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A COMPARISON OF FORECASTING ACCURACIES OF ALTERNATIVE REGIONAL PRODUCTION INDEX METHODOLOGIES

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1. Purpose of Study

Staying abreast of current trends in the national economy is a vital task for government, business and individual decisionmakers. The degree to which the various regions of the country are economically integrated is substantial.2/ There are instances, however, when the trends in a regional economy diverge from those in the national economy. For example, according to the findings of the National Bureau of Economic Research the national economy began a recession in January, 1980 which lasted until July 1980. At the same time the Texas economy, on the crest of a booming oil industry and rising petroleum prices, maintained a healthy growth rate.3/ Local government revenue projections and business inventory levels and profit projections are subject to large errors if national trends are myopically followed. To combat such errors regional economic models and production indices began to appear in the 1950's and have since been continually expanded and revised.4/ As standard practice, regional periodicals commonly list regional economic indicators along with national economic data.5/

The purpose of this paper is to study a particular facet of regional economic analysis, regional production index construction. Several alternative methodologies have been proposed and used in the construction of regional production indices.6/ Which of these methodologies provides the most accurate characterization of constant dollar production in regional manufacturing industries? If sophisticated techniques offer improvement, is the additional cost of the sophistication worth it?

A "best" regional production index methodology cannot be determined on the basis of theory alone. The ultimate that can be hoped for is that, after many case studies, a preponderance of evidence will tend to indicate which, if any, methodology appears to be superior. This paper reports the result of one such case study. The region of study is the state of Texas. The production of interest is the real value added by Texas two-digit SIC code manufacturing industries. From this data, tentative conclusions are drawn as to the relative performance of several proposed methodologies.

The remainder of the paper is organized as follows. In section 2 the nature of regional production indices is discussed. In section 3 regional production indices are classified by the method of construction: sum-of-payments methods and empirical production function methods. The performance of the proposed methodologies on the Texas data is summarized in section 4. Some conclusions to be drawn from the Texas experience are presented in the final section.

2. Nature of Regional Production Indices

Regional production indices usually focus on the manufacturing sector of a region while ignoring wholesale and retail trade, mining and utilities. This choice is one of convenience because survey data are more complete for manufacturing than for the remaining sectors. Production in manufacturing is taken to be real value added in two-digit SIC code industries, nominal value added being deflated by an appropriate price deflator.7/ Movements in real value added can then be used to monitor the level of regional economic activity in manufacturing and can serve as a coincident indicator of regional economic activity.

Unfortunately, real value added production data is typically not available on a timely basis.8/ The Annual Survey of Manufacturers provides, after a substantial delay in reporting, annual nominal value added data by state two-digit SIC code industries. Likewise, industry deflators are available only on a yearly basis with delay. Thus, the best that survey data can provide are annual real value added estimates three or more years after the fact. What is needed instead are, at minimum, monthly estimates of real value added by two-digit industries. Hence, real production levels must be estimated by using primary inputs to production processes which are observed on a monthly basis. It has become standard practice to use manhours (L) and kilowatt hours of electricity usage (K) to proxy the traditional economic concepts of labor and capital. These measures are obtainable on a monthly basis from the Bureau of Labor Statistics and the statistics departments of regional Federal Reserve banks and, as a result, are timely and convenient. While vintaged capital stock might be more appropriate as a measure of capital, the lack of availability prevents its usage. Given the high correlation of capital stock and electrical power usage, electric power seems to be a reasonable proxy to use for capital in production processes.9/

To illustrate the nature of regional production indices, let O_i denote the predicted real value added in the i-th industry for a given month obtained by some mathematical transformation of manhours and kilowatt hours used by the industry during the month. Then an index of production for the i-th industry relative to a given base year can be calculated as

$$0_i^* = (0_i/\overline{0}_{i,o}) \cdot 100,$$

where 0_i^* represents the production index for the i-th industry and $\overline{0}_{i,o}$ represents the average monthly production in the i-th industry during the base year. A number like 130.2 has the interpretation that industrial production in the region is 30.2 percent higher at present than during an average month in the base year. If desired, the index can be seasonally adjusted.

Of course, 0_i^* only depicts the current level of activity in the i-th industry. A more comprehensive measure of productive activity in manufacturing as a whole can be obtained by forming a composite index consisting of a weighted average of individual industry indices. One possible way of forming the weighted average is to consider the amount of real value added produced by each industry relative to the real value added produced by the manufacturing sector as a whole. Let w_i ,$0 < w_i < 1$, denote that proportion of total manufacturing real value added produced by the i-th industry in a certain year, usually the most recent year for which complete survey data are available. A manufacturing production index can be calculated as

$$0_M = 100\sum_i(0_i^* \cdot w_i) ,$$

where $\sum_i$ denotes the summation over all two-digit SIC code industries in manufacturing. A number like 124.3 has the interpretation that industrial production in manufacturing as a whole is 24.3 percent higher at present than during an average month in a base year.

The basic ingredient to good index construction is the estimate of the month's real value added by each industry, O_i. The best index, either from the viewpoint of an industry or manufacturing as a whole, would consist of the actual real value added produced each month. In the absence of actual values, the better the estimates O_i, the better the index. Thus, the matter of primary concern becomes one of how to specify a mathematical transformation of manhours and kilowatt hours of electricity usage to estimate as accurately as possible the real value added to products by industries. What should the form of the transformation be and what relative weights should manhours (hereafter labor, L) and kilowatt hours (hereafter capital, K) carry in determining industry output estimates? Should considerations of technical change (improved capital equipment and better trained labor) enter into the estimation process?

Many distinct estimation methodologies have been proposed and are currently in use for the purpose of estimating regional production. The next section classifies these methodologies into two categories according to the paradigm chosen to construct the estimates, O_i. Some additional methodologies will be proposed as well.

3. Classification of Methodologies

Comparisons between regional production index methodologies can best be drawn by classifying them into one of two broad categories: (1) sum-of-payments methods or (2) empirical production function methods. Briefly, the first category includes all methods which use the assumptions of linear homogeneous production and product exhaustion to specify an estimating equation for industry output. The second category includes methods which use fitted production functions to estimate output. These methods are discussed in detail in the following two subsections. In the final subsection some modifications of these methodologies are considered.

3.1 Sum of Payment Methods

A central theme of these methods is the use of the basic product exhaustion theorem derived by assuming perfect competition and two-factor, linear homogeneous production. Euler's Theorem10/ states that physical product, q, can be written as

$$(1) \qquad q = MP_L \cdot L + MP_K \cdot K$$

where MP_L = marginal product of labor, L = units of labor, MP_K = marginal product of capital, and K = units of capital. By multiplying equation (1) by product price, P, value added, $P \cdot q \equiv VA$, can be seen to be

$$(1') \qquad P \cdot q \equiv VA = P \cdot MP_L \cdot L + P \cdot MP_K \cdot K$$
$$= VMP_L \cdot L + VMP_K \cdot K,$$

where $VMP_L = P \cdot MP_L$ is the value of the marginal product of labor and $VMP_K = P \cdot MP_K$ is the value of the marginal product of capital. Let P_L and P_K be, respectively, the per unit prices of labor and capital. According to the profit maximizing conditions $VMP_L = P_L$ and $VMP_K = P_K$, equation (1') becomes

$$(1'') \qquad VA = P_L \cdot L + P_K \cdot K \quad .$$

Thus, value added is the sum of the wage bill, $P_L \cdot L$, and the capital bill, $P_K \cdot K$. Therefore, value added can, under the assumed conditions, be represented as the "sum-of-payments". The index methodologies to be discussed use equation (1'') as a departure point hence the choice of "sum-of-payments" as the label.

