Working Paper 8603

PATTERNS AND DETERMINANTS OF INEFFICIENCY IN STATE MANUFACTURING

By Patricia Beeson and Stephen Husted

Patricia Beeson, visiting economist at the Federal Reserve Bank of Cleveland is on leave from the University of Pittsburgh, where she is assistant professor, Department of Economics. Stephen Husted is assistant professor, Department of Economics, University of Pittsburgh. An earlier version of this paper was presented at the Regional Science Meetings in Denver in November 1984. Research on this project was funded, in part, by two Faculty of Arts and Sciences (FAS) summer research grants from the University of Pittsburgh.

June 1986

Federal Reserve Bank of Cleveland

PATTERNS AND DETERMINANTS OF INEFFICIENCY IN STATE MANUFACTURING

I. Introduction

The relative efficiency of the manufacturing sector across regions in the United States has drawn considerable attention, in view of the regional restructuring of the manufacturing industry in recent years. Some anaiysts have speculated that the decline in the share of national output produced in traditional manufacturing belt states might be the result of a relative decline in the efficiency of manufacturing firms in this region (see Hulten and Schwab [1984] and Beeson [1983]). Efficiency, of course, is not the only factor determining the growth and location of industry. Costs are also important. Firms in areas that are less efficient can compete with firms in more efficient regions, if their inefficiency is offset by lower factor costs. Other oapers have concentrated on differences in relative costs across regions. (See Sahling and Smith [1983]; Bellante [1979]; Newman [1983]; and Carlton [1983]). This paper addresses the question of relative efficiency differences across regions.

Even if the regional shift of the manufacturing sector is not the result of a change in relative efficiency, but due rather to changes in relative costs. relative efficiency levels across regions might be important. If manufacturing activity is moving to regions that are relatively less efficient, the overall efficiency of the economy may decline if inefficiency is inherent to the region. This could have ramifications for such issues as the international competitiveness of U.S. industry. Thus, if there are regional differences in efficiency, it is important to determine why they exist. A number of empirical studies have attempted to examine the sources of inefficiency across regions (see, for example, Aberg 119731; Moomaw [1981a and 1981b]; and Beeson [1983]). In many of these studies. however, it is unclear what is meant by productive efficiency, and the methods used in the estimation are not always consistent with the theory of production.

In this paper, a stochastic frontier production function model is used to measure and compare productive efficiency in the manufacturing sector across states in the United States. The model is estimated using state level manufacturing data for the period 1959 to 1972. In contrast to the standard approach of estimating the average production function for an industry or a region, the frontier production function approach estimates the properties of the "best-practiced" technology. The inefficiency of a state is then measured in terms of that state's average deviation from this "best-practice" frontier.

Using this approach, we find that there is a substantial amount of variation in technical inefficiency across states. There is also an apparent regional pattern to this inefficiency, with the Southern states tending to be the least efficient, while the Mountain and West North Central states tend to be the most efficient. This pattern is changed somewhat by controlling for differences in industry mix, education levels, unionization rates and the level of urbanization across states. Once these factors have been taken into account, manufacturing in the southern states is still significantly less efficient than its counterpart in other regions. States in the traditional manufacturing belt region are now found to be the most efficient, with the exception of the New England states, which are found to be significantly below the average level of efficiency.

In section II of this paper, we define efficiency in production and discuss the methods used in the estimation of technical inefficiency.' In section III, we present the estimates of inefficiency by state and examine some possible sources of the inefficiency. This is followed by a brief discussion of the relationship between efficiency and economic growth. The results are then summarized in section IV.

II. Theory and Methodology

Studies of national or regional growth invariably make use of aggregate production functions as the underlying theoretical structure for their empirical results. These studies generally estimate a production function with a two-sided error term, and hence, are estimating the average economic properties of technology in an industry or region.[2] This formulation is useful for addressing a number of questions. For example, when examining the impact of the oil crisis on production in an industry or region, it may be important to know the average rate at which inputs are substituted. However, when examining questions of efficiency, the appropriate yardstick is not the average output achievable using a given vector of inputs, but rather the maximum output achievable using that vector of inputs.[3] In this case, it would be desirable to compare the output currently being produced in a region with the output that could be produced if all inputs were used efficiently.

For a study of regional efficiency, the appropriate formulation, then, is the frontier production function. A frontier production function describes the maximum amount of output obtainable from a given quantity of a set of inputs--that is, a production function is an efficient frontier. Output levels below those mapped by the function suggest inefficiency in production. Output levels above the function are impossible, barring technology shocks.

Recently, methods have been developed to estimate empirically the parameters of production (and cost) frontiers.[4] These methods not only allow for measurement of inefficiency in production, but also provide estimates of models that are consistent with theory. A typical specification of a frontier model appears below as equation (1):

$$(1) \quad y = f(X)\, e^{-(u-v)},$$

or equivalently:

$$(2) \qquad \ln y = \ln(f(X)) + v - u$$

where: y = output,

X = vector of production inputs,

$f(.)$ = production function

v = stochastic error term with mean 0 and variance σ_v^2

u = a one-sided error term with mean $\mu(>0)$ and variance σ_u^2

$\ln$ = natural logarithm operator

The two-part error term in (1) and (2) above has the following interpretation. The component v represents the effects of stochastic shocks to the production process (such as the effects of weather) or noise in the measurement of the dependent variable. The component $u \geq 0$ constrains output to lie on or below the stochastic frontier and thereby represents technical inefficiency in production. (See appendix 1.) In order to estimate (2), additional assumptions are made about the two-part error. First, both u and v are assumed to be independent of X. Second, each is assumed to be independent of the other. Finally, one must assume a distribution for both components.

