi(\cdot)$ is the standard normal density function. Similarly, for the normal-exponential specification, the conditional mean and mode, respectively, can be expressed as:

$$(14.1) \quad E[\tau_{II_f} | \varepsilon_f] = \hat{\tau}_{II_f} = \hat{\sigma}_v \left[\hat{A}_f + \frac{\phi(\hat{A}_f)}{\Phi(\hat{A}_f)} \right];$$

$$(14.2) \quad M[\tau_{II_f} | \varepsilon_f] = \tilde{\tau}_{II_f} = \begin{cases} \hat{\sigma}_v \hat{A}_f, & \text{if } \hat{A}_f \geq 0; \\ 0, & \text{otherwise,} \end{cases}$$

where $\hat{A}_f = (\varepsilon_f / \hat{\sigma}_v - \hat{\sigma}_v / \hat{\sigma}_f)$. For the half-normal specification, the conditional mean of τ_f given ε_f is

$$(15.1) \quad E[\tau_{III_f} | \varepsilon_f] = \hat{\tau}_{III_f} = \hat{\mu} + \hat{\vartheta} \left[\frac{\phi(\hat{\mu} / \hat{\vartheta})}{\Phi(\hat{\mu} / \hat{\vartheta})} \right];$$

and the mode is

$$(15.2) \quad M[\tau_{III_f} | \varepsilon_f] = \tilde{\tau}_{III_f} = \begin{cases} \hat{\mu}, & \text{if } \hat{\varepsilon}_f \geq 0; \\ 0, & \text{otherwise,} \end{cases}$$

where $\mu_f = \delta_f^2 \varepsilon_f / (1 + \delta_f^2)$ and $\vartheta = \delta_f^2 \sigma_f^2 / (1 + \delta_f^2)^2$. An index of technical efficiency (TE) is then estimated from:

$$(16) \quad \hat{TE}_f = \exp(-\hat{\tau}_f), \quad \text{and / or} \quad \tilde{TE}_f = \exp(-\tilde{\tau}_f).$$

The full-efficient utility has technical efficiency of 1.

Data

The data set used in this study was collected by surveying 26 rural Nevada water utilities in 1992. The water utility companies of rural Nevada differ greatly in size, composition, service diversity, water-input accessibility, and ownership form. Descriptive statistics of the variables used in the study are reported in table 1. Prior to estimation the data are normalized such that the mean of each variable is one without affecting shares or other proportions. Variable inputs are classed into three categories: energy (X_E), labor (X_L), and materials (X_M); measured in thousand kilowatt hours (KHW), labor hours, and thousands of dollars, respectively. Energy price (W_E) is obtained by dividing the total energy cost by KWH of energy used. The unit price of energy, therefore, includes all fixed costs (charges) associated with energy use. The labor price (W_L) is calculated by dividing labor cost by the total hours

Table 1. Summary Statistics of the Variables

Variable	Description	Mean	SD
<i>E</i>	Energy (1,000 KWH)	460.49	669.69
<i>L</i>	Labor (1,000 hours)	6.09	6.34
<i>M</i>	Material costs (\$ thousands)	26.88	39.26
W_E	Energy price (\$/1,000 KWH)	62.31	25.97
W_L	Labor wage (\$/hour)	10.30	4.08
<i>C</i>	Total expenditure (\$ millions)	90.99	91.50
<i>y</i>	Water supplied (million gallons/year)	236.77	265.43
Z_P	Water input (million gallons/year)	258.08	296.49
Z_K	Capital (\$ thousands)	1,346.90	1,587.00
Z_D	Population/square mile	1,163.10	2,889.10
<i>PMC</i>	Metered connections/total connections	0.71	0.44
<i>PL</i>	Distribution pipe length (miles)	26.32	37.85
<i>SL</i>	System water loss (million gallons/year)	23.21	41.50
		<u>Numbers</u>	
$DUM_T = 1$	Firms treating water	10	
$DUM_{S_1} = 1$	Firms with surface water	13	
$DUM_{S_2} = 1$	Firms with groundwater	6	
$DUM_{SD} = 1$	Firms with water and sewer	7	
<i>F</i>	Total number of utilities	26	

of labor used by a utility, assuming a total of 2,040 working hours per person in a year. For materials, defined as a composite cost of all materials used, no price data are available. Assumed constant across utilities, materials price becomes the numeraire in estimation (Eakin and Kniesner). Output (*y*) is the total water supplied in millions of gallons by a utility (net of system loss) per year.