A useful identity of equation (1'') is

$$(1''') \quad VA = \left(\frac{P_L \cdot L}{P \cdot q}\right) \cdot \left(\frac{P \cdot q}{L}\right) \cdot L + \left(\frac{P_K \cdot K}{P \cdot q}\right) \cdot \left(\frac{P \cdot q}{K}\right) \cdot K$$

$$= \left(\frac{P_L \cdot L}{VA}\right) \cdot \left(\frac{VA}{L}\right) \cdot L + \left(\frac{P_K \cdot K}{VA}\right) \cdot \left(\frac{VA}{K}\right) \cdot K \quad .$$

Letting t denote a given time period and assuming equation (1''') holds each period, value added at time t, VA_t, can be written as

$$(1'''') \quad VA_t = \left(\frac{P_L \cdot L}{VA}\right)_t \cdot \left(\frac{VA}{L}\right)_t \cdot L_t + \left(\frac{P_K \cdot K}{VA}\right)_t \cdot \left(\frac{VA}{K}\right)_t \cdot K_t \quad .$$

Thus, for a given period, value added can be viewed as a linear combination of usages of labor and capital with weights

$$(2) \qquad \left(\frac{P_L \cdot L}{VA}\right)_t \cdot \left(\frac{VA}{L}\right)_t$$

and

$$(3) \qquad \left(\frac{P_K \cdot K}{VA}\right)_t \cdot \left(\frac{VA}{K}\right)_t$$

consisting of the products of factor shares in value added and the value added to input ratios. Note that, under the assumed conditions, the factor shares sum to unity

$$(4) \qquad \left(\frac{P_L \cdot L}{VA}\right)_t + \left(\frac{P_K \cdot K}{VA}\right)_t = 1.$$

Of course, equation (1'') also states that the value added can be represented as a linear combination of labor and capital, but, given that value added and wage bill data are more readily available from Census documents, the form of equation (1'''') proves more convenient.

If value added could be observed on a monthly basis, there would be no need to consider equation (1'''') as a device for estimating value added for each industry for the purpose of constructing an industrial index. Observations on labor and capital (electricity) are the only data available on a monthly basis. If, however, numerical estimates for the coefficients represented by (2) and (3) were available, then equation (1'''') in conjunction with monthly observations on L and K could be used to estimate an industry's value added for a given month (or, if multiplied by 12, a prorated estimate of annual production).

The Atlanta, Dallas, and San Francisco regional Federal Reserve Banks have all developed regional production indices using the sum-of-payments approach, i.e. some form of equation (1'''').11/ The difference between their methodologies concerns the way in which the factor shares and output-input ratios are assumed to behave over time. The Atlanta and Dallas (1971) approach assumes that the factor shares are time invariant (at least until the next revision) while output-input ratios are augmented by monthly productivity increments. More specifically, for each industry and a given revision year, the labor factor share, $(P_L \cdot L/VA)$, is calculated from Census data and capital factor share derived as $1 - (P_L \cdot L/VA)$ using the product exhaustion theorem. This complementarity is used because the capital bill, $P_K \cdot K$, is not reported in Census surveys. In a similar manner the output-input ratios, (VA/L) and (VA/K), are calculated in the most recent revision year and are assumed subject to factor specific technological enhancements. These technical change effects are incorporated by multiplying each output-input ratio by a productivity increment of the form

(5) $$(1 + C_i \cdot n), \quad i = L,K ,$$

where C_i represents a monthly productivity increment for the i-th input and $n = 1,2,3,\ldots$ represents the number of months which have elapsed since the last quinquennial year. In summary, the productivity enhanced output-input ratios are assumed to move through time according to the formulas

(6) $$\left(\frac{VA}{L}\right)(1 + C_L \cdot n)$$

and

(7) $$\left(\frac{VA}{K}\right)(1 + C_K \cdot n) \quad .$$

The Atlanta approach is to calculate the productivity increments by the formulas

(8) $$C_L = \left[\frac{\frac{VA_m}{L_m}}{\frac{VA_o}{L_o}}\right]^{\frac{1}{S}} -1$$

and

(9) $$C_K = \left[\frac{\frac{VA_m}{K_m}}{\frac{VA_o}{K_o}}\right]^{\frac{1}{S}} -1 \ ,$$

where VA_o and VA_m represent the real value added in two benchmark years, o and m, L_m, L_o, K_m, and K_o are the labor and capital values in the same benchmark years, and S is the number of months spanning the benchmark years. The benchmark years are usually chosen to be the last revision year for the index and the present revision year. In contrast, the Dallas 1971 methodology calculated productivity increments using the formula

$$(10) \qquad C_L = \left[\frac{\frac{VA_m}{L_m}}{\frac{VA_o}{L_o}} \right] \div S$$

and similarly for C_K.

The San Francisco "sum of payments" methodology for estimating value added is somewhat more involved.12/ The San Francisco methodology assumes the labor factor share satisfies the exponential equation

$$(11) \qquad \left(\frac{P_L \cdot L}{VA} \right)_t = \exp(a_o + a_1 t).$$

Choosing the years o and m as benchmarks, the equations

$$(12) \qquad \left(\frac{P_L \cdot L}{VA} \right)_o = \exp(a_o + a_1 \cdot 0)$$

and

$$(13) \qquad \left(\frac{P_L \cdot L}{VA} \right)_m = \exp(a_o + a_1 m)$$

can be simultaneously solved for a_o and a_1. After solving for a_o and a_1, the general interpolation expression for year t can be written in terms of the benchmark labor factor shares as follows:

$$(14) \qquad \left(\frac{P_L \cdot L}{VA} \right)_t = \left[\left(\frac{P_L \cdot L}{VA} \right)_o \right]^{\frac{m - t}{m}} \left[\left(\frac{P_L \cdot L}{VA} \right)_m \right]^{\frac{t}{m}} .$$

In a similar manner, an exponential trend for the capital factor share using benchmark years o and m provides the general interpolation formula

(15) $$\left(\frac{P_K \cdot K}{VA}\right)_t = \left[\left(\frac{P_K \cdot K}{VA}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{P_K \cdot K}{VA}\right)_m\right]^{\frac{t}{m}} .$$

The San Francisco methodology also assumes exponential trends for the output-input ratios, $(VA/L)_t$ and $(VA/K)_t$. This results in the interpolation formulas

(16) $$\left(\frac{VA}{L}\right)_t = \left[\left(\frac{VA}{L}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{VA}{L}\right)_m\right]^{\frac{t}{m}}$$

and

(17) $$\left(\frac{VA}{K}\right)_t = \left[\left(\frac{VA}{K}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{VA}{K}\right)_m\right]^{\frac{t}{m}} .$$