Given a distribution for u (usually half normal or gamma) and v (normal), then (2) can be estimated by maximum likelihood. The usual procedure is to sample a single cross-section of data. This ensures that the errors are independent across observations. In estimating (2) from a single cross-section, however, there is no way to disentangle separate measures of v and u for each observation. The best one can hope for is an estimate of mean inefficiency over the entire sample (i.e., an estimate of μ). Even this is problematic however, since the estimate of μ depends upon the assumed distribution of u.

This discussion suggests three major problems of the estimation with stochastic production frontiers from a single cross-section of data. First, technical inefficiency is assumed to be independent of the choice of the input mix. This may not be true in the real world. Second, in order to estimate the model and separate the effects of inefficiency from those of noise, specific distributional assumptions must be made about the distribution of u and v, and the choice of distribution is not independent of the resulting estimates. Finally, it is impossible, given only a single cross-section, to estimate technical inefficiency by observation. As Schmidt and Sickles (1984) point out, all of these problems can be overcome if one has a set of panel data (that is, a pooled time series cross-section data set). In particular, using panel data estimation methodology (see Mundlak [1978] and Hausman and Taylor [1981]), it is possible to estimate technical inefficiency by cross-section unit without making distributional assumptions.

Consider the following model:

$$\text{(3)} \quad \ln y_{it} = \alpha + \ln X'_{it}\beta + v_{it} - u_i,$$

$$i = 1,\ldots,N \qquad t = 1,\ldots,T.$$

The data set contains T observations on N observational units (for example, firms, states, etc.). As before. the v_{it} are two-sided errors representing statistical noise and are assumed to be uncorrelated with the regressors. The u_i represent technical inefficiency and again are non-negative. We assume the u_i are iid with mean μ and variance σ_u^2 and are independent of the v_{it}. A particular distribution may (but need not) be assumed for the u_i, and it is no longer necessary to assume that the u_i are independent of the X_{it}.

Depending upon the assumptions that are made, several alternative estimators are available. We will consider two. If the u_i are assumed to be fixed over time for each cross-section of observations, then they can be absorbed into the constant term. α. This generates a model with N different intercepts ($\alpha_i = \alpha - u_i$). The resulting model can be estimated by (OLS) after suppressing the constant and adding N dummy variables.' This model is known as the <u>within estimator</u>.

The within estimator has several "nice" properties. First, since the u_i are treated as fixed, they need not assumed to be independent of the X_{it}. Hence, estimates of ß are consistent as either N or $T\to\infty$. Consistency of the individual intercepts of (α_i) requires $T\to\infty$. Second, the within estimator is simple to calculate. Finally, it is possible to obtain estimates of the u_i (the Cfixedl inefficiency of each cross-section unit). This is done as follows. Given the N estimated intercepts, $\hat{\alpha}_1, \hat{\alpha}_2, \ldots, \hat{\alpha}_N$, define:

$$(4) \quad \hat{\alpha} = \max(\hat{\alpha}_i)$$

$$\text{and } \hat{u}_i = \hat{\alpha} - \hat{\alpha}_i$$

then, given the logarithmic specification of the production frontier an index of efficiency, IE, can be calculated as:

$$(5) \quad IE = 100e^{-u_i} = 100e^{-(\hat{\alpha} - \hat{\alpha}_i)}$$

This amounts to treating the most efficient unit of observation in the sample as 100 percent efficient. Also, as Schmidt and Sickles (1984) point out, this will be true as $N\to\infty$. Further, the estimates of $\hat{\alpha}$ and $\hat{u}_i$ are consistent as N and $T\to\infty$.

Suppose that the u_i are treated as random and uncorrelated with the regressors. In this case, the appropriate estimator (under most conditions) is the generalized least squares (GLS) estimator (see Mundlak [1978]). The GLS estimator is essentially a weighted average of a time series (the within estimator discussed above) and a cross-section estimator. The latter is derived from a regression on the means over time of the regressor for each cross-section unit. The GLS weights are constructed from the covariance matrix, which is a function of σ_v^2 and σ_u^2.

Provided uncorrelatedness between the u_i and the other regressors, the GLS estimator produces consistent estimates of β and a^* $(=a - \mu)$.[6] For samples such as ours, where T is small, the GLS estimator is efficient relative to the within estimator. Estimates of the α_i can be obtained as means over time of the residuals, $\varepsilon_{it} = \ln y_{it} - \ln X'_{it}\beta$. And, following the procedure defined in equations (4) and (5), the a_i can be decomposed into estimates of $\hat{\alpha}$ and $\hat{u}_i$ and an efficiency index can be calculated. The estimates of the $\hat{u}_i$ will be consistent as N and $T \to \infty$.[7]

III. Estimation Results

Inefficiency by State. Our data set includes observations on total manufacturing by state for the 48 contiguous states from 1959 to 1973. We use value added in manufacturing (in $100,000 of 1972 dollars) in state i(i = 1, ..., 48) at time t(t = 1, ..., 15) as our measure of output. These data were taken from various issues of the Census of Manufactures. The price variable used to deflate the nominal output levels is the implicit price deflator for total manufacturing. This was taken from the National Income and Product Accounts. For our measure of labor we chose total production workers hours (in 100s of man-hours) in manufacturing in state i at time t. Our source for this measure was also various issues of the Census of Manufactures.

