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Technological Progress and Diffusion: Decomposing Total Factor Productivity Growth in Brazilian Manufacturing

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SUMMARY

TECHNOLOGICAL PROGRESS AND DIFFUSION: DECOMPOSING TOTAL FACTOR PRODUCTIVITY GROWTH IN BRAZILIAN MANUFACTURING*

Armando Castelar Pinheiro**

*This paper is a summary of part of chapter 4 of my Ph.D. dissertation and has benefited from comments made by Albert Fishlow, Bronwyn Hall and Sherman Robinson and from computer assistence by Marcia Pimentel Pinto.

**Da Diretoria de Pesquisa do IPEA.

ABSTRACT

Abstract

In this paper we estimate the rate of total factor productivity (TFP) growth in 80 sectors of Brazilian manufacturing industry and use production functions to decompose TFP growth into technological progress and changes in efficiency. We find that growth of TFP was caused, in most sectors, by technological progress (advances in the frontier production function). While parametric TFP change averaged 2.6% p.a. in the 1970-80 period, best practice TFP advanced at about 3.3% p.a., whereas efficiency declined annually at a rate of 0.7%. Technological progress was more important in the paper and printing (4.2% p.a.), construction (4.2% p.a.), and chemical (3.7% p.a.) complexes, and stayed below average for the textile and footwear (3.1% p.a.), metal-mechanic (3.0% p.a.) and agroindustrial (3.0% p.a.) complexes.

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1. INTRODUCTION

Output growth is the result of an increased use of inputs and of changes in total factor productivity (TFP). Productivity change has been a leading source of output growth in nowadays developed countries. It should come as no surprise, therefore, that so much effort has been spent trying to determine the sources of TFP growth, a variable that Abramovitz described as the "measure of our ignorance". A step in this direction consists in decomposing the growth of TFP into changes in technical efficiency and advances in the technological frontier. For developing countries, in particular, distinguishing between the two has important policy implications, as potential productivity gains arising from technological mastery (gains in technical efficiency) may surpass and cost less than achieving rapid technological progress. Nishimizu and Page Jr. (1982), for instance, have shown that Yugoslavia's stagnant level of productivity resulted from a perverse combination of a positive rate of technological progress and the slow diffusion of technical change, leading to advances in the frontier and reductions in the average efficiency with which best practice technology is used.

The objective of this paper is to decompose the rate of TFP change in the 1970-80 period for 80 sectors of the Brazilian manufacturing industry into technological advance and changes in technical efficiency. To achieve that goal it is necessary to measure TFP change using production functions rather than index numbers. Frontier production functions are estimated for each sector, for 1970 and 1980, by maximum likelihood. The analysis focuses on deterministic frontiers but stochastic and COLS frontiers are also estimated and compared to the deterministic frontier when relevant.

The plan of the paper is as follows. Next section describes the methodology used in the analysis and reviews the literature on frontier production functions. In section 3 the data used in the frontier estimation is described. The results obtained are presented in section 4. A final section summarizes the paper's main conclusions.

2. METHODOLOGY

2.1. The Underlying Model

Following Nishimizu and Page Jr. (1982), we start with the definition of the production possibility set of an establishment:

$$G\,[y(l,t),\ x(l,t);\ l,\ t] \leq 0 \qquad (1)$$

y and x are, respectively, the vector of outputs and inputs of establishment l at time t. The arguments l and t appear in G to indicate the levels of marginal factor products of establishment l at time t. If y is separable from x, and there is an appropriate index of output (Y(l,t)),[1] then the set of feasible output and input vectors can be equivalently represented by:

$$Y(l,t) \leq F[x(l,t);\ l,t] \qquad (2)$$

where F[. ; l,t] describes the frontier production function for establishment l at period t. It is now possible to define technical efficiency for establishment l at time t, e(l,t), as:

$$e(l,t) = Y(l,t)/F[x(l,t);\ l,t]\ ,\ (0 \leq e \leq 1) \qquad (3)$$

Taking first differences in the logs in expression (3), one obtains that output growth can be decomposed into the expansion of potential output and changes in technical efficiency:

$$\begin{aligned} \ln Y(l,t) - \ln Y(l,t-1) = {} & \ln F[x(l,t);l,t] - \\ & \ln F[x(l,t-1);l,t-1] + \\ & + \ln e(l,t) - \ln e(l,t-1) \end{aligned} \qquad (4)$$