Wide variations across utilities are observed regarding variable inputs use and their prices. Variation in energy use and its price is due to the following: (a) utilities' operations size, (b) volume discount on energy consumption received by large utilities, and (c) water-input sources. A utility that uses groundwater usually consumes more energy compared with a utility that draws from a mountain lake or spring. Variation in labor input price may reflect local market conditions and the structure of the institution. Some utilities in our sample are very small and only hire part-time labor for some specific operations. As a result their per hour wage rate is low compared with a utility that hires full-time labor.

One major problem in a study of water utilities is how to account for the water input. This is one of the most important inputs, but pricing owned-water input (from owned-sources) is very difficult because there is usually no competitive market for that water. Some researchers like Ziegler and Bell use a two-step method to determine the price of owned

water, specifying a relationship between the expenses of self-supplied water and the quantity of water. Costs associated with drawing water depend on the type of water-input sources. Some studies have attempted to measure the imputed value (opportunity cost) of owned water and have used the price of purchased water as a price estimate (Teeples and Glycer). Due to the difficulties associated with obtaining data for estimating the imputed cost of owned water input, Z_p , especially for the rural water utility companies, water input is introduced as a control variable in this study following Feigenbaum and Teeples. The total amount of water produced (million gallons) by and/or available to a firm for delivery during a year is considered as water input.

In addition to water input (Z_p), population density (Z_D) and capital (Z_K) are introduced as control variables. Since most water utilities are natural monopolies and by regulation they must serve a given geographical area, population density plays an important role in defining their network infrastructure. Densely populated areas require higher water pressure, more fire hydrants, and frequent repairs and maintenance. Population density (Z_D) is defined as the service population per square mile of an area served; capital (Z_K) the current value of the water utilities' assets.

The variables used in the second step of estimation for explaining inefficiency of a utility in Model A are DUM_{SD} , DUM_{S_1} , DUM_{S_2} , DUM_T , PMC , $\ln PL$, and $\ln SL$. This may not be an exhaustive set to explain technical inefficiency, but technical inefficiency departure from the frontier can be systematically explained in terms of the above set of variables. Technical efficiency of a rural water service may depend on the size of operation and vintage of the infrastructure. Total length of distribution pipelines (PL) is used as a measure of the size of operation. The system loss variable (SL), the quantity of water loss in the distribution process due to leakages and breakdowns of pipelines, is introduced to capture the vintage of infrastructure. There would be higher system loss and more maintenance the older the infrastructure becomes. Thus, higher system loss will not only widen the gap between the observed output and the frontier output but also would increase the water delivery cost.

The service quality depends partly on the product pricing structure. With metered water service, customers pay for blocks of water used and the rates are usually progressive. The administrative cost of metered pricing is high compared to flat-rate pricing. However, Bhattacharyya et al., show that metered service makes users conservation-conscious and makes utilities more efficiency conscious. This is because through metering the utility becomes aware of leaks for early repair and possible areas of overcapacity. This in turn helps a water utility to plan for a more efficient water distribution system. Moreover, the time and cost of reading water meters induce a water utility to process the water consumption information to improve water use efficiency. The variable PMC accounts for these firm differences. The PMC is the ratio of the numbers of metered service connections to total service connections.

The water delivery cost and technology depends on water sources. In some cases, especially in mountain areas, water delivery cost from high altitude sources is low and little maintenance is required. On the other hand, groundwater requires not only lumpy investments to pump out water and carry it to any destination but also requires frequent maintenance. Dummy variables DUM_{S_i} are used to account for different water sources. Three possible combinations of sources are: only surface, only ground, and both surface and ground. $DUM_{S_2} = 1$ if only surface source is used and zero otherwise, and $DUM_{S_1} = 1$ if the source is exclusively groundwater and zero otherwise. If a utility uses both sources, $DUM_{S_3} = 1$ and zero otherwise.

Seven out of 26 sample firms not only supply water but also provide sewer services. This

diversity of services is likely to generate economies of scope for the firm. Such a firm can recycle the treated waste water for outdoor watering. The same set of technical and administrative staff (except for some specialized work) can maintain both facilities. Firms are controlled for such complementariness by introducing a dummy variable DUM_{SD} in the $\psi(Q; \beta)$ function. DUM_{SD} equals one if the utility provides both sewer treatment and drinking water, and zero otherwise. Finally, a dummy variable DUM_T is included. $DUM_T = 1$ if a utility treats water before final delivery, and it assumes a value of zero if the utility does not treat water input. Treating water before delivery improves the quality of service. However, it is costly and in some cases requires substantial investments. Whether treatment improves a water utility technical efficiency is an empirical question, the sign and significance of the estimated coefficient of the dummy variable DUM_T would indicate that.

