Incentives and technical inefficiencies in the production of local public services*

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June, 2002

Abstract

This paper presents an empirical model of public production that allows us to statistically examine ‘incentive’ factors that may influence the internal effort level of local governments. Our model theoretically validates the application of the frontier analysis to the study of the incentive effect in local public finance. We analytically show that the very factors that influence the effort choice affect the moments of the technical inefficiency term in the frontier regression, whose stochastic property is based upon an exogenous inefficiency parameter that is unobservable to econometricians. We nonetheless show that the previous applied studies that claim to examine the incentive effect are based upon misspecified models, by demonstrating that the incentive effects are also present in the behavioral part of the frontier regression. Lastly, with cross-section data for Japanese municipalities, we provide an example that empirically implements our model to statistically examine the incentive effect. Our model dispenses with the popular method of maximum likelihood, and therefore is robust against the distributional assumption of the error terms.

1 Introduction

Inefficiency in the public sector is one of the major concerns in public economics. The literature typically examines local characteristics as an incentive for policy makers to mitigate or aggravate inefficiencies in producing public services. For example, Hayes and Chang (1990) examine the effects of different institutional forms of city management – city manager form or mayor-council form – to see which form provides a larger incentive to lower cost. In addition to this institutional factor, Davis and Hayes (1993) investigate the effects of several local characteristics, and relate the size of population to the level of monitoring, with an implicit assumption that monitoring discourages bureaucrats from cheating. On the other hand, Grossman et al. (1999) consider, among others, residential immobility and intergovernmental transfers. They

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follow the typical argument that less competitive pressure from competing cities –
associated with low residential mobilities – induces local policy makers to exploit
citizens and firms in their jurisdictions, and that more reliance on fiscal transfers
from higher levels of governments yields mis-perception of true tax prices by voters
and a less careful assessment of the quality of local services by local authorities.

These studies are straightforward applications of the stochastic frontier analysis
which utilizes the concept of technical inefficiency defined as a deviation from the
best performance attainable for a given set of conditioning variables (e.g., Kumbhakar
and Lovell 2001). A stochastic frontier regression is typically formulated as $y = f(\cdot) + v + u$ where $f(\cdot)$ describes the behavior of an economic agent according to
economic theory (‘cost function’ or ‘production function’), $v$ is standard disturbance
term with $E(v) = 0$, and $u$ is stochastically distributed technical inefficiency that
is truncated below (for cost function) or above (for production function) zero. The
focus of the applied studies is on examining the influence of a certain set of exogenous
variables as incentives to mitigate or aggravate inefficiencies. Operationally, they set
up a model that allows the incentive factors to influence the distribution of technical
inefficiencies, and estimate it to see if such variables exert significant influence on $E(u)$
and/or $\text{Var}(u)$. It is in effect postulated that the incentive effects are revealed only
in the technical inefficiencies. This, however, may not be a compelling assumption,
since incentives by default affect the behavior of economic agents which corresponds
to $f(\cdot)$, but not to $u$.

In this paper, we present a model of public production that explicitly accounts
for the internal effort level of local governments, and derive an empirical specification
that allows us to statistically examine ‘incentive’ factors that may influence the effort
level of decision makers. We introduce a three-stage model of local public production,
by extending the standard two-stage model (e.g., Bradford et al. 1969, Brueckner
1981, Duncombe and Yinger 1993) to a model that incorporates the model of unob-
servable effort choice originally developed in the context of the management choice

As we shall see in the next section (Section 2), our model distinguishes itself from
Dalen and Gomez-Lobo (1997) and improve on the existing public-sector related
frontier studies as follows. First, our model allows the exogenous factors or ‘incentive
factors’ to affect the effort choice of local government. In Dalen and Gomez-Lobo
(1997), less concerned with the incentive effect that we are discussing, the marginal
cost of effort by the management is modelled as independent of external factors. Given
the current interest of this paper, we extend their setup and, in so doing, present a
statistical model where we can examine the existence of such incentive effect.