Our capital stock data require more discussion. For some time, studies of production and/or productivity at the state level have been hampered by the lack of data on statewide capital stocks. Recently, however, researchers at the Federal Reserve Bank of Boston have calculated estimates of state level manufacturing capital stock using the perpetual inventory technique (see Browne, Mieszkowski, and Syron [1980]). Their series runs from 1954 to 1976. In our study, we restrict our attention to the shorter sample period, 1959-73. This is for three reasons. First, 1959-73 represents the peak-to-peak of two complete business cycles. Second, by dropping the years 1974-76 from our sampie, we eliminate the potential biasing effects of the 1974 OPEC oil price shock. Finally, the year: from 1954 to 1958 were dropped due to probable estimation problems inherent in the early capital stock data.[8]

The capital stock data are measured in millions of 1972 dollars. Prior to estimation, we scaled these data by the U.S. capacity utilization rate for that year." Data on thi's last variable were taken from the Federal Reserve Bulletin. We chose the translog proauction function as our empirical model of the frontier. This model is especially useful, since it allows for neutral- and factor-augmenting technical change as well as nonconstant returns to scale. In addition, nested within the translog specification are the more familiar Cobb-Douglas and CES production functions. The model is given below:

$$
\begin{aligned}
(6)\quad \ln Y_{it} = {} & \alpha + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_{LK} \ln L_{it} \ln K_{it} \\
& + \beta_{LL} \bullet .5(\ln L_{it})^2 + \beta_{KK} \bullet .5(\ln K_{it})^2 + \beta_T T \\
& + \beta_{TT}(.5T^2) + \beta_{LT} \ln L_{it} \bullet T + \beta_{KT} \ln_{it} \bullet T - u_i + v_{it}
\end{aligned}
$$

where

Y_{it} = output of state i (i = 1, ...,48) at time t (t = 1, ...,15),

L_{it} = labor input in state i at time t,

K_{it} = capital input in state i at time t,

T = time trend,

u_i (≥ 0) = state-specific technical inefficiency,

v_{it} = random error,

a, β_{ij} = parameters to be estimated.

We will specify our assumptions about the u_i shortly. The v_{it} are assumed to be normally distributed, with mean zero and variance σ_v^2, and are assumed to be independent of the u_i.

In table 1, we present our estimates of the production frontier for total manufacturing using alternatively, the within and GLS estimators. As the table shows, the fits are very strong using either estimator. Moreover, with few exceptions, the estimates are virtually identical, using either estimation technique. Since the individual coefficients of the translog are not readily interpretable, we have calculated the output elasticities of labor and capital (ε_L and ε_K, respectively) and the rate of technical change (ε_T). These elasticities are all evaluated at the means of the data and are presented at the bottom of table 1. The values of these elasticities are consistent with many empirical studies of U.S. manufacturing using data aggregated at the national level.

The sum of ε_L and ε_K provides a measure of returns to scale (RTS). Both estimation techniques produce elasticity estimates that imply increasing returns to scale in manufacturing. The more efficient GLS estimates produce values of RTS similar to those reported by Harris (1982) and Nerlove (1967). Estimates of the rate of technological change, ε_T, are essentially identical and, again, are consistent with many studies of U.S. aggregate manufacturing over this time period.

In table 2, we present the ranking of states generated by ordering the states according to the size of the individual state intercept. We also report the value of the individual state intercepts produced using the two estimation techniques and estimates of the efficiency levels of each of the states relative to the most efficient state. These estimates of efficiency (IE_W for within model and IE_G, for the GLS model, columns 4 and 7) were calculated according to equation (5).

Several points emerge from an examination of table 2. However, before we consider these estimates, the question arises as to how to distinguish between the estimators. Clearly, this is related, in part, to what one is willing to assume about the u_i. One sacrifices efficiency by assuming that the u_i are fixed effects. Alternatively, the GLS estimates are more efficient than the within estimates if the u_i are independent of the regressors. Hausman (1978) suggests a test of this assumption. The test he proposes amounts to adding the mean-differenced set of regressors to the GLS specification and then testing the joint restriction that the coefficients of these additional variables equal zero. We performed this test. The test statistic equals 16.57 and is distribution χ^2_8. The value of this statistic is slightly smaller than the 5 percent critical level, 16.32, and hence, we are unable to reject the hypothesis of uncorrelatedness.

Given this last result, much of the remaining discussion will center on the GLS estimates. However, we note in passing that there are several similar characteristics between the two sets of estimates. First, while the levels of efficiency appear to be somewhat higher using the GLS technique, the rankings are similar using either technique. The Spearman rank correlation coefficient between these two sets of rankings is 0.85, which is significant at all levels of confidence.

Second, both sets of rankings suggest a rather wide divergence in efficiency levels, but with many states bunched fairly closely together in the center of the distribution. For either estimator, 75 percent of the states lie within one standard deviation of the mean level of efficiency. The states that lie above and below the one standard deviation bound are virtually identical in tne two cases. In fact, the same eight states appear at the bottom of the two rankings, albeit in slightly different order.