Combining the results of equations (14) - (17), the San Francisco "sum-of-payments" formula for estimating industry value added becomes

(18) $$VA_t = W_{1t} \cdot L_t + W_{2t} \cdot K_t$$

where the time-varying weights are

(19) $$W_{1t} = \left[\left(\frac{P_L \cdot L}{VA}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{P_L \cdot L}{VA}\right)_m\right]^{\frac{t}{m}} \left[\left(\frac{VA}{L}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{VA}{L}\right)_m\right]^{\frac{t}{m}}$$

and

(20) $$W_{2t} = \left[\left(\frac{P_K \cdot K}{VA}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{P_K \cdot K}{VA}\right)_m\right]^{\frac{t}{m}} \left[\left(\frac{VA}{K}\right)_o\right]^{\frac{m-t}{m}} \left[\left(\frac{VA}{K}\right)_m\right]^{\frac{t}{m}}.$$

For all of the "sum-of-payments" methodologies the output-input ratios (VA/L) and (VA/K) are computed by using real historical value added values obtained by deflating nominal (current) value added by an appropriate price index.

3.2 Empirical Production Function Methods

A major change in the Dallas Federal Reserve Bank's Texas Industrial Production Index (TIPI) occurred in 1975 with the specification and estimation of Cobb-Douglas production functions to predict real value added in these industries where output is not directly observable on a monthly basis. The 1975 TIPI monograph voiced a major criticism of the sum-of-payments method as implemented by the Atlanta and Dallas (1971) Federal Reserve Banks. It criticized these versions for the implausibility of their fixed proportions assumption. Variable proportions production was suggested as an appropriate alternative. As stated in the 1975 TIPI monograph:13/

> (One) source of error in the 1971 index has been use of a fixed proportions model to predict output from the input series. The present revision of TIPI makes explicit use of a variable proportions model, the Cobb-Douglas model. A fixed proportions production model implies that changes in factor prices do not affect ratios used in the production process.
>
> This assumption will not cause serious trouble when prices change slowly over time. However, with recent dramatic increases in energy costs, the kilowatt hour series is bound to be affected. The main argument for a fixed proportions model is that most industrial

> production is capital intensive and, therefore, insensitive to small changes in input prices. While such an observation may be valid over a period of time when the firm is not free to simultaneously adjust the level of all factors of production, it is doubtful that such is the case in the long run.
> ...
> In this revision, it is recognized that changes in factor prices cause change in input-output ratios. This supposition is more believable than a fixed proportions model...

The fixed proportions criticism is potentially a valid one if it leads to a methodology which provides superior forecasts of industry output. Of all the regional production index methodologies published to date, the 1975 TIPI is the only one using empirical production functions to estimate industrial output. The Cobb-Douglas production function was the variable proportions function chosen because of the ease in estimating it and the direct interpretations offered by its parameters. The input coefficients are the output elasticities and their sum represents the returns to scale in production. In the linear homogeneous case, the output elasticities coincide with the respective factor shares.

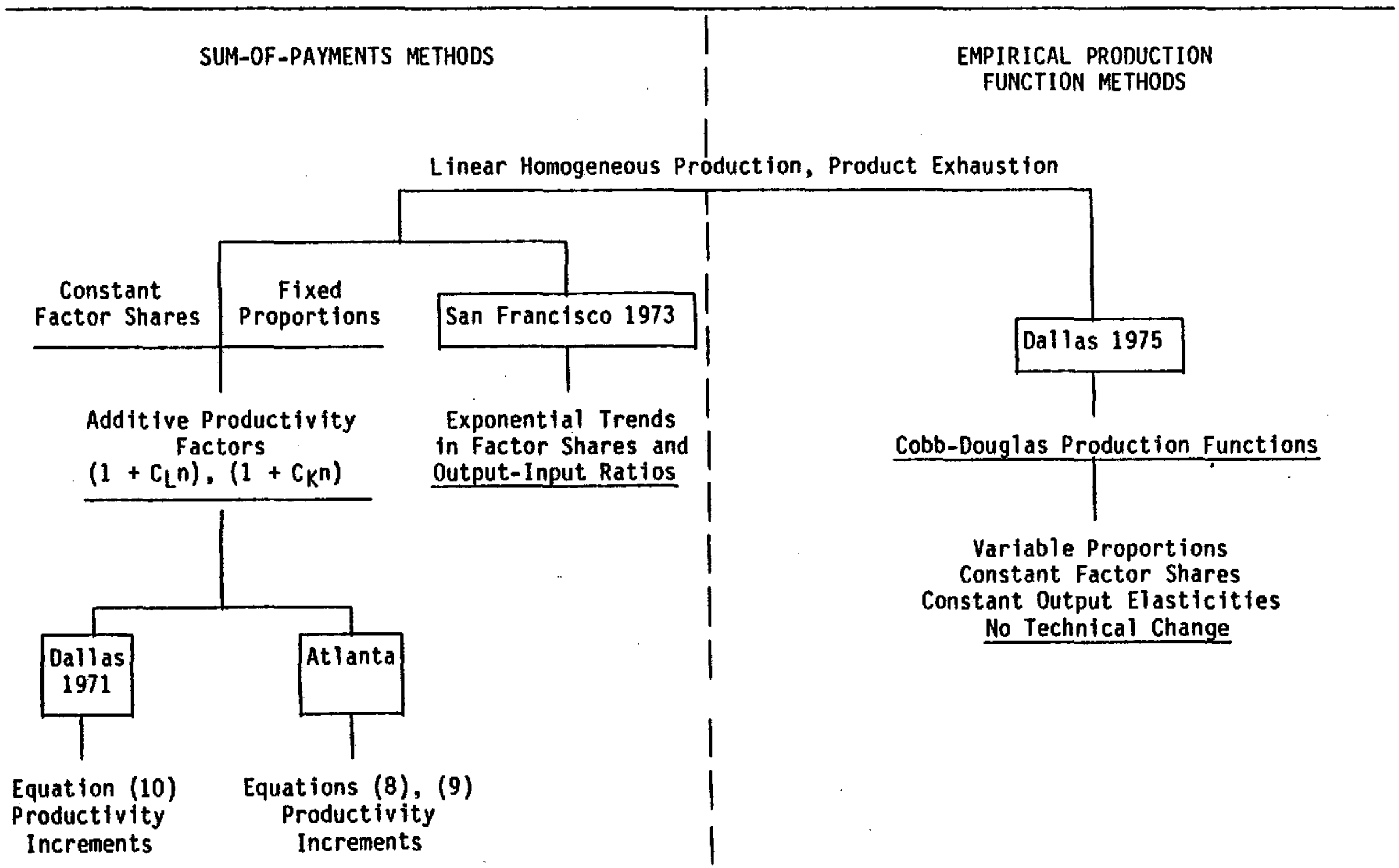
In the 1975 TIPI revision, the dependent variable of the Cobb-Douglas function was the natural logarithm of annual value added in each industry while the independent variables were the natural logarithms of the book value of capital14/ and manhours of labor by industry. Constant returns to scale were imposed and no adjustments were made for possible technological change. Once the industry production functions were estimated, they were "converted" to Cobb-Douglas functions with manhours and kilowatt hours of electricity consumption as inputs15/ and used as tools for estimating industry production given monthly observations of manhours and electricity consumption. The method of estimation was taken to be ordinary least squares or ridge regression16/ depending upon an informal inspection of the degree of multicollinearity present in the data17/.