Second, starting from somewhat restrictive but frequently used specifications, we
shall analytically derive an empirical model that is amenable to the stochastic fron-
tier analysis. Our theoretical specification does validate the ad-hoc characterization
of the incentive effects in terms of the inefficiency term in the previous studies. As
in Dalen and Gomez-Lobo (1997), our model includes inefficiency parameter ($\theta$) that
is exogenous to decision makers. By assuming that the parameter is stochastically
distributed across municipalities with its values being truncated below zero, we shall
show that a scale transformation of the inefficiency parameter constitutes the ineffi-
ciency term (i.e., $u = b\theta$ with $b$ being the scale). We will also demonstrate that the incentive factors affect the scale ($b$) and, therefore, the technical inefficiency ($u = b\theta$). This then indicates that the very factors that influence the effort choice (i.e., the incentive factors) also affect the moments of the technical inefficiency term.

Third, our model also indicates that the incentive effects are also revealed in the behavioral part of the frontier regression, i.e., $f(\cdot)$. This implies that the existing studies that claim to examine the incentive effect are possibly based upon misspecified models, since they simply employ the standard theory to derive $f(\cdot)$ that does not account for the endogenous effort choice.

Fourth, we as an example empirically implement our model with the cross section of Japanese municipal data in Section 3. The applied studies of the frontier analysis typically use the method of maximum likelihood (ML). However, a proper ML estimator requires the correct parametric specification of the distributional patterns of technical efficiency $u$ and standard disturbance $v$, including their heteroskedastic patterns. This may be quite difficult, given the setup of our model in particular or those of the applied studies in general. Our estimation procedure, on the other hand, dispenses with the ML method, and therefore does not require the parametrically specified distributions. In addition, while our estimator may lack the asymptotic efficiency, it is robust in the presence of heteroskedasticity.

2 Model

2.1 The general set up

Our model starts with the standard two-stage model of public production that distinguishes between the direct outputs produced by a government and the level of the public services actually consumed by citizens (e.g., Bradford et al. 1969, Brueckner 1981, Duncombe and Yinger 1993). We extend the standard model into a three-stage model, which can be conceptualized as the standard model conditional on the effort level that is chosen in the third stage of the public production process.

First, consider the first process which is analogous to the standard theory of firm. Assume a local government produces a direct output $g$, with a technology:

$$g = g(x, \phi)$$

(1)

where $x$ is a vector of factor inputs and $\phi$ is an inefficiency factor such that $\partial g/\partial \phi < 0$. The inefficiency factor is decomposed as:

$$\phi = \theta - e$$

where $\theta$ is an inefficiency parameter exogenous to the decision maker; and $e$ is the level of cost-reducing effort made by the local government. For a given level of $g$ and $e$, a conditional cost function is given as:

$$c(g, w, \theta - e) = \min_x \{w'x \mid g(x, \theta - e) \geq g\}$$

(2)
where \( \mathbf{w} \) is a vector of prices of factor inputs. The standard properties apply to functions (1) and (2), and \( \partial g / \partial \phi < 0 \) implies \( \partial c / \partial e < 0 \).

Second, the direct output \( g \) is transformed into its service level \( z \) that is of interest to citizen-consumers. The transformation may be influenced by the number of consumers (i.e., population) \( n \) and other local characteristics \( \mathbf{a} \). This relation, known as ‘crowding function’ or ‘congestion function’, is expressed as:

\[
  z = z( g, n, \mathbf{a} )
\]

where \( \partial z / \partial g > 0 \) and \( \partial z / \partial n < 0 \). From (3), we derive:

\[
  g = \gamma( z, n, \mathbf{a} ) \equiv z^{-1}( z, n, \mathbf{a} )
\]

which is the level of direct production that is necessary to keep the consumed service level for a given set of population and local characteristics. We then substitute (4) into (2) to obtain the standard two-stage cost function conditional on \( e \):

\[
  c( \gamma( z, n, \mathbf{a} ), \mathbf{w}, \theta - e ) .
\]