Isolating the effect of technological improvements from higher input usage in (4) one has:

$$\begin{aligned} \ln Y(l,t) - \ln Y(l,t-1) = {} & \ln F[x(l,t);l,t] - \\ & - \ln F[x(l,t);l,t-1] + \\ & + \ln F[x(l,t);l,t-1] - \\ & - \ln F[x(l,t-1); \\ & l,t-1] + \ln e(l,t) - \\ & - \ln e(l,t-1)] \end{aligned} \qquad (5)$$

[1]See Blackorby and Schworm (1988) for a discussion on aggregator functions and indexes for output and inputs.

or:

$$TFPC_p = \ln[Y(1,t)/Y(1,t-1)] - \{\ln F[x(1,t);1,t-1] - \ln F[x(1,t-1);1,t-1]\} = \ln F[x(1,t);1,t] - \ln F[x(1,t);1,t-1] + \ln e(1,t) - \ln e(1,t-1) \tag{6}$$

which defines the parametric measure of TFP change.[2] Note that TFP change is measured using estimates for each sector's production function in 1970 and in 1980, in this way avoiding the need to assume price-taking and profit-maximizing behaviour by firms, that is, that factors are paid their marginal products (which, when using index numbers, permits equating output elasticities with respect to each input to the respective share in total costs).

TFP change can then be decomposed into two elements. First, a gain in productivity arising from shifts in the frontier beyond the extent that can be accounted for by the utilization of larger volumes of the inputs ($\ln F[x(1,t);1,t] - \ln F[x(1,t);1,t-1]$). This term will be called technological progress.[3] Second, a change in TFP that arises from variations in the technical efficiency with which the available technology is used ($\ln e(1,t) - \ln e(1,t-1)$). This term will be called efficiency change and will be associated with technological diffusion and mastery.

It is clear from expression (6) that the empirical analysis can be broken up into: (i) estimating the frontier production functions and the technical efficiency levels in 1970 and 1980, and (ii) decomposing TFP change in each sector according to (6).

[2]Following Nishimizu and Page Jr. (1982), we call the TFPC estimates obtained using the production function "parametric estimates," whereas the values obtained using index numbers will be called "nonparametric." Note also that there is an index number problem, as TFPCP could be alternatively decomposed as

$$TFPC_p = \ln[Y(1,t)/Y(1,t-1)] - \ln F[X(1,t);\ 1,t] - \ln F[X(1,t-1);\ 1,t] = \ln F[X(1,t-1);1,t] - \ln F[X(1,t-1);1,t-1] + \ln e(1,t) - \ln e(1,t-1).$$

[3]This term is sometimes called "best-practice TFP change." See Handoussa, Nishimizu and Page Jr. (1986).

Before that, however, we will briefly review the literature on frontier production functions and describe the data used in the empirical analysis.

2.2. Frontier Production Functions[4]

An average production function relates current output to a given vector of input quantities and a certain technology. A frontier production function, on the other hand, is the locus of maximal possible outputs that a firm can attain given the available technology and once the amount of each of the inputs is fixed. However, the main motivation behind the estimation of frontiers has not traditionally been to compare its analytical form with that of the average production function but rather to measure firm or sector technical efficiency levels, defined as the ratio of actual to best practice or potential output.