Finally, we note that regardless of our choice of estimators, states from the same or nearby regions often display similar levels of technical efficiency. For instance, using the GLS rankings. four of the 10 most efficient states come from the Mountain (MTN) region and three from the West North Central (WNC) region. Using the within estimator, five of the 10 most efficient are MTN states. and four are WNC. Using the GLS rankings, four of the 10 least efficient states are from the East South Central (ESC) region, and three are from the South Atlantic (SA) region. The comparable numbers for the within estimator are four from the ESC and two from the SA

In summary, the results from tables 1 and 2 indicate the following general conclusions regarding aggregate manufacturing in the U.S.:

1. Estimates of the production frontier suggest that aggregate U.S. manufacturing occurs under conditions of increasing returns to scale. This implies that any study of aggregate manufacturing that approximates the share of one factor of production as unity, minus the sum of shares to other factors, will produce biased measures of such important variables as total factor productivity growth.
2. There is evidence of substantial technical inefficiency in U.S. manufacturing.
3. There is an apparent regional pattern to technical inefficiency in U.S. manufacturing.

These three results argue strongly for the use of frontier estimation methodology employed in this paper. They also raise questions regarding regional patterns in technical inefficiency. In the next section, we consider two of these questions: First, what determines the level of technical inefficiency? Second, how does technical inefficiency in production relate to other aspects of production, such as total factor productivity and patterns of industrial location?

Sources of Inefficiency. In the previous section, we noted substantial differences in the level of state technical inefficiency in manufacturing. What could lead to differences in inefficiency across states? Several factors come to mind. First, differences could simply be due to aggregation biases In particular, there are substantial differences in industrial mix across states. Second, differences could be due to basic differences in the quaiity of the labor force or in the labor-relations climate across states. A third possibility is that states differ by degree of urbanization. If the presence of larger cities led to a faster degree of dissemination of new technologies, then this could also help to explain state-by-state inefficiency levels.

To test these variables as potential explanations, we estimated the following model:

$$(7) \quad \hat{u}_i = \gamma_0 + \gamma_1 DUR_i + \gamma_2 EDUC_i + \gamma \, UNION_i + \gamma_4 METRO + \text{Regional Dummies} + \varepsilon$$

where

$\hat{u}_i$ = level of technical inefficiency for state i calculated from the GLS estimates. (Equation (4) and column 6 of table 2.)

DUR_i = production of total manufacturing in state i accounted for by durable goods output.[10] Expected sign, uncertain. Source, Census of Manufactures.

$EDUC_i$ = percent of the labor force in state i with a minimum of a high school education (average of annual values 1959-73). Expected sign, negative. Source, Census of Population.

$METRO_i$ = percent of the population in state i living in metropolitan areas (average of annual values 1959-73). Expected sign, negative. Source, Census of Population.

$UNION_i$ = percent of production workers in state i that is unionized (1973-75 CPS surveys). Expected sign, uncertain. Source, Freeman and Medoff (1979, table 4).

We estimated equation (7) using ordinary least squares (OLS) under several alternative hypotheses regarding regional affiliation of states and coefficient equality restriction on the regional dummy variables. Specifically, we found in two instances that several states exhibited patterns of behavior that were significantly different from the majority of states within a U.S. Census region. Kentucky, for instance, appeared to have a much lower level of technical inefficiency than the remainder of the ESC region. Since Kentucky seemed to match more closely the performance of states from the ENC region, and given Kentucky's proximity to that region, we changed the regional affiliation to ENC. Similarly, Delaware, West Virginia, and Maryland did not appear to have levels of technical inefficiency that matched well with the remainder of the SA region states.. Given that these states are contiguous, we separated them from the SA region and grouped them into a new region, dubbed MSA. To test the validity of these groupings, vis a vis the census definitions, we ran two separate regressions. A test of the null hypothesis that the states belonged to the Census groupings yielded an F statistic of 9.33, which is significant at all usual confidence levels.[11] After redefining regional affiliation, we considered a variety of restrictions on equality of regional dummies. The model that yielded the highest R^2 is:

$$\underset{(.137)}{\hat{u}_i = .625} + \underset{(.142)}{2.44DUR} - \underset{(.0026)}{.0082EDUC} + \underset{(.0024)}{.0049UNION} - \underset{(.0007)}{.0029METRO}$$

$$- \underset{(.059)}{.079ENC} - \underset{(.064)}{.112MSA} - \underset{(.047)}{.118WNC} + \underset{(.062)}{.193SA} + \underset{(.073)}{.099ESC} + \underset{(.048)}{.122NE}$$

Mean of $\hat{u}_i = .312$ $\quad \bar{R}^2 = .61$ $\quad$ S.E. R. = .098

(standard errors in parentheses)

The results above seem remarkably strong. The regression model explains more than 60 percent of the cross-sectional variation in u. Both EDUC and METRO have the expected signs and are significantly different from zero at the 5 percent significance level. UNION is also significant at the 5 percent level. The positive sign of UNION suggests that as the unionization rate rises across states, so does the level of technical inefficiency. This result does not seem to be controversial. Finally, the mix of output between durables and nondurables across states may contribute to technical inefficiency. The coefficient of DUR is positive and significant at the 10 percent level suggesting that technical inefficiency rises with the share of durable goods output in total manufacturing.

Holding the effects of the economic variables above constant, it is clear from the signs and from the precision of estimation of the regional dummies that regional effects are important. Clearly, the South and the North East display higher levels of technical inefficiency, while states from the MSA, ENC, and WNC display lower-than-average levels of technical inefficiency.

Efficiency and Growth. Is technical inefficiency important? The answer to that question would seem to depend upon the relationship between technical inefficiency and other dimensions of economic performance. Economic theory, which is based on maximizing behavior, offers very little guidance on this issue.