Third, the management of the local government chooses its effort level \( e \) to reduce exogenous inefficiency \( \theta \), considering its private cost that making effort \( e \) entails. We model this private cost as:

\[
  \psi( e; \mathbf{s} )
\]

where \( \partial \psi / \partial e > 0 \) and \( \mathbf{s} \) is a vector of the incentive factors that influences the effort level. The management chooses its effort level so as to minimize the total cost:

\[
  c( \gamma( z, n, \mathbf{a} ), \mathbf{w}, \theta - e ) + \psi( e; \mathbf{s} ) .
\]

We thus obtain the effort level as:

\[
  e^* = e( z, n, \mathbf{a}, \mathbf{w}, \theta, \mathbf{v} ) \equiv \arg \min_e \{ c( \gamma( z, n, \mathbf{a} ), \mathbf{w}, \theta - e ) + \psi( e; \mathbf{s} ) \} .
\]

This is in turn substituted for \( e \) in (5) to yield an incentive-adjusted cost function:

\[
  c^* ( z, n, \mathbf{a}, \mathbf{w}, \theta, \mathbf{v} ) \equiv c( \gamma( z, n, \mathbf{a} ), \mathbf{w}, e( z, n, \mathbf{a}, \mathbf{w}, \theta, \mathbf{v} ) - \theta )
\]

which is the function we shall estimate.

### 2.2 Specification

To empirically implement the foregoing analysis, we need to specify the cost function (2), the congestion function (3), and the incentive function (6). First, we consider production technology. We follow the convention of the literature to aggregate factor inputs into labor and capital, which are then reflected as wage rate \( \mathbf{w} \) and rental price of capital \( \mathbf{r} \) in the cost function. We assume the Cobb-Douglas form for the production function (1), which implies the Cobb-Douglas specification for the cost function (2):

\[
  c = A \exp( \phi ) \mathbf{w}^{\beta} \mathbf{r}^{\beta} g^{\beta} .
\]
where $A$ and $\beta'$ are parameters. With this specification, the effect of an increase in effort to reduce cost is:

$$\frac{\partial c}{\partial e} = -c$$

which is called the ‘Arrow effect’ by Dalen and Gomez-Lobo (1997). It shows that, when cost levels are higher, the cost savings from increasing effort are also higher. In the context of local public finance, this effect implies that a larger municipality has a larger incentive to reduce its cost. If our specification is appropriate, we then validly compare the Arrow effect of local governments by simply comparing their expenditure levels.

Second, we specify the congestion function as:

$$z = g \cdot n^{-(\lambda_0 + \lambda_n \ln n + \sum_j \lambda_j a_j)}$$

where $a_j$ is a local characteristic (i.e., an element of vector $a$), and $\lambda_j$'s are parameters. This specification amends the popular specification of $z = gn^{-\alpha}$ (Borcharding and Deacon 1972, Bergstrom and Goodman 1973), in that it allows congestion elasticity to vary by including $\ln n$ (Hayes and Slottje 1987) and local characteristics to affect the congestion through $\sum \lambda_j a_j$ (e.g., Hayes 1986, Duncombe and Yinger 1993).