Frontier production functions, originally proposed by Farrell (1957), were scarcely used until the late sixties, when two innovations enhanced their attractiveness as analytical tools: (i) the introduction of parametric frontiers[5] and (ii) the development of specific statistical estimation procedures.[6] Frontier production functions are, therefore, a relatively new field of study and as a consequence most of the empirical work in this area dates from the last two decades. It is interesting to note, too, that applications to developing countries have not lagged much behind those for the developed world. Examples of frontier studies in LDC's include Meller (1976) for Chile, Lee and Tyler (1978) for Colombia, Page Jr. (1980) and Martin and Page Jr. (1983) for Ghana, Pitt and Lee (1981) for Indonesia, Nishimizu and Page Jr. (1982) for Yugoslavia, Page Jr. (1984) for India, Handoussa, Nishimizu and Page Jr. (1986) for Egypt, Chen and Tang (1987) for Taiwan, and Noh (1987) for Korea.

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[4]This section is partly based on the review article of Forsund, Lovell and Schmidt (1980).

[5]See Aigner and Chu (1968) and Timmer (1971) for important contributions in this regard.

[6]See Afriat (1972), Richmond (1974), Schmidt (1976), Aigner **et al.** (1977), Meeusen and Van den Broeck (1977) and Greene (1980a and 1980b) for important contributions on the theoretical development of statistical frontiers.

Frontiers were estimated for Brazilian manufacturing in the aggregate by Lee and Tyler (1978) and at sector level by Tyler (1978 and 1979), Rossi (1984) and Braga and Rossi (1986). Studies for different sectors in the manufacturing industry were also conducted by Alves (1987) for Minas Gerais. This paper, however, is the first concerned with the use of frontiers to decompose the rate of TFP change in Brazil.

Frontiers can be classified according to at least three different criteria: first, whether or not a parametric specification is assumed for the frontier, nonparametric frontiers being less restrictive; second, according to whether or not the residuals are assumed to be all one-sided, probabilistic and stochastic frontiers allowing some firms to be "super-efficient"; and third, depending on whether or not any assumptions are made with respect to the probability distribution of the residual, statistical frontiers allowing tests about the significance of the estimates.

Nonparametric frontiers are obtained as the piecewise linear convex hull of extreme points of input-output ratios in the isoquant space and have as main advantages the ease of estimation and the fact of being specification-free. On the other hand, they assume constant returns to scale and are very sensitive to outliers. In studies focusing on the Brazilian manufacturing industry, nonparametric frontiers have been used by Tyler (1979), in his paper about the plastics and the steel sectors, and by Alves (1987), who worked with a sample of firms located in the state of Minas Gerais.

In a deterministic parametric frontier all establishments must lie on or below the frontier. A formal representation is given by;

$$\ln Y = \ln F(x) - u, \qquad u \geq 0 \tag{7}$$

where, Y is the actual output of the firm, f(x) is the parametric frontier production function, and e^{-u} is the establishment's technical efficiency level $(0 < e^{-u} \leq 1)$.

Usually ln F(x) is assumed to be a linear function in the parameters. If this is the case, four different methods can be used to estimate the frontier: linear programming (LP), quadratic programming (QP), corrected ordinary least squares (COLS) and maximum likelihood (ML).

Linear Programming was the method utilized by Aigner and Chu (1968) who first estimated a parametric frontier, specified as a Cobb-Douglas function. Their problem can be represented as that of finding a solution to:

$$\mathrm{Min}_a \; \Sigma\, u_i$$

$$\text{s.t.} \qquad u_i = a_0 + \Sigma_j\, a_j \ln X_{ji} - \ln Y_i$$

$$u_i \geq 0 \qquad (8)$$

LP have been widely used in studies with deterministic frontiers due to its easy of estimation and to the fact that technical efficiency levels of individual firms are obtained as by-products of the solution to (8).[7] More recently, this technique gained a new appeal, as it has been shown that monotonicity and global concavity can be imposed on a linearly homogeneous translog function as linear restrictions on some of the parameters.[8]

The use of LP to determine the parameters of the frontier production function presents two noteworthy problems. First, as no assumption is made with respect to the distribution of the inefficiency residuals, it is not possible to derive the statistical properties of the estimates (e.g., their standard deviations or t-ratios). Schmidt (1976) has shown that if the u_i's are independently and identically distributed (i.i.d.) according to an exponential distribution, then the solution to (8) is a maximum likelihood estimator (MLE). That, however, is of little consequence in this case, since there is no guarantee that these MLE have their desirable asymptotic properties. A second problem is that there will be only as many observations on the frontier as there are parameters to be estimated. This is a purely mathematical result and there is no economic reason why only (or all these) firms should be at the frontier.