However, the relationship between technical inefficiency and productivity growth has been analyzed to some extent. Caves (1984) argues that the relationship between technical inefficiency and productivity growth could be positive or negative. For instance, if technical inefficiency results from "sub-optimization by organizational coalitions, it seems plausible that the failing should affect both static and dynamic efficiency." On the other hand, if productivity growth is embodied in capital and cannot be refitted to old capital goods, under most empirical schemes for measuring capital, high growth rates of productivity would be statistically correlated with high levels of technical inefficiency. Using a single cross of industry-level data, Caves found some weak evidence to suggest that the correlation between inefficiency and productivity growth is negative, implying that persistent technical inefficiency reduces the likelihood for innovation and adoption of new methods of production.

We also briefly investigated this issue. Using data from Beeson (1986), we ran simple OL[illegible]ssions between values of $\hat{u}$, and levels of total factor productivity gr[illegible] by state. We consider two different dependent variables. First, $\dot{TFP}_1$, is the average rate of growth in total factor productivity growth in state manufacturing from 1959 to 1973. $\dot{TFP}_2$ is the analogous variable over the shorter sample period 1965-73. The results of these regressions are

$$\text{(1)} \quad \dot{TFP}_1 = \underset{(.002)}{.028} + \underset{(.0059)}{.0009}\,\hat{u}$$

mean of $\dot{TFP}_1$ = .028 $\bar{R}^2$ = - .021 S.E.R. = .006

$$\dot{TFP}_2 = \underset{(.002)}{.021} + \underset{(.018)}{.027}\,\hat{u}$$

mean of $\dot{TFP}_2$ = .025 $\bar{R}^2$ = .023 S.E.R. = .009

(standard errors in parentheses)

As the results suggest, there is virtually no evidence to support a link between total-factor productivity growth and technical inefficiency. The coefficient of $\hat{u}$ in the second regression is significantly positive at the 15 percent confidence level. This result is mildly contradictory to the industry findings reported by Caves.

As we noted in our introduction, technical inefficiency may be a determinant of industrial location. To test this hypothesis, we collected data on various measures of state manufacturing activity for the five-year period immediately following the period covered in our study. These data included measures of the average annual change in real value added in manufacturing, in production worker hours, in total employment, and in production worker employment. The source for these data was the <u>Census of Manufactures</u>. In alternate experiments, these four variables were regressed on IEG--our measure of <u>efficiency</u> in production. If efficiency is a determinant of industrial activity, we would expect the coefficient on IEG to be positive. This was the case in all four regressions:

$$\%\Delta \text{ real value added} = \underset{(.026)}{.001} + \underset{(.0004)}{.0004}\ \text{IEG}$$

mean of dependent variable = .030 $\bar{R}^2$ = .005 S.E.R. = .028

$$7'\ \text{production worker hours} = \underset{(.022)}{-.037} + \underset{(.0003)}{.0006}\ \text{IEG}$$

mean of dependent variable = .008 $\bar{R}^2$ = .069 S.E.R. = .022

$$\%\Delta \text{ total manufacturing employment} = \underset{(.020)}{-.021} + \underset{(.0003)}{.0005}\ \text{IEG}$$

mean of dependent variable = .016 $\bar{R}^2$ = .052 S.E.R. = .020

$$\%\Delta \text{ production worker employment} = \underset{(.021)}{-.028} + \underset{(.00003)}{.00005}\ \text{IEG}$$

mean of dependent variable = .010 $\bar{R}^2$ = .048 S.E.R. = 0.22

(Standard errors in parentheses)

Given the poor performance of the first regression reported in this set, we cannot establish a strong link between the growth in manufacturing and technical efficiency levels. The remaining three regressions, however, do seem to point to a positive and significant relationship between labor utilization and technical efficiency levels.

IV. Conclusions

In this paper, we sought to examine the question of whether states differ in terms of technical inefficiency in their manufacturing sectors. Using a frontier production approach and data for the period 1959-73, we have found significant differences in inefficiency levels. Then. using data on the characteristics and regional affiliation of the various states, we set out to explain the. pattern of these inefficiency levels. We found that education, union activities, and urbanization levels were all significant variables in explaining inefficiency. In addition, very significant regional patterns in inefficiency emerged, with the South and New England displaying high levels of inefficiency, and the traditional manufacturing belt regions being more efficient. Finally, we looked to see to what extent state inefficiency explained other measures of manufacturing performance. We found that while there was no correlation between this variable and total factor productivity growth, there was some evidence to support the notion that growth in manufacturing employment is positively related to state efficiency.

A number of interesting questions remain to be considered. A strong test of the validity of our result; would be to replicate our analysis at the industry level. It would also be interesting to consider, using new data, whether and how patterns of state inefficiency change over time.

Appendix

Measures of production inefficiency have been developed by Farrell (1957). Let $y = f(X_1, X_2)$ be a production function, wherein X_1 and X_2 are productive inputs, and y is a single output. Suppose further that $f(\cdot)$ displays constant returns to scale, so that $f(\lambda X_1, \lambda X_2)=\lambda f(X_1, X_2)$. Then let $\tilde{y}$ be the unit isoquant.