Third, the incentive function (6) is specified as:

$$\psi(e; s) = \exp[q(s)e] - 1.$$ (12)

which is an extension of the exponential specification by Dalen and Gomez-Lobo (1997) who assume the constancy of the coefficient $q$ on $e$. On the other hand, we allow the coefficient to be influenced by a vector of incentive factors $s$, and specify $q(s)$ in a linear form as:

$$q(s) = \gamma_0 + \sum_k \gamma_k s_k$$ (13)

where $s_k$ is an element in $s$. (However, we keep using $q(s)$ for notational convenience for now.) The marginal private cost of effort is $\partial \psi / \partial e = q(s) \exp[q(s)e]$, which implies that the incentive factors affect the optimal effort level chosen by the decision maker. In fact, from (8), the optimal effort is given as:

$$e^* = \frac{1}{1 + q(s)} \ln \left[ q(s)^{-1} A \exp(\theta) w^{\beta_w} r^{\beta_r} \left( z \cdot n^{\lambda_0 + \lambda_n \ln n + \sum_j \lambda_j a_j} \right)^{\beta_g} \right].$$ (14)

Substituting this into (10) specifies the incentive-adjusted cost function (9) as:

$$c = q(s)^{1+q(s)} \left[ A \exp(\theta) w^{\beta_w} r^{\beta_r} \left( z \cdot n^{\lambda_0 + \lambda_n \ln n + \sum_j \lambda_j a_j} \right)^{\beta_g} \right] \frac{q(s)}{1 + q(s)}.$$ (15)

By logging this equation, indexing the variables with subscript $i$, and adding the standard disturbance term $v_i$, we finally obtain the following regression model:

$$\ln c_i = \ln \left( \frac{q(s_i)}{1 + q(s_i)} \right) + \frac{q(s_i)}{1 + q(s_i)} \cdot \left( \ln A + \beta_w \ln w_i + \beta_r \ln r_i \right) + \frac{q(s_i)}{1 + q(s_i)} \cdot \left( \ln z_i + (\lambda_0 + \lambda_n \ln n_i + \sum_j \lambda_j a_{ji}) \cdot \ln n_i \right) + v_i + \frac{q(s_i)}{1 + q(s_i)} \theta_i.$$ (15)
It may be instructive to compare (15) to the model that may have been used in the standard public-sector related frontier analysis. With our specifications, it would be derived from (10) and (11) as:

$$\ln c_i = \ln A + \beta_w \ln w_i + \beta_r \ln r_i + \beta_y \left( \ln z_i + (\lambda_0 + \lambda_n \ln n_i + \sum_j \lambda_j a_{ji}) \cdot \ln n_i \right) + \psi_i + \phi_i$$

where \(\psi_i\) is the standard disturbance term. It is evident from (16) that inefficiency factor \(\phi_i\) functions as the technical inefficiency term, which is assumed to be distributed as a non-negative stochastic variable. Since \(\phi_i \equiv \theta_i - e_i\), this setup requires effort level \(e\) to be exogenous. However, it should be clear from (8) or (14) that such an assumption is untenable, since by construction the effort is a endogenously chosen variable.\(^1\)

In our model (15), on the other hand, the inefficiency term is

$$[q(s_i)/(1 + q(s_i))]|\theta_i$$

where \(\theta_i\) is a non-negative value that is unobservable for econometricians but is validly assumed to be exogenously distributed across municipalities. Note that the inefficiency term is affected by exogenous factors \(s_i\) that originally influence the marginal cost of effort in the local government. The inefficiency term takes on the form of ‘scale’ transformation of \(\theta_i\), with the ‘scale’ being \(1/(1 + q(s_i))\). Since

$$\text{Var} \left[ q(s_i)/(1 + q(s_i)) | \theta_i \right] = [q(s_i)/(1 + q(s_i))]^2 \sigma_\theta \text{ and } E \left[ q(s_i)/(1 + q(s_i)) | \theta_i \right] = [q(s_i)/(1 + q(s_i))] \mu_\theta \text{ where } \mu_\theta \equiv E[\theta_i] \text{ and } \sigma_\theta \equiv \text{Var}[\theta_i],$$

the incentives \(s_i\) affect the variance as well as the mean of the stochastic inefficiency term.\(^2\) This in fact provides an analytical foundation that relates incentives to the distribution of technical inefficiencies, which is postulated on ad hoc basis in the existing public sector related frontier analysis.