3.3 Some Possible Modifications

To repeat, two different approaches to regional production index construction have been reviewed: sum-of-payments methods and empirical production function methods. These approaches and their assumptions are summarized in Chart 1. A commonality between the two approaches is the assumptions of linear homogeneous production and product exhaustion within each industry. Apart from this, the two approaches are quite different. Among the sum-of-payments methodologies we have twins, the Dallas 1971 and Atlanta indices and a first cousin, the San Francisco 1973 index. Both the Dallas 1971 and Atlanta indices assume constant factor shares and additive productivity factors. They are not, however, identical twins. The Dallas 1971 index calculates productivity increments according to the formula (10) while the Atlanta index uses the "compound interest formulas" (8) and (9). The San Francisco 1973 index assumes that, though the factor shares and output-input ratios satisfy product exhaustion, they follow exponential trends over time.

CHART 1

TWO APPROACHES
TO
REGIONAL PRODUCTION
INDEX CONSTRUCTION



To present, there has been only one empirical production function method proposed and used, that being the Cobb-Douglas production function approach implemented in the 1975 Dallas TIPI index. Though variable proportions are allowed between factor inputs, manhours and electricity, constant factors shares and output elasticities are assumed. In addition, technical change was not modeled for fear of reducing the sensitivity of the index.

Many derivatives of these methodologies can be suggested which might overcome possible weaknesses. One troubling aspect of the sum-of-payments methodologies is the calculation of productivity factors. The choice of two "atypical" years for benchmarking could result in distorted productivity factors or in the case of the San Francisco methodology distorted exponential time paths. These distortions could, in turn, lead to substantial over or understatement of actual industry production levels.

Which productivity estimates for manufacturing industries are "good" and which are "bad"? One partial answer to this question can be obtained by examining the economic literature on industrial productivity. Using this literature, industry productivity factors can be determined. Then a "benchmark" sum-of-payments methodology using these external productivity factors can be specified and used for purposes of comparison.

Though there are many sources for estimates of manufacturing productivity, probably one of the most recent and thorough studies on productivity trends is the work of Kendrick and Grossman.18/ These authors construct annual total factor productivity indices for several sectors of the U.S. economy including the two-digit SIC code industries in U.S.

manufacturing during the years 1948-1976.19/ Using these indices, semi-log regressions of the form, $\ln TFP_i = \beta_1 + \beta_2 T + e$, can be estimated, where TFP_i = total factor productivity index of the i-th industry and T = 1,2,... represents successive years in the sample. Assuming national productivity trends reflect those at the regional level, value added in the i-th industry could be estimated by the formula

$$(21)\quad VA_t = \left\{\left(\frac{P_L \cdot L}{VA}\right)_0 \cdot \left(\frac{VA}{L}\right)_0 \cdot L_t + \left(\frac{P_K \cdot L}{VA}\right)_0 \cdot \left(\frac{VA}{K}\right)_0 \cdot K_t\right\} \cdot \exp(\hat{\beta}_2 \cdot t),$$

where $(P_L \cdot L/VA)_0$ and $(P_K \cdot K/VA)_0$ represent factor shares in a given base year, $(VA/L)_0$ and $(VA/K)_0$ represent output-input ratios in the same base year, and $\hat{\beta}_2$ is an efficient estimate of the exponential growth rate of total factor productivity in a given industry obtained from the Kendrick and Grossman data. Should alternative sum-of-payments methods using regional specific productivity factors perform just as well in some statistical sense as this "benchmark" sum of payments method, then the productivity factors calculated from regional value added - input ratios must be judged to be adequate. This is a point of investigation in the next section of this paper.

One objection that might be raised concerning the choice of the Cobb-Douglas functional form is its lack of flexibility. Why not fit a constant elasticity of substitution (CES) production function so that factor shares might be allowed to vary over time?20/ Another even less stringent functional form is the transcendental logarithmic (translog) production function. However, work done by Sullivan support the contention that, in terms of forecasting state manufacturing output, the Cobb-Douglas model does, for all practical purposes, as well as the more flexible functional forms.21/ In addition, research reported by Zarembka, Nerlove and others would seem to suggest that the elasticity of substitution for most U.S. manufacturing industries is close to unity thus supporting the applicability of the Cobb-Douglas functional form.22/ Given the present findings of the literature, the return would appear to be small for investigating more flexible functional forms for the purpose of fitting empirical production functions.

If the functional form chosen for estimating manufacturing output is not an issue, the issue of the choice of independent variables is of concern. In the 1975 Dallas TIPI revision it was thought appropriate that capital value be imputed by using national capital-labor ratios and then "converting" what is, in theory, a labor-capital stock production function to a production function with labor and energy flows as inputs. The capital-labor ratio computation of capital stock is likely, however, to lead to strident multicollinearity problems especially if year-to-year changes in the capital-labor ratio are minimal. As an alternative, it might be proposed that the Cobb-Douglas function with labor and energy as inputs should be estimated directly.

Another issue is the method of estimating the Cobb-Douglas production function. Direct estimation of the Cobb-Douglas function via ordinary least squares (OLS) is very susceptible to the effects of multicollinearity. As energy and labor usage are not likely to move independently of each other through time, OLS estimates of the parameters of the Cobb-Douglas function are likely to be very imprecise. One way to combat the effects of multicollinearity is to use valid prior information.

Before describing the use of prior information in the empirical production function approach, some notation must be established. Direct estimation of industry value added by means of the Cobb-Douglas production function involves the estimation of the equation

$$VA_t = A\, L_t^{\alpha} K_t^{\beta} \exp(e_t)$$

or

$$(22) \qquad \ln(VA_t) = \ln A + \alpha \ln(L_t) + \beta \ln(K_t) + e_t,$$

where VA_t = real value added for a given industry at year t, L_t = annual manhours for a given industry at year t, K_t = annual electricity usage for a given industry at year t, A is an unknown parameter representing a basic level of production when L = K = 1, α and β are the output elasticities of labor and capital, and e_t is a disturbance term assumed to be distributed independently and identically as a normal random variable with zero mean and constant variance. If disembodied technical change is assumed, $A = A_0 \cdot \exp(a + \lambda T)$, the estimating equation becomes

$$(23) \quad \ln(VA_t) = C + \alpha \ln(L_t) + \beta \ln(K_t) + \lambda T + e_t,$$

where λ is the exponential rate of technical change, $C = \ln A_0 + a$, and T = 1,2,..., n is an index representing n successive years of observations. Ordinary least squares estimation of either (22) or (23) may yield imprecise coefficient estimates because of the potential collinearity between the explanatory variables. One way to combat the multicollinearity problem is to supplement the data with prior information on the parameters α, β, and λ.

