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TECHNICAL INEFFICIENCY AND PUBLIC CAPITAL IN U.S. STATES: A STOCHASTIC FRONTIER APPROACH*

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ABSTRACT. This paper estimates a translog stochastic frontier production function in the analysis of all 48 contiguous U.S. states in the period 1970–1983, to attempt to measure and explain changes in technical efficiency. The model allows technical inefficiency to vary over time, and inefficiency effects to be a function of a set of explanatory variables in which the level and composition of public capital plays an important role. Results indicate that U.S. state inefficiency levels are significantly and positively correlated with the ratio of public capital to private capital. The proportion of public capital devoted to highways is negatively correlated with technical inefficiency, suggesting that not only the level but also the composition of public capital influences state efficiency.

1. INTRODUCTION

The role of public infrastructure investment in the decline of U.S. output and productivity growth since the early 1970s has received renewed attention from an increasing number of researchers in the last decade. Some authors argued that the slowdown in public investment after the early 1970s partially explains the productivity slowdown observed around the same time. However, conclusions from empirical research on the role of the public sector in the provision of infrastructure fall short of offering a useful guide for public decision making. Conclusions range from considering that public infrastructure investment has a significant positive effect on output and growth to considering that public sector capital has no role in affecting private sector productivity. Conflicting evidence appears when one considers the results of different empirical approaches to production function, cost function, and profit function based studies in the U.S.

The economics literature typically uses a production function including public capital stock as an input to estimate the elasticity of public capital. Studies using U.S. national time series have shown a larger contribution of public capital to private performance than state-wide panel data results. The size of the contribution of public capital to private performance varies according

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to the level of aggregation. Vijverberg, Vijverberg, and Gamble (1997) compared the results of a production function, a cost function, and a profit function on annual time series. They attribute the disagreement between the three approaches to multicollinearity. A number of initial studies using U.S. panel data sets (Aschauer, 1989; Munnell, 1990) observed that the impact of aggregate public capital on private sector output and productivity was very significant, being responsible for much of the decline in U.S. productivity that occurred in the 1970s. However, because researchers have allowed for econometric problems such as serial correlation, state-specific characteristics, endogeneity, and measurement errors in panel data estimations, results and conclusions have changed dramatically. Recent evidence based on U.S. state-level production functions leads to the controversial conclusion that total public infrastructure has an insignificant impact on private production (Holtz-Eakin, 1994; Evans and Karras, 1994; Baltagi and Pinnoi, 1995; García-Milà, McGuire, and Porter, 1996).

Results from the regional production function approach provided in the recent literature suffer from a number of problems that remain only partially resolved: (1) usually the approach does not allow for lags in the impact of public capital on private output (García-Milà, McGuire, and Porter, 1996); (2) first differencing overrides any long-term relationship (Munnell, 1992); and (3) acute public capital endogeneity issues and out-of-state public capital spillover effects are not well captured (Vijverberg, Vijverberg, and Gamble, 1997). Notwithstanding, an even more serious limitation in the empirical literature on public infrastructure productivity is that it has developed independently of the production frontier approach. The effect has been to omit the influence of the level and evolution of technical inefficiency on the production function and on the estimated elasticities. Therefore, estimation of the parameters employing the usual econometric techniques is unlikely to produce estimates of production frontiers. Rather, estimates of the so-called average performance production functions are obtained. Interpreting the latter as frontier functions is bound to underestimate production possibilities and input elasticities, and to preclude measurement of technical inefficiencies by assuming them away (Greene, 1993).

The frontier approach to total factor productivity (TFP) measurement makes it possible to distinguish between shifts in technology from movements towards the best-practice frontier. By estimating the best-practice production function (an unobservable function) this approach calculates technical efficiency as the distance between the frontier and the observed output. Two different techniques have been used to measure technical efficiency under the frontier approach that differ in the assumptions imposed on the data: nonparametric linear programming techniques or Data Envelopment Analysis (DEA), and the stochastic frontier approach (SFA).

Recent research into the estimation of inefficiency in studies considering the whole regional economy (country or state level) as the observation unit is summarized in Table 1. Those studies comparing a sector or a set of subsectors

TABLE 1: Estimates of Technical Efficiency and Productivity at the Regional Level for the Whole Economy Using a Production Frontier Approach

Reference	Unit of Observation (Period)	Outputs	Inputs	Method
Färe, Grosskopf, Norris, and Zhang (1994)	17 OECD countries (1979–1988)	Real GDP	Total employment Nonresidential Capital Stock	DEA, Malmquist Index
Koop, Osiewalski, and Steel (2000)	44 countries (1965–1990)	Real GDP	Total employment Nonresidential Capital Stock[a]	Bayesian SFA
Chambers, Färe, and Grosskopf (1996)	17 APEC countries (1975–1990)	Real GDP	Total Employment Nonresidential Capital Stock	DEA, Luenberger Indicator
Färe and Grosskpf (1997)	17 APEC countries (1975–1990)	Real GDP	Total employment Nonresidential Capital Stock	DEA, Malmquist Index
Taskim and Zaim (1996)	23 countries (1975–1990)	Real GDP	Total employment Nonresidential Capital Stock	DEA, Malmquist Index
Domazlicky and Weber (1997)	48 contiguous U.S. states (1977–1986)	Private contribution to GSP Public contribution to GSP	Private Sector Labor Private Sector Capital Public Sector Labor Public Capital	DEA, Malmquist Index (scores compared with an output distance SF)
Osiewalski, Koop, and Steel (1997)	22 countries (1980–1990)	Real GDP	Total Employment Nonresidential Capital Stock	Bayesian SFA
Ray and Desli (1997)	17 OECD countries (1979–1990)	Real GDP	Total Employment Nonresidential Capital Stock	DEA, Malmquist Index
Maudos, Pastor, and Serrano (1997, 1998b)	17 Spanish regions (1964–1991)	Gross Value Added	Total Employment Nonresidential Capital Stock	DEA, Malmquist Index
Maudos, Pastor, and Serrano (1998a, 1999)	23 OECD countries (1965–1990)	Real GDP	Total Employment Nonresidential Capital Stock Human Capital Stock	SFA, DEA, Malmquist Index
Rao and Coelli (1998)	48 countries (1965–1990)	Real GDP	Total Employment Nonresidential Capital Stock	DEA, Malmquist Index
Koop, Osiewalski, and Steel (1999)	17 OECD countries (1979–1988)	Real GDP	Total Employment Nonresidential Capital Stock	Bayesian SFA