The incentive factors influence the deterministic part of (15) as well. When we compare (15) to (16), we see that the slope parameters in (16) are blown down by \(q(s_i)/(1 + q(s_i)) \in (0, 1)\) and the constant (say, \(h\)) is transformed as \(\ln q(s_i)/(1 + q(s_i)) \) + \([q(s_i)/(1 + q(s_i))]|\theta_i\). That is, if we are to account for the incentives properly, only looking at the inefficiency term is not good enough. If (15) is the true data generating process, the standard specification (16) commits a specification error which results in inappropriate estimators. This implies that the models employed in the previous studies are misspecified if the incentive effects are present as they presume.

### 3 An empirical example

In this section, we apply the model specified in the previous section to the cross section data of Japanese municipalities. The purpose of this exercise is to provide a

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\(^1\)It may still be claimed that the effort level can be stochastic, say, by adding a disturbance term to (14), which is of course untenable since the deterministic part still remains as (14) in \(\phi\).

\(^2\)Several studies assume that the incentive factors only affect the mean but not the variance. Such an assumption may only be permissible for the case of the location transformation as \(\text{Var}[q(s_i) + \theta_i] = \text{Var}[\theta_i]\).
procedure that empirically implements the preceding theoretical formulation, rather than a definite empirical evidence that characterizes the structure of local public production in Japan.

3.1 Statistical model and estimation method

A typical frontier analysis utilizes the method of maximum likelihood (ML) which requires parametric distributional specifications of $\theta_i$ and $v_i$. Given the degree of nonlinearity of our model, however, the ML estimates may not be computed without difficulties. Furthermore, while the efficiency term is clearly heteroskedastic with $\text{Var}\{q(s_i)/(1 + q(s_i))\theta_i\} = [q(s_i)/(1 + q(s_i))]^2 \sigma_\theta$, the standard disturbance $v_i$ is also suspected to be heteroskedastic, since our data are cross-sectional. To allow for such heteroskedasticity in an ML estimation, we have to exactly specify the pattern of $\text{Var}(v_i)$, conditioning it on some set of exogenous variables which may or may not be included in the regression model (15). However, if the pattern is not appropriately specified, the desirable properties of the ML estimator will be lost. Unfortunately, we do not have a priori theory that suggests the form of the skedastic function, and it will be very difficult to select a proper set of conditioning variables for the skedastic function associated with (15).

Given these difficulties, our estimation strategy is to employ the least squares estimator which dispenses with the parametric distributions of the disturbances. We only assume that $\theta_i$ is an i.i.d. random variable which is truncated below zero with $E(\theta_i) = \mu_\theta$ and $\text{Var}(\theta_i) = \sigma_\theta^2$, and that $v_i$ is distributed as independently with $E(v_i) = 0$ but with an unknown pattern of heteroskedastic variance $\sigma^2_{vi}$. We then adjust the regression model by re-writing the last line in (15) as:

$$q(s_i)/(1 + q(s_i))\theta_i + v_i \equiv q(s_i)/(1 + q(s_i))\mu_\theta + \xi_i$$

where $\xi_i \equiv \{q(s_i)/(1 + q(s_i))\} (\theta_i - \mu_\theta) + v_i$. Now, $\mu_\theta$ is parameter (which is unidentified) in the model, and $\xi_i$ is regraded as the error term. Since $E(\xi_i) = 0$ and $\text{Var}(\xi_i) = \{q(s_i)/(1 + q(s_i))\}^2 \sigma_\theta^2 + \sigma^2_{vi}$, the least squares estimator is consistent, if not efficient, when all the regressors are exogenous or predetermined\(^3\). Since $\text{Var}(\xi_i)$ is not homoskedastic, the variance-covariance matrix of the LS estimator is inconsistent. Although it is difficult to properly specify the pattern of $\text{Var}(\xi_i)$ because of the unknown pattern of $\sigma^2_{vi}$, we can still obtain a valid variance-covariance matrix, using White’s heteroskedastic consistent covariance matrix estimator (HCCME).