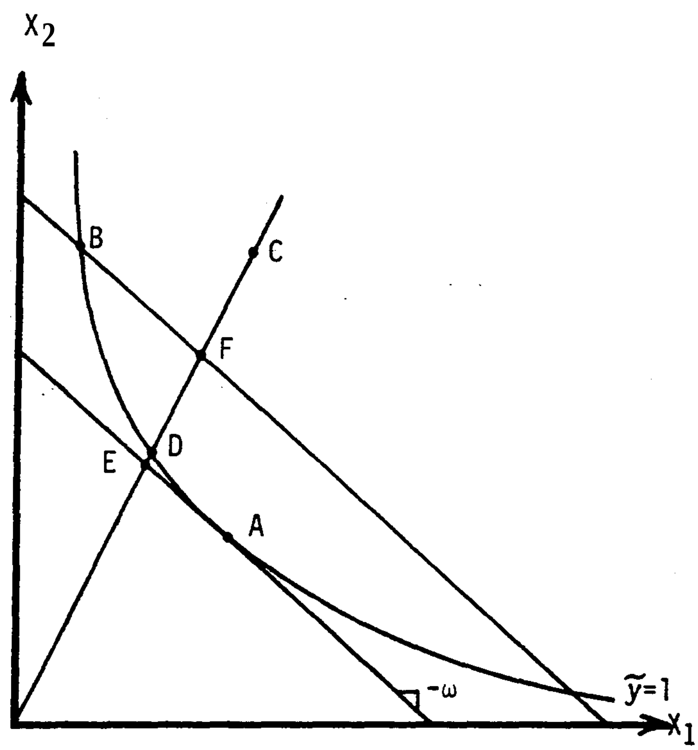

Figure 1

Consider the input choices (for one unit of output) A, B, and C. Production of one unit is technically efficient if the input mix chosen lies on the unit isoquant.[12] Thus, both A and B represent technically efficient input choices. However, only A is both technically and allocatively efficient, since given factor price ratio, ω, A. represents the cost-minimizing input mix for unitary output.'' An index of the level of efficiency at point B is given by:

$$E_B = OE/OF.$$

The input choice at point C reflects both allocative and technical inefficiency. An index of the level of efficiency at point C is:

$$E_C = OE/OC = OE/OD \cdot OD/OC.$$

where:

OE/OD = index of allocative efficiency at point C.

OD/OC = index of technical efficiency at point C.

Thus, total efficiency is the product of allocative and technical efficiency.[14] By this definition, E_A would have a value of unity. A measure of inefficiency associated with points like C would be $1 - E_C$.

Notes

1. This section borrows heavily from Schmidt and Sickles (1984).

2. An alternative interpretation of these "average" production functions is that they assume that all firms (regions) are equally efficient, and that all errors are the result of technology shocks. This is a testable, but seldom tested, hypothesis.

3. Studies, such as those by Hulten and Schwab (1984); Gollop and Jorgenson (1980); and Kendrick and Grossman (1980), that calculate rates of total factor productivity growth based on factor shares use methodology consistent with their underlying theory. However, these latter studies can be criticized on

two grounds. First, they rely on untested theoretical assumptions about the structure of the underlying technology, such as constant returns to scale. Second, standard statistical inference cannot be performed on the estimates from these studies.

4. For a detailed discussion of this methodology, see Forsund, Lovell, and Schmidt (1980).

5. Alternatively, one could retain the constant and add N-1 dummies, or estimate the model by OLS after expressing all of the data as deviations from their cross-section means.

6. Hausman (1978) describes several tests of uncorrelatedness.

7. If uncorrelatedness cannot be rejected, another estimator is available. This is the maximum likelihood estimator (MLE). Maximum likelihood estimates can be obtained, provided one assumes distributions for the u_i and the v_{it}. Pitt and Lee (1981) have derived the likelihood function for the case where the v_{it} are normal, and the u_i are half normal. Other cases are possible, but have not appeared in the literature. The reader should note that the asymptotic properties of the MLE estimator have not been fully developed, although Schmidt and Sickles (1984) make some conjectures about these properties.

8. For more on this point, see Beeson (1983).

9. Data on capacity utilization by state are not available

10. This variable was constructed as the average of values of the following formula:

DUR_i = [state i is output in SIC's 24, 25, 32-39]/ total manufacturing in state i for the years 1958, 1963, 1967, 1972, and 1977.

11. Evidence that homogeneity in a variety of contexts does not exist within Census regions can be found in Murphy and Hofler in (1984) and Beeson (1983).

12. Formally, production is technically inefficient if, for the production plan $(y^o, \tilde{x}^o)$ - where $\tilde{x}$ is a vector of production inputs--$y^o < f(\tilde{x}^o)$.

13. Formally, the production plan $(y^o, \tilde{x}^o)$ is said to be allocatively efficient if, for given input prices, ω_i, and ω_j, $f_i(\tilde{x}^o)/f_j(\tilde{x}^o) = w_i/\omega_j$.

14. Production can also be scale-inefficient. This would be the case if production did not occur at the point where profits are maximized.

TABLE 1
PARAMETER ESTIMATES OF THE PRODUCTION FRONTIER

Variable (1)	Mean value (2)	Within estimate (3)	GLS estimate
Constant			.008 (.372)
lnL	7.867	1.1045* (.119)	.940* (.096)
lnK	7.555	.111 (.123)	-.046 (.103)
lnL lnK	61.282	.201* (.054)	.199* (.052)
.5 $\ln L^2$	31.979	-.225* (.049)	-.210* (.046)
.5 $\ln K^2$	29.446	-.191* (.065)	-.167* (.061)
T	8	.032* (.006)	.041* (.005)
.5T^2	41.333	.0001 (.0003)	.0002 (.0003)
T lnL	63.287	-.0069* (.0021)	-.0063* (.0021)
T lnK	61.312	.0069* (.0026)	.0050* (.0024)
$\bar{R}^2$		.999	.969
s^2		.0029	.0030
ε_L		.798 (.032)	.742 (.003)
ε_K		.305 (.034)	.298 (.027)
ε_T		.029 (.001)	.028 (.001)
R.T.S.		1.103	1.040

NOTE: Standard errors in parentheses.
*indicates coefficient is significantly different from zero at the 1 percent level.