Notes: APEC: Asian-Pacific Economic Community. GDP: gross domestic product. GSP: gross state product. DEA: Data Envelopment Analysis. SFA: stochastic frontier approach

[a]Effective factor corrections: years of schooling in the labor force in 1985; quality of country data; percent of labor force in agriculture in 1981; producer durable capital stock as a percentage of total capital stock. Variables to explain efficiency variations: average inflation and economic freedom index.

of the economy are not considered in this paper. Some major shortcomings may be observed in the preceding literature: (1) a large number of papers have focused only on the use of nonparametric approaches; (2) in stochastic frontier approaches no model has been formulated for the technical inefficiency effects in terms of appropriate explanatory variables; (3) most empirical studies have not included the services of public capital as an input in the production process, probably owing to the unavailability of international data on public capital.

Research efforts measuring efficiency and productivity at the country or state level have mainly concentrated on the use of nonparametric frontiers following the initial paper of Färe, Grosskopf, and Knox Lovell (1994), which decomposed a Malmquist input-based productivity index into overall technical efficiency change and technological change. This approach is mainly limited by the usual assumption that there is no random error in the data. In this case, any measurement error in constructing the frontier, inaccuracies in measuring input and output, or luck affecting outcomes, may alter the measured efficiency of all the regions that are compared to this region or linear combinations involving this region (Berger and Humphrey, 1997). Those studies using a stochastic frontier approach have not attempted to explain inefficiency and productivity variation across regions and through time, with the exception of Koop, Osiewalski, and Steel (2000) who considered inflation and economic freedom as variables explaining efficiency variation. Consequently, the potential role of the level and composition of public capital in influencing variation and changes in inefficiency and productivity has not been analyzed.

An additional limitation of this literature stems from the shortage of international data on public capital, with the notable exception of Domazlicky and Weber (1997), which introduced public capital as a separate input into the production frontier function. All the international country comparisons reported in Table 1 used data sets from the Penn World Tables (PWT), described in Summers and Heston (1991), which do not provide information about public capital. Domazlicky and Weber (1997) used the nonparametric linear programming approach to measure a Mamlquist TFP index for the growth in gross state product (GSP) over the period 1977–1986 for the 48 contiguous U.S. states using four inputs (private sector labor and capital, and public sector labor and capital) and two outputs (private and public contribution to GSP). These authors observe: (1) a slight overall productivity growth, (2) considerable regional variation in efficiency and productivity, (3) that almost all productivity growth is due to technical change, and (4) that the initial levels of efficiency are negatively correlated with productivity growth (a catching-up form of convergence in productivity).

The principal aim of this paper is to estimate a translog stochastic frontier production function in the analysis of the 48 contiguous U.S. states in the period 1970–1983, in order to measure and explain changes in technical efficiency. The model uses real GSP as the output and total employment, private capital, and public capital as inputs. The model allows technical inefficiency to vary over time, and inefficiency effects to be a function of a set of explanatory variables in which the level and composition of public capital plays an important role.

This study differs from previous work on efficiency and productivity measurement in U.S. states in that it estimates a stochastic production frontier function for the whole economy explicitly introducing public capital as an input, which allows the estimation of technical efficiency. It further differs by using the approach developed by Battese and Coelli (1995) in which the inefficiency effects are modeled as an explicit function of a number of public capital variables (i.e., the level and composition of public capital) that are thought to influence the level of technical inefficiency. The slowdown in public investment and productivity in the U.S. states after the early 1970s has been the subject of many studies. However, to our knowledge this paper is the first U.S. state-level study to estimate efficiency using the Battese and Coelli (1995) model and also the first to explore the influence of the intensity and composition of public capital on technical inefficiency.

Technical inefficiency scores obtained by estimating the stochastic function are also compared with those obtained using a nonparametric and nonstochastic approach, the Data Envelopment Analysis (DEA). Other studies have compared the efficiency scores and rank correlations between these methods or measured the consistency of the methods in identifying the units in the most and least efficient quartiles. This is the first comparison in the literature between the two methods that does not only rely on simple correlations between efficiency scores. Efficiency scores obtained from parametric and nonparametric approaches are tested using factors explaining inefficiency variation between states.

The paper continues with the following structure. Section 2 outlines the stochastic frontier approach with the inefficiency effects models. Empirical results derived from these models and discussion are presented in Section 3. The empirical results allow us to present efficiency scores and factors explaining efficiency. The final section summarizes the findings of this research.

2. METHODOLOGY

Our method constructs a best-practice frontier from the data in the sample (i.e., we construct a national frontier and compare individual states to that frontier). Frontier approaches do not necessarily observe the true (unobserved) technological frontier, only the best-practice reference technology. An observation is technically inefficient if it does not minimize its input given its output. Efficiency scores of unity imply that the state (the unit of observation) is on the national frontier in the associated year. Efficiency scores lower than unity imply that the state is below the frontier: in this case, a further proportional increase in output is feasible, given productive factor quantities and technology. We assume that each state attempts to maximize output from a given set of inputs. Note that regional or country studies consider the sum of all micro-units as a single production unit and assume away differences between firms within each national industry.

The panel data set used in this research covers the 48 contiguous U.S. states for the period 1970 through 1983. The data consist of 14 annual observations. The gross state product Y is used as a measure of output. Total employment L, total private capital K, and total public capital G represent the inputs in the production function, as in previous studies measuring public capital productivity (Aschauer, 1989; Munell, 1990; García-Milà, McGuire, and Porter, 1996). Public capital is broken into three categories: highways, water and sewers, and other. The source for the gross state product data is the Bureau of Economic Analysis (BEA). Total employment is the number of employees by state as measured by the Bureau of Labor Statistics (BLS), U.S. Department of Labor. Monetary values are evaluated at 1972 prices. A total of 672 observations are involved for a fourteen-year period. Detailed sources and a more accurate description of data construction may be found in García-Milà and McGuire (1992) and García-Milà, McGuire, and Porter, (1996). The private capital stock variable was calculated using a state-level investment series in private structures and equipment that the BEA maintained until the early 1980s. It is the loss of these investment series data that limits our analysis to no later than 1983. García-Milà and McGuire (1992) describe these data and the process used to convert investment flows to stocks. Table 2 presents the summary statistics for the variables included in the analysis. They involve the mean value and the standard deviation, together with the minimum and maximum values.