Results

The parameter estimates obtained from the first step, with heteroskedasticity corrected standard errors, are reported in table 2. This part is common for all three distributional specifications and is required for estimating inefficiency of the water utilities. Thirty out of 44 parameters are statistically significant at the 10% level. (Note that the intercept parameter, α_o , is not reported in table 2 as it is estimated in the second step). These parameters are used to estimate \hat{B}_f using (11). Table 3 reports the ML estimates of the constant term, α_o , and the six different sets of parameter estimates, obtained from the estimation of the three different log-likelihood functions (10.1–10.3) with and without the firm-specific variables. In estimating all three specifications of Model A, σ_1^2 is normalized to unity as it cannot be identified along with the intercept term β_o in (12).

The LDC tests reject all three models without firm-specific variables, that is, Model Bs in favor of Model As. Thus, models which explain inefficiency in terms of firm differences, that is, Model As, are preferred. Next, we perform the Vuong test to select among Model As the one that is closest to the DGP. Two classes of nonnested models are compared at a time. First, the normal-exponential model, Model IIA, is compared with the half-normal model, Model IIIA. The estimated test statistic is 1.43. Therefore, the model selection test fails to discriminate between the two models at even 90% level of confidence. Similar comparison is done between the truncated-normal, Model IA, and the normal-exponential, Model IIA. The estimated test statistic is 3.31, which rejects the Model IIA in favor of the Model IA at the 95% level of confidence. Next, Model IA is compared against Model IIIA. The estimated test statistic of 5.32 rejects the half-normal specification in favor of the truncated-normal specification at the 95% level of confidence. The nonnested model selection tests indicate that the truncated-normal specification is closest to the DGP out of the three distributional specifications.

Since the LDC model selection tests preferred Model As compared to Model Bs, efficiency estimates obtained under Model A are presented. Although the subsequent Vuong tests selected the truncated-normal (IIIA) specification over the normal-exponential (IIA) and half-normal (IIIA), inefficiency estimates of all three A models are reported. The estimates of average technical efficiency evaluated at the mean and mode of all three models, IA, IIA, and IIIA, are shown by types of organization in table 4. The average efficiency estimates from Model Bs are also provided.

Ideally, these estimates of technical efficiency should reflect the effects of cross-sectional variability in the data. For example, the variability of energy prices between utilities in the

Table 2. Parameter Estimates of the Indirect Production Function of Rural Nevada Water Utilities

Parameter		Parameter		Parameter	
$\tilde{\alpha}_E$	-0.27E-3 (0.35E-3)	α_{EM}	-0.55E-5 (0.15E-4)	α_{CD}	0.0046 (0.0011)
$\tilde{\alpha}_L$	-0.72E-3 (0.56E-3)	α_{EC}	-0.0029 (0.0010)	α_{CK}	-0.0088 (0.0015)
$\tilde{\alpha}_M$	0.98E-6 (0.21E-5)	α_{EP}	-0.0013 (0.43E-3)	α_{PD}	0.0086 (0.0048)
α_C	0.99E-3 (0.62E-3)	α_{ED}	-0.0023 (0.73E-3)	α_{PK}	0.0073 (0.0103)
α_P	1.0488 (0.0104)	α_{EK}	0.0039 (0.0013)	α_{DK}	0.0140 (0.0063)
α_D	0.0595 (0.0109)	α_{LM}	0.87E-5 (0.60E-5)	α_{o1E}	-0.0043 (0.0022)
α_K	0.0071 (0.0098)	α_{LC}	-0.0036 (0.62E-3)	α_{o2E}	0.0021 (0.97E-3)
α_{EE}	0.82E-3 (0.50E-3)	α_{LP}	-0.0016 (0.46E-3)	α_{o3E}	-0.0026 (0.0018)
α_{LL}	0.0015 (0.87E-3)	α_{LD}	-0.0022 (0.19E-3)	α_{o1L}	0.0043 (0.0022)
α_{MM}	0.65E-5 (0.19E-4)	α_{LK}	0.0049 (0.36E-3)	α_{o2L}	0.0021 (0.96E-3)
α_{CC}	0.0066 (0.0011)	α_{MC}	-0.97E-5 (0.37E-5)	α_{o3L}	0.0026 (0.0018)
α_{PP}	-0.0150 (0.0050)	α_{MP}	-0.38E-5 (0.21E-5)	α_{o1M}	0.20E-4 (0.77E-4)
α_{DD}	0.0248 (0.0032)	α_{MD}	-0.21E-6 (0.17E-5)	α_{o2M}	-0.14E-5 (0.23E-4)
α_{KK}	-0.0349 (0.0093)	α_{MK}	0.56E-5 (0.42E-5)	α_{o3M}	0.76E-5 (0.44E-4)
α_{EL}	0.0021 (0.73E-3)	α_{CP}	0.0029 (0.49E-3)	L	382.51

Note: Asymptotic standard errors are in parentheses, and **L** is the value of the log-likelihood function.