Under the assumption of perfect competition, α represents the labor share of value added. Current and previous values of labor shares for state two-digit manufacturing industries are available from the Annual Survey of Manufacturers. Thus, the estimated value of α should be somewhere in the neighborhood of the survey values. The properties of the Cobb-Douglas production function require that the sum of output elasticities, $\alpha + \beta$, equal the returns to scale in the industry, $r \equiv \alpha + \beta$. Several studies have been made of the returns to scale in two-digit national manufacturing industries.23/ The estimate of the returns to scale in a given industry should be consistent with these report results. Likewise, data is readily available on technical progress in two-digit national manufacturing industries.24/ The estimate of the rate of technical change in an industry should reflect the findings of the available data. Thus, prior information is currently available for labor factor shares, returns to scale, and rates of technological progress. One way to incorporate this information into the empirical production function approach is to use Bayesian estimation. For illustrative purposes, the Bayesian estimation approach is described for the i-th SIC code industry. The methodology can be similarly applied to any two-digit industry.

Assume interest centers on estimating equation (23). Let all of the sample observations on this model be represented by the matrix form

(24) $$\underline{y} = X\underline{\beta} + \underline{e} ,$$

where

$$\underline{y} = \begin{bmatrix} \ln(VA_1) \\ \ln(VA_2) \\ \vdots \\ \ln(VA_n) \end{bmatrix} ; X = \begin{bmatrix} 1 & \ln(L_1) & \ln(K_1) & 1 \\ 1 & \ln(L_2) & \ln(K_2) & 2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \ln(L_n) & \ln(K_n) & n \end{bmatrix}$$

$$\underline{\beta} = \begin{bmatrix} C \\ \alpha \\ \beta \\ \lambda \end{bmatrix} ; \underline{e} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix},$$

and n is the number of sample observations concerning the i-th two-digit industry. Furthermore assume $\underline{e}$ is distributed as a multivariate normal random vector with zero mean and scalar variance - covariance matrix $\sigma^2 I$. Let $R\underline{\beta}$ denote independent linear combinations of the coefficient vector $\underline{\beta}$. Assume that prior information exists of the form

$$P(R\underline{\beta}) \sim N(R\overline{\underline{\beta}}, \Psi) ,$$

where $\sim$ means "distributed as", $R\overline{\underline{\beta}}$ represents the mean of the normal prior distribution and Ψ is the precision of the prior distribution. Then, for given σ^2, the Bayes estimator which minimizes posterior expected loss is[25]

$$\tilde{\underline{\beta}} = (X'X + \sigma^2 R' \Psi^{-1} R)^{-1} (X'\underline{y} + \sigma^2 R' \Psi^{-1} R\overline{\underline{\beta}}) .$$

In actuality σ^2 is unknown but can be estimated by ordinary least squares. The choice of $R\overline{\underline{\beta}}$ and Ψ is detailed in the following section. Hopefully, Bayesian estimation of the Cobb-Douglas production function will prove to be an improved variant of the empirical production function approach.

4.1 Performance of Competing Methodologies

For the purpose of examining the forecasting accuracies of the various competing methodologies, a data base was constructed which consists of annual data spanning 1967-1978 on Texas manhours, kilowatt hour electricity consumption, real value added, and payroll of all employees (both production and administrative) by two-digit SIC code industries. Texas manhours were obtained from the Bureau of Labor Statistics while the statistics department of the Dallas Federal Reserve Bank collects the kilowatt hour data by means of extensive questionnaire mailings. The value added and payroll data were obtained from various volumes of the Census of Manufacturers and Annual Survey of Manufacturers both published by the Census Bureau of the Commerce Department. The SIC code industries covered in the data base are

Sic Code	Title
20	Food and kindred products
22	Textile mill products
23	Apparel & allied products
24	Lumber and wood products
25	Furniture and fixtures
26	Paper and allied products
27	Printing and publishing
28	Chemical and allied products
30	Rubber and plastic products
32	Stone, clay and glass products
33	Primary metal industries
34	Fabricated metal products
35	Machinery, except electrical
36	Electrical machinery
37	Transportations equipment

SIC code industry 21 (tobacco) was not included since it is so small in Texas as to be ignored by the Census. SIC code 29 (petroleum) is one of the industries where output is directly observed so there is no interest in determining an accurate forecasting rule for it. Due to the reclassification of SIC codes by the Census Bureau, the SIC code industries 31 (leather), 38 (instruments), and 39 (miscellaneous manufacturers) were not included in this data base.

For the purpose of calculating real value added, national price deflators for these two-digit industries were obtained from the Bureau of Economic Analysis of the Commerce Department in Washington, D.C. The base year for these deflators is 1972. These national price deflators were taken to be indicative of Texas industrial prices. Previous experience at the Dallas Bank with regional deflators has shown that Texas deflators differ little from their national counterparts.26/

In order to choose between the various methodologies, the data were divided into two parts; the 1967-1972 data were chosen to be the within-sample data while the 1973-1978 data were chosen to be the out-of-sample data. That is, the 1967-1972 data were used to secure the needed estimates and/or ratios to make a proposed methodology operational while the 1973-1978 data were used to gauge the accuracies of the proposed methods in predicting real value added by Texas industries. The measures of forecasting accuracy chosen for inspection were mean absolute error (MAE) and root mean square error (RMSE). These measures are defined as:

$$MAE = \frac{\sum_{t=1}^{n} \left| A_t - P_t \right|}{n}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (A_t - P_t)^2}{n}} ,$$

where A_t = actual real value added in a given industry at time t in the out-of-sample period, P_t = predicted real value added at time t, and n is the number of observations in the out-of-sample period (in the present case, n = 6).

The out-of-sample forecasting accuracies of the sum-of-payments methods are presented in Table 1. The first sum-of-payments method assumes constant factor shares and value added to input ratios in each industry and is distinguished by the fact that no productivity factors are used. Thus, this method uses the formula

$$VA_t = \left(\frac{P_L \cdot L}{VA}\right)_o \cdot \left(\frac{VA}{L}\right)_o \cdot L_t + \left(\frac{P_K \cdot L}{VA}\right)_o \cdot \left(\frac{VA}{K}\right)_o \cdot K_t$$

where $(P_L \cdot L/VA)_o = 1 - (P_K \cdot K/VA)_o$ is the fixed labor share and $(VA/L)_o$ and $(VA/K)_o$ are fixed value added to input ratios. Instead of using any one year to measure the labor share, the labor share was calculated as the average labor share of the years 1967-1972. The capital factor share was calculated as one minus the labor share. The value added to input ratios were calculated using 1972 real value added in the given industry and manhours and kilowatt hours used by the industry in the same year.

The other sum-of-payments methods investigated differ from the first only in the way that their productivity factors were calculated and implemented. For the second method displayed in Table 1, the productivity factors were calculated using equation (10) with the benchmark years for calculating value added to input ratios of 1967 and 1972 and S being 5. These productivity factors are those adopted by the 1971 version of TIPI. The third method displayed used the Atlanta formulas (8) and (9) to calculate productivity factors. Both the second and third methods implemented their productivity factors by using the "additive" formula (5).