I consider a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1995) model. The stochastic production frontier model allows: technical inefficiency and input elasticities to vary over time in order to detect changes in the production structure; and inefficiency effects to be a function of a set of explanatory variables the parameters of which are estimated simultaneously with the stochastic frontier. Time-invariant efficiency would be an unrealistic assumption given that elimination of slack compresses the efficiency distribution, whereas generation of slack works the opposite way (Kumbhakar, Heshmati, and Hjalmarsson, 1997). The approach is stochastic and states may be off the frontier because they are inefficient or

TABLE 2: Summary of Statistics for Variables in the Stochastic Frontier Models

Variable	Sample Mean	Standard Deviation	Minimum	Maximum
Gross State Product (Y)	27227.69	30989.69	2028.09	181907.90
Total Employment (L)	2115.40	2182.68	157.04	13035.77
Private Capital (K)	38832.96	44587.96	2602.31	287842.90
Public Capital (G)	10631.46	11932.12	1136.23	60643.98
Public Capital / Private Capital (G/K)	0.31	0.08	0.15	0.61
Percent Highways / Public Capital (H/K)	46.07	10.02	25.87	72.98
Percent Water and Sewers / Public Capital (WS/K)	12.40	3.52	4.97	21.77

Number of observations: 672.

Source: García-Milà, McGuire, and Porter (1996).

because of random shocks or measurement errors. Efficiency is measured by separating the efficiency component from the overall error term.

The stochastic frontier production function model with panel data is written as

$$Y_{it} = f(\mathbf{X}_{it};\beta_t)e^{(V_{it}-U_{it})} \tag{1}$$

where

- $\mathbf{Y}_{it}$ is the gross state product at the tth observation (t = 1,2,...,14) for the ith state (i = 1,2,...,48);
- f(•) represents the production technology;
- $\mathbf{X}_{it}$ is a vector of input quantities of the ith state in the tth time period;
- β_t is a vector of unknown parameters in the tth time period;
- $\mathbf{V}_{it}$ are assumed to be independent and identically distributed random errors that have normal distribution with mean zero and unknown variance σ_V^2);
- $\mathbf{U}_{it}$ are nonnegative unobservable random variables associated with the technical inefficiency in production, such that, the observed output falls short of its potential output for the given technology and level of input.

In the technical inefficiency effects model the error term is composed of the following two components: technical inefficiency effect and statistical noise. A state-specific effect is not explicitly considered in the estimated production function model because it would be considered as persistent technical inefficiency that implies that we do not consider the existence of unobserved systematic effects that vary across states in the production function (Heshmati, Kumbhakar, and Hjalmarsson, 1995).

The technical inefficiency effect U_{it} may be specified as

$$\mathbf{U}_{it} = \mathbf{z}_{it}\delta + \mathbf{W}_{it} \tag{2}$$

where

- $\mathbf{U}_{it}$ are nonnegative random variables that are assumed to be independently distributed as truncations at zero of the N($\mathbf{m}_{it}$, σ_U^2) distribution;
- $\mathbf{m}_{it}$ is a vector of state-specific effects, with $\mathbf{m}_{it} = \mathbf{z}_{it}\delta$;
- $\mathbf{z}_{it}$ is a vector of variables that may influence the efficiency of the state;
- δ is a vector of parameters to be estimated;
- $\mathbf{W}_{it}$, the random variable, is defined by the truncation of the normal distribution with mean zero and variance σ^2, such that the point of truncation is $-\mathbf{z}_{it}\delta$.

Two-step procedures to estimate the determinants of technical inefficiency, previously used in the parametric literature, suffer from a fundamental contradiction. The second stage involves the specification of a regression model for the predicted technical inefficiency effects that contradicts the identical distribution assumption of the first stage. The Battese and Coelli (1995) model overcomes this contradiction and allows the simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model.

Given the aim of this study, the investigated sources of regional differences in technical efficiency are limited to the influence of the public capital as a potential determinant of differences across states. Four explanatory variables associated with technical inefficiency are defined in order to test the influence of the level and composition of public capital on inefficiency variation: (1) the ratio of public capital to private capital *G/K*, (2) the proportion of public capital invested in highways *GH*, (3) the proportion of public capital invested in waters and sewers *GS*, and (4) the year t. The variable t in the inefficiency effects model of Equation (2) specifies that inefficiency effects may change linearly with respect to time.

The interest of this study in the inefficiency effects model is to focus on the role of the public capital variables. However, the set of explanatory variables chosen in this paper is quite limited. Addressing only manufacturing, and not including public capital in the production function, Beeson and Husted (1989) find that industrial mix, labor-force characteristics and urbanization levels explain an important part of the variation in efficiency across states. In this case, it is necessary to control for unobserved differences across states because state-specific characteristics not captured by the public capital may influence the efficiency of a state. State-specific effects are included in the set of explanatory variables in the inefficiency effects models using 47 dummy variables.

To limit the restrictive properties imposed on the production process, the following translog production function is chosen and tested against the restricted Cobb-Douglas functional form

$$y_{it} = \beta_0 + \sum_{j=1}^{3} \beta_j \mathbf{x}_{jit} + \beta_t t + \sum_{j=1}^{3}\sum_{h=1}^{3} \beta_{jh} \mathbf{x}_{jit} \mathbf{x}_{hit} + \beta_{tt} t^2 + \sum_{j=1}^{3} \beta_{jt} \mathbf{x}_{jit} t + \mathbf{V}_{it} + \mathbf{U}_{it} \tag{3}$$

where $\mathbf{y}$ is the log of gross state product and $\mathbf{x}$ is a vector of the logarithms of the three inputs considered ($j,h = L, K, G$) where the technological change can be specified as an additional input (time trend t) representing the rate of technical change or the shift in the production function over time. This specification makes it possible to consider time varying coefficients and nonneutral technical change.