Table 3. Maximum Likelihood Parameter Estimates under Alternative Distributional Specifications

Parameter	Model					
	IA T-N	IIA N-Exp	IIIA H-N	IB T-N	IIB N-Exp	IIIB H-N
α_o	-0.0412 (0.0379)	-0.1830 (0.0335)	-0.2019 (0.0496)	-0.0412 (0.0015)	-0.1513 (0.0345)	-0.1749 (0.0274)
β_o	0.3815 (0.2034)	0.3085 (0.0585)	0.7703 (0.4864)			
β_T	0.3371 (0.1542)	0.1853 (0.0844)	-3.3024 (1.0988)			
β_{SD}	-0.7077 (0.1621)	-0.1443 (0.0635)	0.7872 (0.4926)			
β_{S_1}	0.3754 (0.2244)	0.0143 (0.0974)	1.0733 (0.9810)			
β_{S_2}	0.5102 (0.2081)	0.1694 (0.0626)	-2.1843 (0.9462)			
β_{PMC}	-0.2567 (0.1284)	-0.0252 (0.0504)	0.2616 (0.4035)			
β_{PL}	0.3464 (0.0746)	0.1990 (0.0338)	0.2683 (0.3843)			
β_{SL}	0.60E-3 (0.0041)	-0.1673 (0.0214)	-0.2502 (0.1438)			
σ_v	0.1369 (0.0348)	0.0434 (0.0710)	0.0499 (0.1032)	0.0434 (0.0127)	0.2281 (0.1026)	0.0743 (0.0485)
σ_u				0.1327 (0.0224)	0.0434 (0.0244)	0.2412 (0.0603)
μ	0.1158 (0.0818)			0.1235 (0.0383)		

Note: Asymptotic standard errors are in the parentheses.

Glossary: T-N is truncated-normal; N-Exp is normal; H-N is half-normal.

sample may be due to the volume discounting used by the large firms in their purchases of energy. The lower energy prices may then be systematically directed toward the large firms and may also reflect higher efficiency (in addition to possible market power) on the part of those large firms. This observation is consistent with the literature on the volume discounting (Carlton and Perloff). A failure to accommodate the possible volume discounting effect from purchases of energy may bias efficiency estimates against larger firms. Due to incomplete information on volume discounting in energy purchases by the large firms in our sample, we were not able to explicitly include the effects of volume discounting in our econometric model.

Table 4. Mean Technical Efficiency of Water Utilities by Ownership

Utility Group	Units	T-N Model		N-Exp Model		H-N Model	
		IA Mean	IA Mode	IIA Mean	IIA Mode	IIIA Mean	IIIA Mode
Private	2	0.9061 (0.0233)	0.9130 (0.0468)	0.8002 (0.0714)	0.8002 (0.0714)	0.7860 (0.0605)	0.7860 (0.0605)
County govt.	5	0.8350 (0.0937)	0.8666 (0.0767)	0.7660 (0.1019)	0.7678 (0.1057)	0.7368 (0.0751)	0.7368 (0.0752)
Water dist.	7	0.8569 (0.0746)	0.8624 (0.0834)	0.7653 (0.1068)	0.7690 (0.1152)	0.7436 (0.1115)	0.7484 (0.1228)
Municipality	12	0.8643 (0.1133)	0.8956 (0.1099)	0.7981 (0.1249)	0.8028 (0.1318)	0.7837 (0.1212)	0.7872 (0.1263)
Model A	26	0.8599 (0.0934)	0.8824 (0.0913)	0.7833 (0.1084)	0.7868 (0.1146)	0.7641 (0.1048)	0.7670 (0.1105)
Model B	26	0.8763 (0.0928)	0.8796 (0.0928)	0.8028 (0.1051)	0.8062 (0.1109)	0.7928 (0.0934)	0.7839 (0.1130)

Note: Standard deviations are in parentheses.