A fourth method is essentially the same as the others except two-digit industry, national productivity data compiled by Kendrick and Grossman27/ for the years 1948-1972 were used in conjunction with semi-log regressions to estimate industry productivity growth rates.28/ These productivity estimates were assumed to be accurate representations of Texas productivity growth rates and were incorporated by means of the formula

$$VA_t = \left\{ \left(\frac{P_K \cdot L}{VA}\right)_0 \cdot \left(\frac{VA}{L}\right)_0 \cdot L_t + \left(\frac{P_K \cdot K}{VA}\right)_0 \cdot \left(\frac{VA}{K}\right)_0 \cdot K_t \right\} \cdot \exp(\hat{\beta}_2 \cdot t),$$

where $\hat{\beta}_2$ is an efficient estimate of the exponential growth rate of total factor productivity in a given industry obtained from the Kendrick and Grossman data.

Finally, the San Francisco method29/ described in Section 3.1 was also used to predict real value added in the out-of-sample period. The exponential growth paths for the labor and energy shares and the value added to input ratios were calculated using 1967 and 1972 as benchmark years.

In Table 1 the accuracies of each of these methods are reported for each SIC code industry. Weighted averages of the mean absolute errors and root mean square errors of the industries are also reported where the weights are those obtained by calculating the fraction of the total 1972 value added produced by the respective industries. Using the weighted MAEs and RMSEs as a guide, the two superior methods are methods 3 and 4. The Atlanta productivity factors perform substantially better than the 1971 TIPI productivity factors. Inspection of the data revealed that the 1971 TIPI productivity factors were generally quite large and often lead to upwardly biased estimates of real value added. Furthermore, the Atlanta method with its fixed factor shares and productivity incremented value added to input ratios does seem to marginally outperform the exponential growth path methodology assumed in the San Francisco method. The Atlanta productivity formula also seems to offer some "inside information" as to regional productivity differences that do not get factored into the Kendrick-Grossman national productivity data. Given these results, it appears that, of the sum-of-payments methods, the use of fixed factor

TABLE 1
PREDICTIVE ACCURACIES
OF
SUM OF PAYMENTS METHODS

SIC Code	FIXED FACTOR SHARES AND VA TO INPUT RATIOS								EXPONENTIAL TIME PATHS OF FACTOR SHARES AND VA TO INPUT RATIOS		Value Added 1972	Weights
	No Productivity Factors		1971 TIPI Productivity Factors		Atlanta Productivity Factors		Kendrick-Grossman Productivity Factors		San Francisco Method			
	METHOD 1		METHOD 2		METHOD 3		METHOD 4		METHOD 5			
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE		
20	237.17	272.91	1359.70	1608.90	158.67	190.13	162.37	196.04	192.82	236.03	1716.6	.127
22	38.26	42.94	8.35	9.76	36.55	40.97	29.32	33.21	29.09	32.18	49.2	.004
23	197.93	209.30	187.96	219.16	217.87	230.33	162.91	170.96	300.54	327.05	551.9	.041
24	57.87	66.06	278.81	299.95	33.73	41.24	40.77	46.43	58.33	65.53	369.4	.027
25	23.05	33.46	121.32	131.73	20.10	25.55	19.89	24.90	39.42	52.77	199.0	.015
26	69.63	78.39	236.73	297.38	38.19	57.42	48.85	63.86	73.49	82.40	342.0	.025
27	24.08	33.52	489.60	566.19	61.10	72.39	48.28	52.15	130.84	149.13	659.5	.049
28	1361.20	1407.80	2383.30	2787.00	750.55	914.63	839.21	973.54	939.46	1042.50	3189.8	.235
30	25.45	28.65	428.65	510.45	69.99	91.68	33.15	48.87	56.08	73.44	349.1	.026
32	41.27	46.42	493.62	549.48	43.05	48.81	33.82	40.05	51.13	63.00	610.9	.045
33	169.04	197.75	329.59	367.50	231.81	279.19	169.96	199.60	336.24	383.41	784.9	.058
34	137.66	178.78	980.25	1211.30	102.49	119.05	206.16	273.53	143.98	181.46	1089.6	.080
35	499.46	550.85	1377.10	1668.60	143.57	189.00	423.51	466.00	223.37	262.87	1449.9	.107
36	146.97	182.67	1190.00	1354.70	227.74	256.26	118.25	150.50	130.99	151.44	938.2	.069
37	310.79	345.21	554.84	700.39	329.26	362.31	206.66	249.60	516.05	559.97	1260.6	.093
WEIGHTED AVERAGE TOTALS	478.92	512.39	1191.71	1406.92	297.85	357.04	331.05	386.59	383.82	432.58		

shares and productivity incremented value added to input ratios using the Atlanta type productivity factors is to be recommended. Hereafter, we will refer to this method as the Atlanta method.

The empirical production function methodologies offer alternatives which might prove superior to the sum-of-payments methods. In Table 2 the predictive accuracies of various production function methodologies for the out-of-sample period are summarized. All of the production function methods result from choosing different methods to estimate Cobb-Douglas production functions of the form (22) or (23). Three major estimation methods were considered: ridge regression, ordinary least squares (OLS), and Bayesian estimation. As commented in footnote 17 above, ridge regression via the ridge trace method is an *ad hoc* technique and thus is generally not to be recommended. However, for the purpose of comparing the 1975 TIPI methodology with the other methods proposed here, the ridge estimates for the output elasticities of labor and capital from the Dallas 1975 study were included.30/

The ordinary least squares estimates were obtained for each industry in the usual manner of minimizing the sum of squared errors. The Bayesian estimation approach was the method chosen to bring to bear valid prior information.

Given previous studies of U.S. manufacturing and the availability of annual labor shares for Texas industries, prior information concerning the output elasticity of labor, α, the returns to scale of the industry, r, and the exponential rate of technical change, λ, is available for estimating production functions of the form (22) or (23). The prior mean of α for each industry, $\bar{\alpha}$, was chosen to be the sample mean of the industry's labor shares for the years 1967-1972. The sample standard deviations of the factor shares never exceeded 0.05 for any industry. For the purpose of being conservative in the implementation of the prior information, the prior standard deviation of α was set equal to 0.05 for all industries. The prior mean for the returns to scale, $\bar{r}$, for each industry was taken to be 1.00 because of the central role assumed for constant returns to scale in the specification of the prior on α. This supposition is supported in Moroney's study of returns to scale in U.S. two-digit manufacturing industries where he reports estimates made by himself, Hildreth-Liu, and Fergueson.31/ The overall mean of the returns to scale estimates is 1.003 with standard deviation 0.07. In line with Moroney's study the prior standard deviation of r was set to 0.07 for all industries. Finally, the Kendrick-Grossman national productivity data was used to fit semi-log regressions on time to obtain an estimate, $\bar{\lambda}$, of the rate of technical change for each industry. These estimates were chosen to be the prior means for λ in each industry. To be on the conservative side, the prior standard deviation of λ was chosen to be 0.005 because this exceeds the standard errors of the estimates $\bar{\lambda}$ for all industries.