The output-based Farrell measure of technical efficiency of each state i in year t may be estimated as

$$TE_{it} = \frac{f(\mathbf{x}_{it};\beta_t)\exp(V_{it})}{y_{it}} = \exp(-U_{it}) = \exp(-\mathbf{z}_{it}\delta - \mathbf{W}_{it})$$

Inefficiency scores obtained from the stochastic translog production frontier are compared with those obtained using a linear programming approach. In this study we also use a nonparametric method based on DEA to compute efficiency scores in the described panel data set. DEA is a linear programming methodology that uses data on the input and output quantities of a group of states to construct a piecewise linear surface over the data points. A detailed description of the DEA approach to efficiency measurement may be found in Färe, Grosskopf, and Knox Lovell (1994). This frontier surface is constructed by solving a sequence of linear programming problems, one for each state in the sample. In the output oriented case, the DEA method seeks the maximum proportional increase in output production with fixed input levels.

Having data for i states in the time period analyzed, the linear programming problem that is solved for the ith state in the year t, having input and output data ($\mathbf{x}_{it}$,$\mathbf{y}_{it}$), in an output orientated DEA model with variable returns to scale (VRS) is computed as follows (Färe, Grosskopf, and Lovell, 1994)

$$\text{Max}_{\lambda,\phi}\ \phi_{it} \tag{5}$$

subject to

$$-\phi_{it}\mathbf{y}_{it} + \mathbf{Y}\lambda \geq 0$$

$$\mathbf{x}_{it} - \mathbf{X}\lambda \geq 0$$

$$\mathbf{e}^T\lambda = 1$$

$$\lambda \geq 0$$

where $\mathbf{X}$ is a 48 × 3 matrix of input quantities for all 48 states in year t,
$\mathbf{Y}$ is a 48 × 1 matrix of output quantities for all 48 states in year t,
$\mathbf{x}_{it}$ is a 3 × 1 vector of input quantities for the ith state and year t,
$\mathbf{y}_{it}$ is a 1 × 1 vector of output quantities for the ith state and year t,
λ is a 48 × 1 vector of weights,
$\mathbf{e}^T$ is a 48 × 1 row vector of ones, and
ϕ_{it} is a scalar.

ϕ^{-1} is a technical efficiency score that varies between zero and one. To solve the above linear program we use one output (gross state product) and three inputs (total employment, private capital, and public capital). In the nonparametric programming approach, any departure from the frontier is considered as inefficiency.

3. EMPIRICAL RESULTS

Average Efficiencies

Following Battese and Coelli (1995) maximum likelihood estimation (performed using FRONTIER 4.1; Coelli, 1996) was employed to simultaneously estimate the parameters of the stochastic production frontier and the technical inefficiency effects model. The results of this procedure are presented in Table 3. The variance parameters are expressed in terms of $\gamma = \sigma_U^2 \big/ \left(\sigma_U^2 + \sigma_V^2\right)$. The estimates of the first-order coefficients of the variables in the translog function cannot be directly interpreted as elasticities.

A number of statistical tests were carried out to identify the appropriate functional forms and the presence of inefficiency and its trend. As a misspecification analysis we used the log-likelihood ratio tests (LR). LR tests were performed to test various null hypotheses as listed in Table 4. Given the

TABLE 3: Maximum-Likelihood Estimates of Parameters of the Translog Stochastic Frontier Production Function

Variable	Parameter	Coefficient	Standard Error
Stochastic Frontier Model			
Constant	β_0	15.160	1.083***
Private Capital (*K*)	β_K	–7.910	0.713***
Public Capital (*G*)	β_G	2.816	0.574***
Employment (*L*)	β_L	4.409	0.730***
Year (*t*)	β_t	0.177	0.022***
K^2	β_{KK}	0.006	0.181**
G^2	β_{GG}	–1.443	0.124***
L^2	β_{LL}	0.628	0.179***
t^2	β_{tt}	–0.000	0.000
KG	β_{KG}	2.249	0.286***
KL	β_{KL}	–1.502	0.280***
Kt	β_{Kt}	0.099	0.212
GL	β_{GL}	–0.019	0.009*
Gt	β_{Gt}	–0.019	0.006***
Lt	β_{Lt}	0.023	0.008***
Inefficiency Effects Model With State-Specific Effects			
Constant	$\delta 0$	–1.381	0.262***
Public Capital / Private Capital	δ_1	0.089	0.001***
Percent Highways / Public Capital	δ_2	–0.016	0.002***
Percent Water and Sewers / Public Capital	δ_3	–0.007	0.004
Year	δ_4	–2.989	0.003***
Variance Parameters	σ_S^2	0.002	0.000***
	γ	0.372	0.004***
		1064.6	
Log-Likelihood Function			

Notes: The *t*-ratios are asymptotic *t*-ratios.
*** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$.

specification of the technical inefficiency effects model, the first test shows that the null hypothesis that the Cobb-Douglas functional form is preferred to the translog is rejected. The null hypothesis is rejected by the test at the five percent level and hence all results presented here refer solely to the translog. Also, in test 2, the null hypothesis that there is no technological change in the U.S. states production is rejected. Hence, technical change is present in the model.

The null hypothesis explored in test 3 is that each state is operating on the technically efficient frontier and that the systematic and random technical inefficiency effects are zero. The null hypothesis that γ is zero is rejected, suggesting that inefficiency was present in production and that the average production function is not an appropriate representation of the data. Tests 4 and 5 consider the null hypothesis that the inefficiency effects are not a function of the explanatory variables. Again, the null hypothesis is rejected, confirming that the joint effect of these variables on technical inefficiency is statistically significant.

In test 6 the null hypothesis that state-specific effects are not significantly different from zero is considered. Again, the null hypothesis is rejected, confirming that state-specific effects should be included in the inefficiency effects model. The estimate of γ indicates that the proportion of the one-sided error component in the total variance of the composed error term is as high as 37.2 percent. Thus, technical inefficiency is not the dominant source of random error.