TABLE 2

RANKING OF STATES BY EFFICIENCY LEVELS

	Within estimates					GLS estimates			
	State (1)	Region	Inter-cept (2)	s.e. (3)	IEW (in %) (4)	State (5)	Region	Inter-cept (6)	IEG (in %) (7)
1.	Nevada	(MTN)	-.763	.501	100.0	Utah	(MTN)	.320	100.0
2.	Utah	(MTN)	-.998	.590	79.1	Nevada	(MTN)	.308	38.8
3.	N. Dakota	(WNC)	-1.034	.519	76.3	Delaware	(SA)	.275	95.6
4.	Wyoming	(MTN)	-1.041	.521	75.7	Minnesota	(WNC)	.193	88.1
5.	Delaware	(SA)	-1.063	.600	74.1	Colorado	(MTN)	.184	87.3
6.	S. Dakota	(WNC)	-1.084	.525	72.5	Iowa	(WNC)	.169	86.0
7.	Colorado	(MTN)	-1.208	.611	64.1	Arizona	(MTN)	.159	85.1
8.	Arizona	(MTN)	-1.226	.608	62.9	Washington	(PAC)	.148	84.2
9.	Nebraska	(WNC)	-1.267	.609	60.4	Kentucky	(ESC)	.147	84.1
10.	Iowa	(WMC)	-1.275	.621	59.9	Missouri	(WNC)	.144	83.9
11.	Minnesota	(WNC)	-1.283	.622	59.5	Kansas	(WNC)	.129	82.6
12.	Kansas	(WNC)	-1.287	.616	59.2	Nebraska	(WNC)	.122	82.0
13.	Vermont	(NE)	-1.300	.576	58.4	California	(PAC)	.113	81.3
14.	Washington	(PAC)	-1.300	.622	58.4	New York	(MA)	.106	80.7
15.	Kentucky	(ESC)	-1.304	.622	58.2	W. Virginia	(SA)	.100	80.3
16.	W. Virginia	(SA)	-1.318	.619	57.4	New Jersey	(MA)	.099	80.2
17.	N. Mexico	(MTN)	-1.334	.548	56.2	Connecticut	(NE)	.075	78.3
18.	Missouri	(WNC)	-1.336	.621	56.4	N. Dakota	(WNC)	.074	78.2
19.	Montana	(WNC)	-1.340	.587	56.2	Massachusetts	(NE)	.071	78.0
20.	Idaho	(MTN)	-1.349	.588	55.7	Wyoming	(MTN)	.065	77.5
21.	California	(PAC)	-1.382	.602	53.8	S. Dakota	(WNC)	.062	77.3

TABLE 2 (CONT'D)
RANKING OF STATES BY EFFICIENCY LEVELS

	State (1)	Region	Within estimates: Intercept (2)	Within estimates: s.e. (3)	IEW (in %) (4)	State (5)	GLS estimates: Region	GLS estimates: Intercept (6)	IEG (in %) (7)
22.	New Jersey	(MA)	-1.395	.613	53.2	Wisconsin	(ENC)	.060	77.1
23.	Oklahoma	(WSC)	-1.398	.612	53.0	Maryland	(SA)	.039	75.5
24.	New York	(MA)	-1.399	.600	52.9	Illinois	(ENC)	.011	73.4
25.	Connecticut	(NE)	-1.406	.621	52.6	Louisiana	(WSC)	.011	73.4
26.	Maryland	(SA)	-1.419	.622	51.9	Michigan	(ENC)	-.001	72.5
27.	Louisiana	(WSC)	-1.420	.622	51.8	Oklahoma	(WSC)	-.002	72.5
28.	Rhode Island	(NE)	-1.420	.608	51.8	Texas	(WSC)	-.014	71.6
29.	Wisconsin	(ENC)	-1.427	.620	51.5'	Florida	(SA)	-.015	71.5
30.	Massachusetts	(NE)	-1.427	.619	51.5	Vermont	(NE)	-.015	71.5
31.	Florida	(SA)	-1.470	.622	49.3	Rhode Island	(NE)	-.022	71.0
32.	Illinois	(ENC)	-1.484	.603	48.6	Ohio	(ENC)	-.026	70.8
33.	New Hampshire	(NE)	-1.485	.601	48.6	Idaho	(MTN)	-.043	69.6
34.	Texas	(WSC)	-1.486	.613	48.5	Montana	(MTN)	-.049	69.1
35.	Michigan	(ENC)	-1.489	.605	48.4	Oregon	(PAC)	-.060	68.4
36.	Oregon	(PAC)	-1.495	.620	48.1	Indiana	(ENC)	-.069	67.8
37.	Ohio	(ENC)	-1.516	.600	47.1	N. Hampshire	(NE)	-.114	64.8
38.	Indiana	(ENC)	-1.555	.613	45.3	Virginia	(SA)	-.121	64.3
39.	Virginia	(SA)	-1.595	.622	43.5	N. Mexico	(MTN)	-.140	63.1
40.	Tennessee	(ESC)	-1.620	.621	42.4	Tennessee	(ESC)	-.140	63.1
41.	Arkansas	(WSC)	-1.628	.615	42.1	Pennsylvania	(MA)	-.164	61.6
42.	Pennsylvania	(MA)	-1.659	.599	40.8	Alabama	(ESC)	-.199	59.5
43.	Alabama	(ESC)	-1.665	.622	40.6	Georgia	(ESC)	-.200	59.5
44.	Georgia	(ESC)	-1.684	.621	39.8	Arkansas	(WSC)	-.206	59.1
45.	Mississippi	(ESC)	-1.718	.616	38.5	N. Carolina	(SA)	-.241	57.1