The second method of estimation uses quadratic programming (QP). The estimates of the parameters are obtained by solving a program similar to (8) that minimizes the sum of the squares of the residuals:

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[7]See Tyler (1979) and Page Jr. (1980) for applications to developing countries using a Cobb-Douglas frontier.

[8]See Nishimizu and Page Jr. (1982), Martin and Page Jr. (1983), Page Jr. (1984), Handoussa, Nishimizu, and Page Jr. (1986) and Noh (1987) for applications of this extended linear program to translog deterministic frontiers.

$$\mathrm{Min}_a \ \Sigma_i \ u_i^2$$
$$\text{s.t.} \quad u_i = a_0 + \Sigma_j \ a_j \ \ln X_{ji} - \ln Y_i$$
$$u_i \geq 0 \qquad (9)$$

Although the number of technically efficient firms is not restricted to be equal to the number of parameters, we still obtain estimates that have no statistical properties. Again, if the u_i's are i.i.d. and their common distribution is half-normal, then the solution to (9) is a maximum likelihood estimator (Schmidt (1976)); but, as with LP, these MLE may lack their usual asymptotic properties. The solutions to (8) and (9) are, respectively, the Least Absolute Deviation and the Least Square estimates of a. It is interesting to note that while the latter is more popular in the average production function problem, the former is preferred in the estimation of frontier production functions. A possible explanation for that is that the solution to (9) is more sensitive to outliers than the LP estimates.

A third way of estimating the frontier production function is by using the Corrected Ordinary Least Squares (COLS) method.[9] This procedure consists in estimating an average production function by ordinary least squares and correcting the value of the intercept to obtain a frontier production function. COLS estimates for the slope coefficients are best linear unbiased and consistent. To obtain a consistent estimate of the intercept term two procedures can be used. First, one may assume a specific distribution for u_i and then use the estimates of its central moments to derive $E(u_i)$, which is then added to the intercept to derive the frontier. Second, one can make use of the fact that the errors are distributed unilaterally to shift the production function upwardly, such that all observations but one lie below the frontier.[10]

The COLS procedure provides estimates with statistical properties (that is, standard deviations and t-ratios)

[9]This alternative estimation procedure was first noticed by Richmond (1974).

[10]See Greene (1980<u>a</u>, p. 31-34) for further elaboration on this subject. See Rossi (1984) and Braga and Rossi(1986) for applications of the COLS procedure to Brazilian manufacturing.

and are seen as good initial solutions to iterate estimation procedures, but since it does not exploit the information that the residuals are one-sidedly distributed this method cannot be optimal, at least asymptotically. Obviously, COLS estimates are less efficient the more asymmetric is the error term distribution.

Finally, a frontier production function can be estimated by maximum likelihood, which incorporates advantages of the three methods previously discussed and can also be applied when the frontier is nonlinear in the parameters. MLE are efficient, in the sense that they take into account the skewness of the distribution of the inefficiency residual, have known statistical properties and can have their significance tested, at least asymptotically.

MLE present, however, two important drawbacks. First, they are, as any other nonlinear estimation method, sensitive to the choice of distribution for u_i. Since there is no **a priori** argument on behalf of any particular distribution, this can be regarded as an important disadvantage of the method. Second, the frontier estimation problem provides a set-up in which some of the conventional regularity conditions used to prove the asymptotic properties of MLE do not hold. In particular, since all observations (Y_i) must lie below the frontier ($F(X)$), the condition that the support does not depend on the parameters to be estimated is not satisfied. This second problem with MLE was partially overcome by Greene (1980a), who showed "that the usual desirable properties of maximum likelihood estimators still hold if the density of u satisfies the following conditions: (i) the density of u is zero at u=0; (ii) the derivative of the density of u with respect to its parameters approaches zero as u approaches zero."