A high degree of multicollinearity was observed in the translog stochastic frontier using the condition index. When the objective is to estimate output elasticities, the parameter estimates of the translog form are too unreliable because of the use of a flexible functional form and the attendant multicollinearity. Notwithstanding, multicollinearity is not necessarily a severe problem given that the aim of this paper is to focus on efficiency estimation.

Given the specifications of the general translog stochastic frontier model, the average technical efficiencies of firms in the 48 contiguous U.S. states are

TABLE 4: Generalized Likelihood-Ratio Tests of Hypotheses for Parameters of the Stochastic Frontier Production Function

Test	Null hypothesis (H_0)	Log-Likelihood	Value of λ	Critical Value	Decision (at 5 Percent Level)
1	$H_0 : \beta_{jh} = 0$	567.2	994.8	17.67	Reject H_0
2	$H_0 : \beta_t = \beta_{tt} = \beta_{jt} = 0$	573.5	982.2	10.37	Reject H_0
3	$H_0 : \gamma = \delta_0 = ... = \delta_{51} = 0$	500.8	1127.6	55.19	Reject H_0
4	$H_0 : \delta_1 = ... = \delta_4 = 0$	820.5	488.2	8.76	Reject H_0
5	$H_0 : \delta_0 = 0$	1062.6	4.0	2.71	Reject H_0
6	$H_0 : \delta_5 = ... = \delta_{51} = 0$	582.2	964.8	55.19	Reject H_0

Notes: λ: likelihood-ratio test statistic, $\lambda = -2\{\log[\text{Likelihood}(H_0)] - \log[\text{Likelihood}(H_1)]\}$. It has an approximate chi-square distribution with degrees of freedom equal to the number of independent constraints. The asymptotic distribution of hypothesis tests involving a zero restriction on the parameter γ has a mixed chi-squared distribution, therefore, the critical value for this test is taken from Kodde and Palm (1986), Table 1, p. 1246.

presented in Table 5. The mean technical efficiency of the U.S. states in the period 1970–1983 is estimated to be 87.4 percent. That is, over the period analyzed the average state produced 87.4 percent of maximum attainable output (i.e., their GSP could be increased by 14.4 percent without increasing the input). Mean efficiency values per year range from 91.0 percent in 1979 to 83.5 percent in 1971. The minimum estimated efficiency is 40.7 percent and the maximum is 99.4 percent. There is a relatively small spread of efficiencies, with nearly 73.4 percent of states being more than 80 percent efficient.

Mean efficiency by year presents an overall increasing trend over the observed period. Average efficiency by year increased from the lowest level in 1971 (0.841) to the highest level in 1979 (0.910) and then experienced a relative decline at the end of the period (0.894 in 1983). This means that the contribution of the efficiency change to total factor productivity was an increase in productivity growth.

TABLE 5: Mean Efficiency Values by Year

Year	Mean SF scores (Standard Deviation)	Mean DEA score (Standard Deviation)	Kendall's Tau (Significance)	Spearman's Rho (Significance)
1970	0.841	0.809	0.2886	0.3819
	(0.166)	(0.137)	(0.004)	(0.007)
1971	0.835	0.816	0.2398	0.3107
	(0.164)	(0.130)	(0.015)	(0.032)
1972	0.847	0.830	0.2444	0.3303
	(0.157)	(0.124)	(0.015)	(0.022)
1973	0.865	0.858	0.2252	0.3030
	(0.143)	(0.110)	(0.036)	(0.036)
1974	0.862	0.850	0.2904	0.3826
	(0.142)	(0.110)	(0.000)	(0.007)
1975	0.847	0.842	0.2383	0.3361
	(0.145)	(0.103)	(0.020)	(0.020)
1976	0.861	0.852	0.2606	0.3489
	(0.139)	(0.106)	(0.009)	(0.015)
1977	0.876	0.854	0.2374	0.3118
	(0.131)	(0.104)	(0.040)	(0.031)
1978	0.901	0.846	0.2393	0.3252
	(0.118)	(0.103)	(0.030)	(0.0024)
1979	0.910	0.840	0.2539	0.3447
	(0.112)	(0.103)	(0.013)	(0.0016)
1980	0.904	0.813	0.2842	0.4053
	(0.115)	(0.109)	(0.005)	(0.004)
1981	0.902	0.813	0.3258	0.4828
	(0.119)	(0.109)	(0.000)	(0.000)
1982	0.890	0.820	0.3344	0.4704
	(0.125)	(0.109)	(0.000)	(0.000)
1983	0.894	0.860	0.3217	0.4752
	(0.121)	(0.097)	(0.0000)	(0.000)
Mean of All Years	0.874	0.836	0.2900	0.3654
	(0.138)	(0.112)	(0.000)	(0.010)

Similar to Beeson and Husted (1989) and to Domazlicky and Weber (1997), it is possible to compute a state's level of efficiency in each year. In Table 6, we present the ranking of states according to their efficiency levels in 1970 and 1983, and also according to the average of the period 1970–1983. These rankings suggest a wide divergence in efficiency but 27 of the 48 states present an average efficiency score higher than 90 percent. In fact, there is a significant correlation between the efficiency scores in 1970 and in 1983.

Comparison of Efficiency Estimates

To test the robustness of the efficiency scores obtained from the stochastic frontier, efficiency measures for each state in each period were computed using the DEA linear programming approach. We compare the efficiency scores and rank correlations between the two methods. The average technical efficiency scores using the linear programming method is 0.836. Average DEA efficiency scores for each year between 1970 and 1983 are lower than those obtained from the stochastic frontier (Table 5). The results in Table 5 show that the choice of methodology may influence the average efficiency scores. DEA efficiency scores are much lower than those obtained from the stochastic frontier. DEA estimates are lower because the stochastic frontier approach allows states to depart from the frontier due to both random error and inefficiency, whereas DEA measures random error as part of inefficiency.

Comparison of scores obtained from both methods indicates that the choice of methodology has an apparent impact on the estimated average efficiency scores. More important than the absolute values of the scores is the ranking of states in terms of efficiency. Kendall's tau statistic and Spearman's rho statistic are presented along with the mean efficiency scores for the stochastic and linear programming efficiency measures in Table 5. Both coefficients indicate that the null hypothesis of no significant correlation between the two efficiency measures is rejected at the 5 percent significance level considering the mean of all years. Thus, even though the nonparametric method produces lower efficiency scores than the econometric model, they produce comparable efficiency rankings for the average scores.