Glossary: T-N is truncated-normal; N-Exp is normal-exponential; H-N is half-normal.

Since model selection tests preferred Model IA over the other two models, efficiency estimates obtained from the truncated-normal specification (Model IA), reported in columns 3 and 4 of table 4, are used for discussion. Parallel inferences also can be drawn using the efficiency estimates obtained from the normal-exponential (Model IIA) and half-normal specifications (Model IIIA), as reported in columns 5–6 and 7–8, respectively, of table 4. The modal estimates of technical efficiency, representing ML estimates (Jondrow et al.), are used for interpreting the results. The average technical inefficiency of rural Nevada water utilities is 13.05%, that is, on average they are 88.24% technically efficient, with highest technical inefficiency 39.32%.

Among different organizations, the privately owned utilities are most technically efficient, with average efficiency 91.3% and a minimum of 88%. Water utilities managed by water districts are most inefficient, with an average technical efficiency 85.65%, that is, they produce 15.22% less than their frontier output level. The maximum technical inefficiency of district-operated units is 32.69%. Water utilities operated by county governments are, on average, almost as inefficient as the district-operated units, with average technical inefficiency 14.62%, and a range of 0.31% to 23.22%. The average technical efficiency of the municipality-operated water utilities is 90%, with estimated technical efficiency range from 67.49% to 100%. Municipal governments own both the best and the worst efficient water utilities.

Estimated parameters of the $\psi(Q; \beta)$ function explain inefficiency in terms of firm differences. The estimated parameter of *PMC* is negative, while that of *PL* is positive, indicating that increased metered connections (*PMC*) increases technical efficiency, and bigger infrastructure (*PL*) reduces technical efficiency. Because the average *PMC* is 0.71, technical efficiency may be raised by moving from a flat-rate system to a metered connection

system. The estimated coefficient of system loss (SL) is positive under the truncated normal specification; therefore, higher SL would increase technical inefficiency, and the sample firms can improve their efficiency level through better maintenance of existing pipelines. However, the estimated parameter is not significant.

Parameter estimates of both source dummies, $\hat{\beta}_{s_1}$ and $\hat{\beta}_{s_2}$, are positive and significant, showing that firms relying on a single source of water input, either only surface or only ground, have higher technical inefficiency, *ceteris paribus*, than firms who use both sources. Firms that rely on surface water as their exclusive source of water input are technically less inefficient, *ceteris paribus*, than firms who rely exclusively on groundwater. The estimated parameter of the treatment dummy, $\hat{\beta}_T$, is positive and significant, demonstrating that the water utilities that treat water before delivery are more technically inefficient than those that do not. As a negative value of $\hat{\beta}_{SD}$ indicates, utilities that provide both water supply and sewer treatment services are technically more efficient than the ones supplying drinking water only. This combination of the management of sewer treatment and water supply facilities may improve technical efficiency for utilities.

Conclusion

Small rural governments' effectiveness can be evaluated with Inman's two-step decision making process, in which the first step corresponds to provisionary decisions and the second step refers to production-related decisions. Past studies of local government-owned utilities have examined production efficiency independent of provisionary decision. This study incorporates the provisionary decision in the production function, through an *indirect production function*. Technical efficiency of rural water utilities is determined using frontier production functions. Previous studies have only distinguished between private and public utilities and have not considered the implications of the differences in ownership of public utilities. Here, public utilities are classified into three ownership forms: (a) municipal government operated, (b) county government operated, and (c) water district operated units. Model selection tests are used to identify the form of the distribution for the one-sided error term that follows the data generating process most closely.

Model selection tests are also used to discriminate between the competing models which explain technical efficiency, with and without firm-specific variables. Empirical results provide evidence to choose the models in which inefficiency parameters are functions of firm-specific variables. The models with normal-exponential and half-normal specifications for the one-sided error term are inferior to the ones with a truncated-normal specification. Empirical results show that technical efficiency of the water utilities in rural Nevada averages 88.24%. The private firms are more efficient than the publicly owned water utilities. Among three different types of public water utilities, the ones managed solely by water districts seem to be the least efficient. Water utilities run by municipalities are found, on average, to be most efficient.

The following advice can be provided to rural water utilities to increase efficiency: (a) increase metering and consolidation of service area, (b) reduce water loss in the distribution process, (c) combine drinking water production and sewer treatment management, and (d) diversify water-input sources. Further investigation is needed to understand (a) the wide variation in the efficiency of the municipality-owned units and (b) the higher inefficiency of the units owned by water districts.

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