Note that every parameter in (15) and (17) is not identified, since our data are cross-sectional. First, since $\mu_\theta$ in (17) is the mean value of $\theta_i$, it takes on a common value for all observations in the same period. In addition, since we assume that the rental price of capital $r$ is uniform across regions (e.g., Kitchen 1976, Stevens 1978), the same applied to that variable. Then, the use of cross sectional data makes $\ln A$, $\mu_\theta$ and $\beta_r$ in $r$ unidentifiable, and yields a single estimate $B_0 \equiv \ln A + \beta_r \ln r + \mu_\theta$.

\(^3\)To be exact, we need more conditions for the estimator to be consistent since the model is non-linear. See, for example, Davidson and MacKinnon (1993).
We thus have the actual regression model to be estimated as:

\[
\ln c_i = \frac{\ln (\gamma_0 + \sum_k \gamma_k s_{ki})}{1 + \gamma_0 + \sum_k \gamma_k s_{ki}} + \frac{\gamma_0 + \sum_k \gamma_k s_{ki}}{1 + \gamma_0 + \sum_k \gamma_k s_{ki}} \\
\times \left[ B_0 + \beta_w \ln w_i + \beta_g \cdot \left( \ln z_i + (\lambda_0 + \lambda_n \ln n_i + \sum_j \lambda_j a_{ji}) \cdot \ln n_i \right) \right] \\
+ \xi_i.
\]  

(18)

### 3.2 Data

Our data come from a cross section of Japanese cities (shi) in 1995. We exclude from the sample the designated cities (seireishitei toshi) which have a wider list of expenditure authorities than ordinary cities, and the special wards (tokubetsu ku) in Tokyo metropolis which delegate some of their expenditure responsibilities to the Tokyo metropolitan government. Also excluded are the inflicted areas of the 1995 Great Kobe Earthquake due to the hikes in expenditures necessitated by the natural disaster. The sample size is reduced down to 504, as we further exclude observations which lack at least one of the following variables used for the estimation.

The total cost \( c_i \) is represented by the total expenditures of a city government. Our data for population \( n_i \) are drawn from the National Census. The price of local public labour \( w_i \) is obtained as average wages, i.e., compensation of public employees divided by the number of public employees. The local characteristics fall into three categories: urban factors, demographic factors and spatial factors. As urban factors, we consider the proportion of population in Densely Inhabited Districts or DID population \( (a_1) \) and the ratio of daytime population to nighttime population \( (a_2) \). For demographic factors, we consider percentages of young, i.e., those who are less than 16 \( (a_3) \) and those of elderly, i.e., those who are above 64 \( (a_4) \). Finally, spacial characteristics are to be captured with the total land area \( (a_5) \) and the ratios of DID \( (a_6) \), forested areas \( (a_7) \) and farm lands \( (a_8) \). For the level of total public service \( z_i \), the only available for the variable is ‘total score of public services’ prepared by Nihon Keizai Shinbunsya (1998), which intends to quantify the overall level of Japanese local government services. While this may not be a good measure for the actual quality of the public services, we believe it should give a reasonable correlation with the actual public service levels.

Lastly, we pick two sorts of incentive factors. The first \( (s_1) \) is \( (\log \text{ of}) \) population \( (\ln n) \). As pointed out in the public choice literature (e.g., Nellor 1984), the larger the number of voters, the less influential a single vote on the outcome of an election will be. As such, more will care less about monitoring the local authority, as local population grows. The second is the intergovernmental transfers from the central government. The transfers may be related to inefficiency in local public production.
Table 1: Data description
Sources: a: Ministry of Home Affairs; b Statistic Bureau, Management and Coordination Agency; c: Nihon Keizai Shimbunseya; d: Ministry of Agriculture, Forestry and Fishery.

due to fiscal illusion (e.g., Grossman et al., 1999) or to soft budget-constraint problem (e.g., Maskin 1996). We use two indicators for this variable. One is the ratio of the transfers, that consist of the national disbursements (which are specific purpose matching grants) and the local allocation grants (which are general purpose transfers), to the local expenditures ($s_2$). The other is the ratio of years when the jurisdiction received the local allocation grants during 1975–1994 ($s_3$). Note that the data in the previous year (i.e., 1994) is used so as to circumvent the problem of possible endogeneity.