Convergence

The simple correlation coefficient between a state's technical efficiency level in 1970 and the change in technical efficiency over the period is significant at the 0.01 percent level (–0.810 for the stochastic scores and –0.757 for the deterministic scores). This observation is in coherence with the results of Domazlicky and Weber (1997) for the period 1977–1986. This high correlation indicates that there has been a catching-up process, with those states with lower technical efficiency in 1970 experiencing a greater increase over the period.

The catching-up hypothesis is further tested using the concept of absolute β-convergence proposed by Barro and Sala-i-Martín (1992). β-convergence in efficiency scores implies a tendency towards the equalization of efficiency

TABLE 6: Ranking of States by Stochastic Efficiency Levels

State	Efficiency Level in 1970	Efficiency Level in 1983	Average Efficiency Level, 1970–1983
1. Alabama	0.860(27)	0.935(26)	0.895(28)
2. Arizona	0.605(42)	0.712(44)	0.685(44)
3. Arkansas	0.989(8)	0.993(1)	0.992(3)
4. California	0.652(40)	0.944(23)	0.791(35)
5. Colorado	0.834(29)	0.965(20)	0.934(24)
6. Connecticut	0.920(25)	0.979(19)	0.902(26)
7. Delaware	0.525(46)	0.596(47)	0.526(47)
8. Florida	0.989(9)	0.992(2)	0.992(4)
9. Georgia	0.991(5)	0.992(6)	0.991(7)
10. Idaho	0.832(30)	0.905(31)	0.901(27)
11. Illinois	0.964(18)	0.934(27)	0.954(20)
12. Indiana	0.980(14)	0.980(17)	0.981(12)
13. Iowa	0.872(26)	0.860(35)	0.893(29)
14. Kansas	0.938(23)	0.942(24)	0.943(22)
15. Kentucky	0.950(22)	0.956(22)	0.959(19)
16. Louisiana	0.960(19)	0.983(16)	0.971(17)
17. Maine	0.987(11)	0.989(10)	0.986(10)
18. Maryland	0.802(32)	0.744(41)	0.742(41)
19. Massachusetts	0.990(6)	0.990(9)	0.986(9)
20. Michigan	0.804(31)	0.809(37)	0.825(34)
21. Minnesota	0.715(37)	0.788(38)	0.749(40)
22. Mississippi	0.990(8)	0.992(5)	0.992(6)
23. Missouri	0.978(15)	0.983(15)	0.978(14)
24. Montana	0.766(35)	0.888(34)	0.835(33)
25. Nebraska	0.836(28)	0.684(45)	0.757(38)
26. Nevada	0.581(44)	0.897(33)	0.783(37)
27. New Hampshire	0.954(20)	0.986(14)	0.946(21)
28. New Jersey	0.987(12)	0.986(13)	0.980(13)
29. New Mexico	0.653(39)	0.936(25)	0.847(31)
30. New York	0.982(13)	0.965(21)	0.926(25)
31. North Carolina	0.992(4)	0.993(3)	0.992(1)
32. North Dakota	0.604(43)	0.731(43)	0.700(43)
33. Ohio	0.926(24)	0.931(28)	0.934(23)
34. Oklahoma	0.977(16)	0.988(11)	0.984(11)
35. Oregon	0.725(36)	0.762(40)	0.789(36)
36. Pennsylvania	0.993(2)	0.992(7)	0.992(5)
37. Rhode Island	0.968(17)	0.981(18)	0.966(18)
38. South Carolina	0.993(1)	0.992(4)	0.992(2)
39. South Dakota	0.697(38)	0.679(46)	0.704(42)
40. Tennessee	0.801(33)	0.918(30)	0.872(30)
41. Texas	0.953(21)	0.986(12)	0.975(16)
42. Utah	0.541(45)	0.738(42)	0.682(45)
43. Vermont	0.618(41)	0.814(36)	0.665(46)
44. Virginia	0.988(10)	0.992(8)	0.990(8)
45. Washington	0.453(48)	0.511(48)	0.495(48)
46. West Virginia	0.993(3)	0.920(29)	0.976(15)
47. Wisconsin	0.769(34)	0.903(32)	0.846(32)
48. Wyoming	0.478(45)	0.776(39)	0.752(39)

Note: The number in parenthesis represents the ranking of the state in descending order for each variable.

levels. There is absolute convergence in efficiency scores if less efficient states tend to improve efficiency faster until they catch up with the efficient ones. Let $\gamma_{i,t,t+T} \equiv \log\ (TE_{i,t+T}/TE_{i,t})/T$ be state i's annualized growth rate of technical efficiency between t and $t + T$, and let $\log(TE_{i,t})$ be the logarithm of state i's technical efficiency score at time t. In order to estimate the speed of convergence in technical efficiency between states (the catching-up hypothesis), the following Equation is estimated using nonlinear least-squares (Sala-i-Martín, 1996)

$$(6) \qquad (1/T)\log\ (TE_{i,t}/TE_{i,t-T}) = \alpha - [\log(TE_{i,t-T})]\,(1 - e^{-\beta T})\,(1/T) + \varepsilon_{i,t,\,t+T}$$

where $T = 14$ given that the growth rate of technical efficiency corresponds to the period 1970–1983. Table 7 reports the estimated speed of convergence in technical efficiency across the 48 states, using the stochastic and deterministic data sets. The results in Table 7 refer to the estimate of β when a single equation is estimated for the whole period and no other explanatory variable is included. This corresponds to the case of absolute convergence in the classical approach to convergence analysis. Regional dummies have been introduced into the model, although they appear not to be significant.

The results in Table 7 indicate that there is evidence of β-convergence in the technical efficiency scores of the 48 U.S. states over the period 1970–1983. Stochastic and DEA efficiency scores present significant evidence showing that the catching-up hypothesis cannot be rejected. Scores from the two methods do not present important differences in relation to the estimated speed of convergence between states. Note that convergence in efficiency does not imply convergence in total factor productivity because the production frontier is displaced upwards in each period by those states that first introduce technical innovations.