In summary, the Bayesian prior for model (23) consists of the prior mean $R\underline{\bar{\beta}} = (\bar{\alpha}, \bar{r}, \bar{\lambda})'$ and precision matrix

$$\Psi = \begin{bmatrix} (0.05)^2 & & o \\ & (0.07)^2 & \\ o & & (0.005)^2 \end{bmatrix} .$$

As a counterpart of this "vague" prior information which was intentionally chosen conservatively, "dogmatic" priors can be established for α, r, and λ by setting their respective prior standard deviations equal to zero. This results in restricted least squares estimation where the estimates of α, r, and λ are forced to equal the prior means exactly leaving only the intercept to be estimated via a minimization of the restricted sum of squares.

The above methods similarly apply to estimating equation (22) where no technical change is included. Here the prior of λ has a zero mean and standard deviation.

The results of the predictive accuracies of the various production function methods are summarized in Table 2. The mean absolute errors and root mean square errors of the estimates were calculated using the predicted VA_t deriving from taking the antilogarithm of the predicted value of $\ln(VA_t)$. The Bayesian estimation methods outperformed the ridge and OLS estimation methods apparently because of the implementation of valid prior information. Among the Bayesian estimation methods, the inclusion of the technical change variable seems to be worthwhile and substantially so. The best of the Bayesian estimation methods were the ones using dogmatic priors and technical change. The vague priors on α, r, and λ ran a close second.

The important point to note, however, is the comparison between the best of the sum-of-payments methods and the best of the empirical production function methods. The sum-of-payments methods 3, 4, and 5

TABLE 2

PREDICTIVE ACCURACIES
OF
EMPIRICAL PRODUCTION FUNCTION METHODS

	Ridge Estimation 1975 TIPI		OLS Cobb-Douglas with L, K		OLS Cobb-Douglas with L, K, T		Bayesian Estimation L, K Vague Priors on α and r		Bayesian Estimation L, K Dogmatic Priors on α and r		Bayesian Estimation L, K, T Vague Priors on α, r, and λ		Bayesian Estimation L, K, T Dogmatic Priors on α and r		Bayesian Estimation L, K, T Dogmatic Priors on α, r, and λ	
SIC Code	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
20	374.38	408.12	553.48	596.65	350.73	373.75	222.43	272.27	372.63	406.51	171.70	201.75	178.35	204.37	161.18	196.75
22	34.71	39.67	32.70	37.47	51.75	54.74	35.22	40.80	35.17	40.56	20.13	26.38	21.61	27.35	18.11	24.04
23	239.33	247.54	149.83	172.46	2209.88	3090.91	232.46	241.56	224.10	234.10	134.95	174.55	294.14	305.74	165.23	173.35
24	123.41	136.35	97.25	119.67	246.73	277.80	97.86	115.19	115.72	129.97	32.17	40.25	101.03	114.97	31.45	38.98
25	33.05	43.56	42.62	54.45	731.56	871.12	32.23	43.32	32.58	43.54	22.24	29.00	24.57	33.80	21.79	28.45
26	88.58	95.21	35.03	54.51	35.88	53.91	64.99	75.26	72.82	81.22	37.27	55.97	37.90	56.28	37.33	55.99
27	59.15	59.90	103.79	149.12	617.62	754.60	46.42	54.74	26.39	34.73	34.54	41.73	144.09	153.08	68.44	60.53
28	2066.35	2103.43	2627.73	2698.79	1644.03	1730.91	1877.42	1911.82	2152.71	2045.15	1116.36	1233.11	1020.98	1246.40	1145.03	1178.37
30	79.31	82.71	92.34	132.41	124.49	165.72	73.31	76.82	84.55	87.20	37.85	38.81	61.85	84.56	38.33	40.33
32	51.35	69.00	98.73	144.18	119.67	168.55	45.27	62.28	44.16	60.61	30.67	35.42	56.07	79.05	31.01	36.00
33	134.72	139.56	112.72	141.54	164.60	187.47	136.08	142.96	148.45	158.37	159.30	178.45	256.91	302.09	148.32	159.57
34	316.98	369.95	197.43	257.95	152.00	188.93	245.62	281.39	286.78	328.72	336.70	376.45	68.62	77.87	449.10	513.11
35	879.12	928.03	163.42	224.07	180.91	243.46	797.85	840.72	813.56	857.70	776.85	818.40	462.62	486.40	705.67	742.63
36	404.98	455.31	582.69	670.18	158.85	234.14	389.73	438.63	398.21	447.95	156.58	190.69	112.63	127.94	161.25	196.42
37	276.77	313.45	328.12	361.10	424.42	458.47	281.52	319.01	270.58	310.44	178.44	202.23	371.18	404.40	159.91	168.16
WEIGHTED AVERAGE TOTALS	737.33	768.90	820.69	872.51	670.61	762.79	656.07	687.74	697.26	741.92	473.82	490.23	402.14	472.01	450.29	476.58

showed a clear superiority over the Cobb-Douglas forms estimated by using the various methods, even the methods incorporating prior information. It appears that the less sophisticated techniques work quite well. The logarithmic form of the Cobb-Douglas form does not, in general, render superior predictions of real value added.

Given the results of this out-of-sample analysis, the Atlanta method was chosen for constructing the 1983 revision of the Texas Industrial Production Index. The details of the construction of the 1983 TIPI are contained in 1983 Revision of the Texas Industrial Production Index available upon request.32/

5. Conclusion

Several methodologies which are or have been used in the construction of regional production indices are discussed here. The methods can be classified according to the paradigm used to estimate real value added by industry, either the sum-of-payments approach or the empirical production function approach. The sum-of-payments approach uses the product exhaustion result obtained by assuming industry is perfectly competitive and production is linearly homogeneous. A weighted linear combination of labor and capital is obtained with the weights of the inputs changing over time according to specific assumptions concerning factor productivity or exponential time trends of factor shares. In contrast the empirical production function approach estimates real value added using conventional production functions such as the Cobb-Douglas production function. Variable proportions are a characteristic of this approach though multicollinearity can cause problems in estimation.

Data concerning Texas manufacturing was used to examine which of the many proposed methodologies preformed the best in predicting real value added in an out-of-sample period. The less sophisticated sum-of-payments techniques preformed better than the empirical production function methods even when using prior information. Evidently, the logarithmic form of the Cobb-Douglas function does not lend itself to accurate prediction in this context.

In terms of the costs of index construction, a sum-of-payments method like that used by the Atlanta Federal Reserve Bank is less labor and capital intensive than the empirical production function approaches especially those involving the use of prior information. Experience obtained from the above case study suggests that, in terms of staff hours spent and computer time used, the Atlanta method is approximately one-fourth as expensive as empirical production function methods which used Bayesian estimation and require the fitting of auxiliary equations to obtain prior information.