3.3 Results

We have estimated three models, the results of which are listed in Table 2. The first (Model I) is the case where the incentive factors are excluded. Note that this model can be interpreted as two different models. One is the standard model (16) with the fixed level of effort. The other is the effort-adjusted model (15 or 18) with coefficient $q$ of (13) being independent of exogenous factors (i.e., $q = \gamma_0$). The problem is, if the latter is the true data generating process, $\gamma_0$ is not identifiable from $B_0$, $\beta_w$, and $\beta_g$, and we may wrongly interpret the production parameters$^5$.

On the other hand, if we include the incentive factors, every parameter is identi-
fiable. The second model (Model II) considers all the three incentive factors, while the third model (Model III) excludes the third factor \(s_3\) which indicates the period of the received local allocation grants. In either case, the coefficient for technical returns to scale \((\beta_g)\) is estimated smaller than that in Model I, which implies a larger scale elasticity \((1/\beta_g)\). For Model I, the value of the elasticity is 1.386, whereas it is 2.232 for Model II and 2.186 for Model III. The discrepancies in the production parameters might be due to the identification problem associated with Model I as just mentioned above. On the other hand, while there are variations in \(P\) values, the estimates for the parameters in the congestion functions are rather similar among the three models, which may be due to the fact that all of them are identifiable even in Model I with constant \(q\).

The effects of the incentive factor shows the direction as theory suggests except for the third factor \(s_3\). However, with the smallest \(P\) value being .5110, none of the incentive factors is statistically significant, including the constant. The same applies to Model III where the third factor is dropped. We also tested the restriction which sets all the slope parameters in the incentive function to be zero. The result is similar. The null hypothesis of no incentive effects is not rejected at the standard level of significance, with \(P\) values of .7050 for Model II and .4136 for Model III. Our results then implies that we do not find any significant impacts on effort levels from the factors we considered in this estimation.

4 Concluding Remarks

This paper has presented a model of public production that explicitly accounts for the internal effort choice of the decision makers, and derived an empirical specification that allows us to statistically examine ‘incentive’ factors that may influence the effort choice. The contributions of this paper may be claimed to be as follows. First, we have validated the ad-hoc practice of the public-sector related stochastic frontier analysis that relates the incentive factors to the technical inefficiency term, by analytically showing that the very factors that influence the effort level also affect the moments of the technical inefficiency term. Second, we have pointed out, however, that the existing studies that claim to examine the incentive effect are possibly based upon misspecified models. This is because the behavioral part of the frontier regression has to be adjusted if the incentive factors are to be modelled explicitly. Third, we have provided an empirical procedure that is relatively free from parametric distributional assumption of the error terms and robust in the presence of heteroskedasticity. The purpose of this empirical exercise is to provide an example with the cross section of Japanese municipal data. For a definite empirical evidence, we may need further elaboration on the choice of the relevant variables, including those for the incentive factors.

References

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<td>$H_0$: $\gamma_k = 0 \forall k \geq 1$</td>
<td>$P value$ = .7050</td>
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</table>

Table 2: Estimation results

Note: The P values are based on pseudo-t statistics calculated from White’s heteroskedasticity-consistent covariance matrix estimator. * indicates statistical significance at the .10 levels.


Nihon Keizai Shinbunsya, 1998. 610 shi no gyosei sahibisu suijun ichi-ran (Table of public service levels of 610 cities). Nikkei Chi-iki Joho, (303).