The existence of β-convergence in technical efficiency is directly related to the explanation of convergence in income per capita, which relies on the role of technological diffusion (Sala-i-Martín, 1996). One way to generate convergence in income is to allow the level of technology of the poor economies to catch up with that of the rich. The rate of change in total factor productivity can be decomposed into efficiency-and technical-change. Thus, the rate of change in efficiency for a state can be a function of the distance between its level of use of the best-practice technology and the level of use of the leader. That is, the catching-up hypothesis in terms of efficiency convergence implies that the lagging states are able to imitate the use of the technology in the leading states.

TABLE 7: Estimates of β-Convergence in Technical Efficiency Using Nonlinear Least-Squares

	Stochastic Scores	DEA Scores
Estimate of β	0.0382	0.0388
Standard Error of β	(0.0052)	(0.0065)
Adjusted R^2	0.885	0.578

Regional results of the average (weighted) annual growth rate of technical efficiency using the parametric approach are compared with those obtained using the nonparametric approach in Table 8. On a regional basis, only the Mideast and the Great Lakes regions experienced a decline in technical efficiency over the period 1970–1983. Domazlicky and Weber (1997) estimated the average annual growth rate of efficiency change for the eight regions in the period 1977–1986 using a DEA approach. They also reported the more important decline in efficiency in these two regions. According to the stochastic efficiency scores estimated in our paper, technical efficiency increased at an average annual rate of 2.6 in the Far West and 1.2 in the Rocky Mountain regions, the fastest rates among the eight regions. In both regions the 1970 efficiency level was the lowest among the eight regions.

Inefficiency Variation Between States

Given the differences in technical efficiency levels between states and years, it is appropriate to ask why some states can achieve relatively high efficiency while others are technically less efficient. The parameter estimates for the inefficiency effects model presented in Table 3 suggest a number of public capital related factors that may explain part of the variation in observed efficiency levels. Specifically, we restrict our attention to the role of the intensity and composition of public capital as a determinant of the inefficiency level after controlling for unobserved differences across states using state-specific effects. We test the influence of the level of public capital in relation to private capital (G/K), the composition of public capital (HI/G, WS/G), and the time trend (t) on the inefficiency levels of each state and year. This procedure may be used to help guide public policy.

The robust results of the inefficiency effects model were also compared with those derived from DEA efficiency scores. In order to determine the influence of exogenous variables on efficiency measures obtained using the linear programming approach, we adopted a two-stage approach. These explanatory variables

TABLE 8: Regional Efficiency Change

Region	SFA Scores	DEA Scores
New England (NE)	1.002	1.004
Mideast (ME)	0.999	0.996
Great Lakes (GL)	0.999	0.998
Plains (PL)	1.000	1.002
Southeast (SE)	1.001	1.007
Southwest (SW)	1.004	1.001
Rocky Mtn (RM)	1.012	1.008
Far West (FW)	1.026	1.002

SFA Scores – 1 = average annual rate of technical efficiency according to the stochastic parametric scores.

DEA Scores – 1 = average annual rate of technical efficiency according to the nonparametric scores.

and input variables should be uncorrelated. In the first stage inefficiencies were calculated using a DEA model in which the explanatory factors were ignored. In the second stage, variation in calculated efficiencies was attributed to variation in operating environment by means of a regression model. It is hypothesized that the DEA efficiency measures are some function of the vector $\mathbf{z}_{it}$ and a random disturbance ε_{it}.

DEA efficiency scores could be conceptualized as presenting a censored normal distribution, that is, the values of the dependent variable in the regression model above a threshold are measured by a concentration of observations at a single value. Therefore, ordinary least-squares was not an appropriate method. In view of this, some authors (Kooreman, 1994) conclude that a censored Tobit model is appropriate in order to avoid biased estimates from ordinary least-squares. The Tobit model is based on normally distributed latent variables. However, DEA scores do not fit the theory of sampling censoring that gives rise to Tobit models: the accumulation of sample observations at the highest level of efficiency is intrinsic to the model. Tobit, and also Probit, estimates are inconsistent in the case of nonnormality of the error terms or error term heterogeneity.

Banker and Johnson (1994) proposed a nonmaximum likelihood estimator in an empirical estimation based on the theoretical conditions established by Banker (1993) that was a consistent estimator. Given implausibility of the normally distributed latent efficiency required by Tobit models, and according to Banker and Johnson (1994), we make the assumption that the inefficiencies are log normally distributed, and define the transformation $\theta_{it} = 1/E_{it} - 1 + \omega$, where ω is some very small amount. Thus, inefficiency may be posited as a multiplicative function of the explanatory variables and the random error term

$$\theta_{it} = \delta_0 \Pi_j \mathbf{z}_j^{\delta_j} \mathrm{e}^{v_{it}} \tag{7}$$

where δ_j are the parameters capturing the relationship between the explanatory variables and inefficiency; and $\mathrm{e}^{v_{it}}$ is a random error term that is assumed to be independently and identically distributed and log normally distributed with a mean of unity. As in the inefficiency effects model, explanatory factors are G/K, HI/G, WS/G, and t. As in the inefficiency effects model, state-specific effects are also included in the set of explanatory variables in order to control for unobserved differences across states. The key evidence from the regression model in Table 9, relative to the DEA scores, confirms the results of the inefficiency effects model in Table 3.

The results from the parametric and nonparametric efficiency scores are presented in Tables 3 and 9. Both models were reestimated without the efficiency outliers and no significant differences were found. According to these results, three main conclusions may be drawn. First, factors explaining inefficiency scores from parametric and nonparametric models suggest a high level of coincidence in the sign and the statistical significance of the explanatory

TABLE 9: Factors Explaining DEA Inefficiency Scores (with State-Specific Effects)

Factor	Coefficient	Standard Deviation	t-statistic
Constant	–1.1981	0.4820	–2.49
Log (Public Capital /Private Capital)	1.3571	0.1927	7.04
Log Percent (Highways / Public Capital)	–0.9772	0.2442	–4.00
Log Percent (Water and Sewers / Public Capital)	0.0122	0.0658	–0.19
Year	–0.0129	0.0017	–7.60
R^2 adjusted	0.8986		
F	117.5		
N	672		

variables. In both cases results indicate that the level of public capital in relation to private capital and the proportion of public capital devoted to highways have the most important effects in determining the levels of technical inefficiency.