FOOTNOTES

1. The author is an associate professor of economics at Southern Methodist University, Dallas, Texas. This study was undertaken as part of an evaluation of index methodologies for the 1983 revision of the Texas Industrial Production Index on which the author served as a consultant. The author is extremely grateful to the Federal Reserve Bank of Dallas for its financial support and the guidance and encouragement offered by Jim Pearce and Leroy Laney. Excellent research assistance was provided by Robert Feil, Brian McKee, John Loney, Wayne Maples, and Gary Ziegler. Any opinions expressed are those of the author and not necessarily those of the Federal Reserve Bank of Dallas or the Federal Reserve System.

2. See, for example, R. B. Litterman and R. M. Todd, "As the Nation's Economy Goes, So Goes Minnesota's," Federal Reserve Bank of Minneapolis Quarterly Review (Spring-Summer, 1983), pp. 1-9.

3. During this period Texas manhours in manufacturing grew 2.51% while it fell 9.65% nationwide. Nominal personal income in Texas grew 4.24% while it grew only 2.89% nationwide.

4. Selected references on regional economic models include N. J. Glickmen, Econometric Analysis of Regional Systems (NY: Academic Press), 1977, and P. A. Anderson, "Help for the Regional Forecaster: Vector Autoregression," Federal Reserve Bank of Minneapolis Quarterly Review (Summer, 1979), 2-7. References on regional production indices are cited in footnote 11 below.

5. For example, Texas Business has a regular section which contains Texas residential construction, industrial production, business incorporations and etc. The Dallas Morning News has begun

publication of its own leading indicator for Texas. See "Economic Report Makes New Debut," <u>Dallas Morning News</u>, November 18, 1982.

6. See the several references in the following text and footnotes.

7. Value added is defined in the <u>1977 Census of Manufacturers</u> as follows: "This measure of manufacturing activity is derived by subtracting the cost of materials, suppliers, containers, fuel, purchased electricity, and contract work from the value of shipments. The result of this calculation is then adjusted by the value added by merchandising operations plus the net change in finished goods and work-in-progress inventories between the beginning and end of the year."

8. A few exceptions exist in Texas. For example, petroleum refining (SIC 29) by physical quantity is available on a monthly basis.

9. C. E. Moody, "The Measurement of Capital Services by Electrical Energy," <u>Oxford Bulletin of Economics and Statistics</u>, 36 (February, 1974), 45-52.

10. For a proof see A. C. Chiang, <u>Fundamental Methods of Mathematical Economics</u>, 2nd ed. (New York: McGraw-Hill, 1974), pp. 407-410.

11. <u>Methodology of the Texas Industrial Production Index, 1971</u>, Federal Reserve Bank of Dallas, unpublished manuscript. F. R. Strobel, <u>Sixth District Manufacturing Index, Technical Note and Statistical Supplement</u>, Federal Reserve Bank of Atlanta, January, 1975 and April, 1978. J. Walsh and L. Butler, "The Construction of Industrial Production Indices for Manufacturing Industries in the Twelfth Federal Reserve District," Working paper no. 13, Federal Reserve Bank of San Francisco, February, 1973.

12. The discussion here does not exactly coincide with the San Francisco methodology discussed in Working Paper no. 13 (see footnote 11). Three-factor production is assumed there with inputs labor, energy (capital), and "other factors" represented by X_t. Though X_t is not observable, assuming that $(VA/X_t) \cdot X_t$ is a linear combination of labor and capital allows the specification of a general forecasting formula analogous to equation (18) below. However, in the interest of a unified presentation of the "sum-of-payments" methodology, a two-factor presentation of the San Francisco methodology was chosen.

13. See Methodology of the Texas Industrial Production Index, 1975, Federal Reserve Bank of Dallas, unpublished manuscript, pp. 11,12, and 14.

14. Book value of capital was derived by multiplying U.S. capital-labor ratios by total employment in an industry. The Texas capital-labor ratios were assumed to be close to U.S. averages.

15. The method used to "convert" the estimated Cobb-Douglas production functions with labor and capital as inputs to ones with labor and energy as inputs can be found in Methodology of Texas Industrial Production Index 1975, p. 30.

16. A. E. Hoerl and R. W. Kennard (1970a), "Ridge Regression: Biased Estimation of Nonorthogonal Problems," Technometrics 12:55-67: Ibid, (1970b), "Ridge Regression: Applications to Nonorthogonal Problems," Technometrics 12:69-82.

17. The use of ridge regression in conjunction with the ridge trace technique [see Hoerl and Kennard (1970b)] has no decision theoretic basis and thus must be viewed as an ad hoc technique. For a critical review of ridge regression see D. Conniffe and J. Stone (1973), "A Critical View of Ridge Regression," The Statistician, pp. 22, 181-187.

18. J. W. Kendrick and E. S. Grossman, Productivity in the United States: Trends and Cycles (Baltimore: Johns Hopkins University Press, 1980).

19. Ibid, pp. 141-160.

20. See J. R. Moroney, The Structure of Production in American Manufacturing (Chapel Hill: The University of North Carolina Press, 1972), for a good discussion of the use of the CES production function to measure attributes of production in U.S. manufacturing.

21. B. P. Sullivan, "New Estimates of the Translog Production Function in U. S. Manufacturing, 1951-1971," unpublished Ph.D. dissertation, (University of North Carolina, Chapel Hill, February 1974).

22. See P. Zarembka, "On the Empirical Relevance of the CES Production Function," Review of Economics and Statistics, 152 (February 1970), pp. 47-53; P. J. Dhrymes and P. Zarembka, "Elasticities of Substitution for Two-Digit Manufacturing Industries: A Correction," Review of Economics and Statistics 152 (February 1970), pp. 115-117; and M. Nerlove, "Recent Empirical Studies of the CES and Related Production Functions," in The Theory and Empirical Analysis of Production, ed. M. Brown (New York: National Bureau of Economic Research, 1967), pp. 56-112.

23. See Table 2.3 in J. R. Moroney, The Structure of Production in American Manufacturing (Chapel Hill. University of North Carolina Press, 1972), p. 30.

24. Kendrick and Grossman, op. cit.

25. See P. A. V. B. Swamy and J. S. Mehta, "Ridge Estimation of the Rotterdam Model," Journal of Econometrics, 22 (1983), p. 370.

26. See Methodology of the Texas Industrial Production Index, 1971, p. 8.

27. Kendrick and Grossman, *op. cit.*

28. The semi-log regressions were of the from $\ln(TFP_i) = \beta_1 + \beta_2 T + e$, where TFP_i = total factor productivity index of the i-th industry and T = 1,2,..., represents successive years in the sample. Corrections were made for autocorrelated errors when necessary.

29. Recall the San Francisco methodology described in this paper differs slightly from that of the actual San Francisco methodology of working paper 13 reported in footnote 11 above.

30. Note that not all of the estimates of industry elasticities in the Dallas 1975 revision were ridge estimates. Some were OLS estimates. Also since that study used data which differs from the present data with respect base year, deflators, and the proxy for capital stock, the 1975 equations were refit with a new intercept, the 1975 output elasticities being forced to hold with certainty.

31. Refer to footnote 23.

32. For copies write Ms. Judy Scott, Research Department, Federal Reserve Bank of Dallas, Dallas, Texas 75222.