TABLE 2 (CONT'D)
RANKING OF STATES BY EFFICIENCY LEVELS

	Within estimates					GLS estimates		
State (1)	Region	Intercept (2)	s.e. (3)	IEW (in %) (4)	State (5)	Region	Intercept (6)	IEG (in %) (7)
46. N. Carolina	(SA)	-1.749	.612	37.3	Mississippi	(ESC)	-.289	54.4
47. S. Carolina	(SA)	-1.763	.621	36.8	S. Carolina	(SA)	-.290	54.3.
48. Maine	(NE)	-1.769	.613	36.6	Maine	(NE)	-.364	50.5

References

Aberg, Y. "Regional Productivity Differences in Swedish Manufacturing," Regional and Urban Economics, vol. 3, no. 2 (May 1973), pp. 131-56.

Beeson, P. "Essays in Regional Productivity, Ph.D. Thesis, University of Oregon, 1983.

________. "Total Factor Productivity Growth and Agglomeration Economies in Manufacturing, 1959-73," mimeo, University of Pittsburgh, 1986.

Bellante, D. "The North-South Differential and the Migration of Heterogeneous Labor," American Economic Review, vol. 69, no. 1 (March 1979), pp. 166-75.

Browne, L., P. Mieszkowski, and R. Syron. "Regional Investment Patterns," New England Economic Review, July/August 1980, pp. 5-23.

Carlton, D. "The Location and Employment Choices of New Firms: An Econometric Model with Discrete and Continuous Endogenous Variables," Review of Economics and Statistics, vol. 65, no. 3 (August 1983), pp. 440-49.

Caves, R. "Interindustry Differences in Productivity Growth and Technical Inefficiency," Paper Prepared for the Conference on Interindustry Differences in Productivity Growth, American Enterprise Institute, Harvard University, 1984.

Farrell, M.J. "The Measurement of Productive Efficiency," Journal of the Royal Statistical Society, vol. 120, no. 3, 1957, pp. 253-81.

Forsund, F.R., C.A.K. Lovell, and P. Schmidt. "A Survey of Frontier Production Functions and their Relationship to Efficiency Measurement," Journal of Econometrics, vol. 13, no. 1 (May 1980), pp. 5-25.

Freeman, R.B., and J.L. Medoff. "New Estimates of Private Sector Unionism in the United States," Industrial and Labor Relations Review, vol. 32, no. 2 (January 1979), pp. 143-74.

Gollop, F.. and D. Jorgenson. "U.S. Productivity Growth by Industry," in J. Kendrick and B. Vaccara, eds., New Developments in Productivity Measurement, NBER Series in Productivity Measurement. Volume 44. Chicago: University of Chicago Press, 1980, pp. 17-124.

Harris, R. "Estimates of Inter-Regional Differences in Production in the United Kingdom, 1986-78," Oxford Bulletin of Economics and Statistics, 1982, pp. 241-59.

Hausman, J.A., and W.E. Taylor. "Panel Data and Unobservable Individual Effects," Econometrica, vol. 49, no. 6 (November 1981), pp. 1377-98.

Hausman, J. A. "Specification Tests in Econometrics," Econometrica. vol. 46, no. 6 (November 19781, pp. 1251-71.

Hulten, C.R., and R.M. Schwab. "Regional Productivity Growth in U.S. Manufacturing: 1951-78," American Economic Review, vol. 74, no. 1 (March 1984). pp. 152-62.

Kendrick, J., and E. Grossman. Productivity in the United States: Trends and Cycles. Baltimore: The Johns Hopkins University Press, 1980.

Moomaw, R.L. "Productive Efficiency and Region," Southern Economic Journal, vol. 48, no. 2 (October 1981a), pp. 344-57.

______. "Productivity and City Size: A Critique of the Evidence," Quarterly Journal of Economics, vol. 96, no. 4 (November 1981b), pp. 675-88.

Mundlak, Y. "On the Pooling of Time Series and Cross-Section Data," Econometrica. vol. 46, no. 1 (January 1978), pp. 69-85.

Murphy, K. J., and R. A. Hofler. "Determinants of Geographic Unemployment Rates: A Selectively Pooled-Simultaneous Model," Review of Economics and Statistics, vol. 66. 1984, pp. 216-23.

Nerlove, M. "Recent Empirical Studies of the CES and Related Production Functions," in M. Brown, ed.. The Theory and Empirical Analysis of Production, NBER Studies in Income and Wealth, Volume '32. New York: Columbia University Press, 1967, pp. 55-122.

Newman, R. "Industry Migration and Growth in the South," Review of Economics and Statistics, vol. 65, no. 1 (February 1983), pp. 76-86.

Pitt, M., and L.F. Lee. "The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry," Journal of Development Economics, vol. 9, 1981, pp. 43-64.

Sahling, L., and S. Smith. "Regional Wage Differentials: Has the South Risen Again?" Review of Economics and Statistics, vol. 65, no. 1 (February 1983), pp. 131-35.

Schmidt, P., and R. Sickles. "Production Frontiers and Panel Data," Journal of Business and Economic Statistics, vol. 2, no. 4 (October 19841, pp. 367-74.