Second, those observations with higher levels of public capital in relation to private capital show lower levels of efficiency. The stochastic and linear programming model results indicate that the amount of public capital to private capital is positively correlated with technical inefficiency, implying that increases in public capital intensity are associated with greater technical inefficiency. Consequently, increases in the ratio of public to private capital will result in reduced technical efficiency levels. Note that this result refers to productive efficiency in transforming input into output and not to the overall contribution of public capital to GSP. That is, the positive significance of the ratio of public capital to private capital implies that public capital intensity may have been wasted in inefficient capital management.

Finally, the composition of public capital is also an important factor influencing inefficiency levels. State decision makers not only decide about the amount of public investment; they also make decisions about the composition of public investments. The parameter estimate associated with the percentage of public capital devoted to highways (*HI*/*G*) is negative and significant in the inefficiency effects models and also in the DEA two-stage approach. The significant negative coefficient concerning the proportion of public capital devoted to highways suggests that increasing this percentage while keeping other factors constant tends to reduce technical inefficiency. Thus, some types of infrastructures appear to be more productive than others.

According to the parametric approach, for a given level of public and private capital a higher proportion of highway infrastructure in the composition of public capital of a state contributes to significantly lower technical inefficiency. The coefficient associated with highways is higher and more significant than the rest of public capital, indicating that this component in the public capital mix contributed most to a positive influence on efficiency. These results may indicate that states used highway improvement to increase efficiency. This is in concordance with studies showing that total highway capital contributes significantly to economic growth and productivity (Nadiri and Mamuneas, 1996; Fernald, 1999). On average, the total amount of real public capital remained nearly constant over the period analyzed (from a level of 100.0 in 1970 to a level of 101.0 in 1983), and the ratio of public to private capital decreased from 1.000 in 1973 to 0.841 in 1986. However, the proportion of public capital in highways decreased from 48.46 percent in 1970 to 43.64 percent in 1983. Therefore, in the average state the influence of public capital on technical efficiency has resulted in an increase in inefficiency.

The parameter associated with the percentage of public capital devoted to water and sewers is also negative but not significant in the inefficiency effects model, and also the sign and significance level are confirmed in the DEA two-stage approach. Consequently, results indicate that the composition of public capital is a significant factor in determining the level of technical efficiency in each state. Finally, the parameter estimate associated with the time trend suggests that this variable has a significant influence on the level of inefficiency: the efficiency level in each state (after controlling for the rest of the variables including state-specific effects) has been increasing during the period.

In Table 9 it may be observed that the contribution of the public capital and state-specific effects explain 89.9 percent of the observed differences obtained in the linear programming model. Nevertheless, only a relatively small proportion of the variation in efficiency can be accounted for by the public capital variables. When Equation (7) is estimated omitting the state-specific effects variables, a very low adjusted R^2 is obtained (0.021) with a significant F-test. These results indicate that the unobserved effects represented by the state specific variables account for an important part of the variation in efficiency.

4. SUMMARY AND CONCLUSION

In this paper I set out to provide estimates of technical inefficiency in the U.S. states and to explain variation in technical inefficiency between states through decisions concerning the level and composition of public capital. A translog stochastic frontier production function with inefficiency effects is applied. The results indicate that inefficiency is present in production, and that the traditional average response function and the Cobb-Douglas functional form are not an appropriate representation of the data. Both estimation methods are evaluated using three criteria: average efficiency scores, rank correlation of efficiency scores, and the consistency of the method in identifying factors explaining efficiency variation between states. Efficiency scores and conclusions as to the determinants of efficiency obtained using a two-stage DEA linear programming approach do not differ significantly from those obtained from the inefficiency effects model.

The findings indicate that the choice of efficiency estimation method can make a significant difference in relation to average efficiencies. In general, DEA estimates are expected to be lower than econometric estimates. Also, the rankings are only partially well preserved between the econometric and mathematical programming method. However, both methods provide similar results regarding explanatory factors of variations in efficiency scores.

The results indicate that there is evidence of β-convergence in the technical efficiency scores of the 48 U.S. states over the period 1970–1983. This means that there has been a catching-up process, with those states with lower technical efficiency in 1970 experiencing a greater increase over the period. This result favors the technological diffusion explanation of income convergence between states.

The majority of U.S. states operate close to maximum technically-feasible production levels, given that 59.8 percent of states present efficiency scores higher than 90 percent. The mean technical efficiency is estimated to be 87.4 percent. The analysis of the role of public capital as a determinant of inefficiency shows that the level of public capital in relation to private capital and the proportion of public capital devoted to highways have the most important effects in determining the levels of technical inefficiency.

The results of the inefficiency effects models suggest that the ratio of public capital to private capital is positively correlated with technical inefficiency. The composition of public capital also appears as an important factor influencing inefficiency levels given that our analysis has shown that the proportion of public capital devoted to highways is negatively correlated with technical inefficiency. Thus, in the context of a state-level production frontier, the obvious policy implication of our analysis is that there is evidence that an increase in the public to private capital ratio may negatively influence overall technical efficiency. However, this effect may be compensated or even reversed if the capital is properly spent on infrastructures that positively affect efficiency, as highways appear to be.

The findings indicate that the choice of efficiency estimation method may make a significant difference in some aspects. First, DEA efficiency scores are expected to be lower than parametric estimates because DEA identifies random noise as inefficiency. Second, the efficiency ranking of the 48 U.S. states presents some differences according to the method choice; although we demonstrate that a significant rank correlation remains between the average scores of the two methods. This study also finds evidence that the choice of method is irrelevant if one is interested in comparing the quantitative influence and statistical significance of some determinants of inefficiency.

This paper uses the 48 contiguous U.S. states as the observation unit. This is a less aggregate observation unit than that used in most of the previous literature. However, greater spatial disaggregation is desirable and represents a limitation in the approach. Nevertheless, given the difficulties to obtain public and private capital series at the state level, it is no easy task to obtain them for substate regions.

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