Neither the exponential nor the half-normal densities meet the above conditions, and this makes the estimates obtained by LP or QP less attractive. As noted by Greene, however, the gamma density satisfies both these requirements, and if that is the distribution assumed for the residuals, then the MLE will keep their interesting asymptotic properties. The deterministic frontier problem can then be stated as finding a solution to:

$$\text{Max}_{a,\tau,P}\ L^* = T\ (P \ln\tau - \ln\Gamma(P)) + (P-1)\ \Sigma_i \ln(\epsilon i) - \tau\ \Sigma_i\ \epsilon_i$$

$$\text{s.t.} \qquad \epsilon_i = \ln(F(a,\ X_i)) - \ln(Y_i) \geq 0,$$

$$\tau > 0, \text{ and } \qquad P > 2 \tag{10}$$

where **a** is the vector of parameters of the frontier production function $F(\mathbf{a}, X_i)$, and T is the number of observations in the sample.

The stringent requirement that in a deterministic frontier all observations lie on or below the frontier leads to two important problems. First, the results become very sensitive to measurement errors and, in particular, to the presence of outliers. Second, there is an implicit assumption that all inefficiency is endogenous; that is, there is no room for external shocks or inefficiencies arising from factors outside the control of the establishment.[11]

A solution to these problems was first suggested by Aigner and Chu (1968) and later implemented by Timmer (1971), in what became known as the probabilistic frontier. The method consists in estimating successive deterministic frontiers, discarding, from one step to another, a fixed percentage of extreme observations, until the estimates for the frontier converge.[12]

But a more ingenious solution to these problems is the stochastic frontier advanced by Aigner **et al.** (1977) and Meeusen and Van den Broeck (1977). Formally, the model may be written as:

$$\ln Y = \ln F(x) + (u + v) \tag{11}$$

The stochastic production frontier is given by F(x).exp(v), where v has a symmetric distribution and reflects measurement errors and exogenous shocks, while u has a one-sided distribution and accounts for the establishment's technical inefficiency. In this paper, u is assumed to be distributed according to a half-normal and v to a normal distribution.[13] The

[11]See Zellner, Kmenta and Dreze (1966) for an interesting discussion on the nature of the inefficiency error of a profit maximizing firm and on its consequences for econometric estimation.

[12]Note that this method is of difficult application when the number of observations in the working sample is not large. See Alves (1987) for an application to Brazil.

[13]Since now the value of Y is no longer required to be lower than **F(X)**, the regularity conditions are satisfied and the MLE have their desirable asymptotic properties.

problem can be formally represented as that of finding a solution to:

$$\text{Max}_{a,\theta,\sigma^2} L^* = T/2 \ln(2/\pi) - T \ln(\sigma) + \Sigma_i^T \ln[1 - \Phi(\epsilon_i \theta/\sigma)] - (1/2\sigma^2) \Sigma_i^T \epsilon_i^2$$

$$\text{s.t.} \quad \epsilon_i = u_i + v_i = \ln(F(a, X_i)) - \ln(Y_i)$$

$$u_i \geq 0 \quad , \quad -\infty \leq v_i \leq \infty$$

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \quad \text{and } \theta = \sigma_u/\sigma_v \qquad (12)$$

where $\Phi(x)$ is the cumulative distribution of the standard normal.

Deterministic frontiers have the level of technical efficiency of each establishment as a direct by-product of the estimation problem, a feature that has been an important inducement for using deterministic frontiers, despite the problems discussed before. After all, the measurement of inefficiency levels has been the main motivation for estimating frontier production functions. The same does not happen with the stochastic frontier, for which only the composite error term $\epsilon_i = u_i + v_i$ and the average technical efficiency of the sector can be estimated. This shortcoming of stochastic frontiers has been partly overcome by Jondrow **et al.** (1982), who suggested the use of either $E(u_i|\epsilon_i)$ or $M(u_i|\epsilon_i)$, respectively the mean and the mode of the conditional distribution of u_i given ϵ_i, as estimates of the inefficiency level of the establishments.[14] For the half-normal case, the mathematical expressions for $E(u_i|\epsilon_i)$ and $M(u_i|\epsilon_i)$, as derived by Jondrow **et al.** (1982), are:

$$E(u_i|\epsilon_i) = \sigma^* \left[\frac{\Omega(\epsilon_i \theta/\sigma)}{1 - \Phi(\epsilon_i \theta/\sigma)} - \epsilon_i \theta/\sigma \right] \qquad (13)$$

$$M(u_i|\epsilon_i) = -\epsilon_i (\sigma_u^2/\sigma^2) \quad \text{if } \epsilon_i \leq 0 \qquad (14)$$

$$= 0 \quad \text{if } \epsilon_i > 0$$

[14]An alternative way to deal with the problem is through the use of pooled data for a panel of firms, for which the inefficiency error is assumed to be time invariant. See Pitt and Lee (1981) for an application.

where $\Omega(x)$ is the density function of the standard normal.

The Cobb-Douglas production function has been the specification most widely used in frontier problems. In studies focusing on Brazil, it was used by Tyler (1978 and 1979), Lee and Tyler (1978), Rossi (1984) and by Braga and Rossi (1986). More recently, the use of flexible functional forms, such as the translog, generalized Leontief and the quadratic functions has become very popular. They are particularly interesting in the frontier set-up, since lack of flexibility has always been pointed out as one of the disadvantages of parametric frontiers. In this paper the frontiers are represented by a translog production function because: (i) it enables the comparison between the nonparametric estimates of TFP growth of Pinheiro (1989) with the parametric measures of this paper -- in the same fashion, that is one of the reasons why constant returns to scale are imposed to the translog function; (ii) necessary and sufficient conditions for global concavity can be imposed on translog production functions without excessive difficulty; (iii) most recent studies on frontier estimation have used the translog function and by keeping up with tradition the results can be compared with those in the literature;[15] and (iv) unless we have some knowledge about the technology to be represented, there are no pre-test criteria to prefer one flexible functional form to another.[16]

The translog production frontier is given by

$$\ln(F(a\ ,\ X_i)) = a'Z_i = a_o + \Sigma_j{}^4\ a_j\ \ln(X)_j + 1/2\ \Sigma_k{}^4\ \Sigma_j{}^4\ a_{jk}\ \ln(X)_j\ \ln(X)_k = a_o + a'Z + Z'A\ Z \qquad (15)$$

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[15]The translog form has been used, among others, by Greene(1980b), Nishimizu and Page Jr. (1982), Martin and Page Jr. (1983), Page Jr. (1984), Handoussa, Nishimizu, and Page Jr. (1986), Chen and Tang (1987) and Noh (1987). Note also that the translog is a generalization of the Cobb-Douglas function.

[16]See Blackorby, Primont and Russel (1977), Fuss, McFadden and Mundlak (1978), Berndt and Khaled (1979), Appelbaum (1979) and Lau (1986) for further elaboration on the choice among flexible functional forms.

Although, at least in principle, flexible functional forms capture more closely the actual technology being used, it is not unusual in empirical studies to find oneself with coefficients that do not meet the theoretical requirements for F(.) to represent a frontier production function. In particular, it is not uncommon to reach a specification that is not concave and sometimes not even monotonic. The problem of imposing monotonicity and concavity to flexible functional forms has been extensively studied in the literature, although no simple universal way has been found to deal with the problem.[17] Nishimizu and Page Jr. (1982) dealt with this problem by imposing constant returns to scale, monotonicity and concavity as linear restrictions of their linear program. In our case this is equivalent to require that the parameters satisfy

$$\Sigma_j^4 \; a_j = 1 \tag{16}$$

$$\Sigma_j^4 \; a_{jk} = 0 \; , \; k = 1,4 \tag{17}$$

$$a_j \geq 0 \qquad , \; j = 1,4 \tag{18}$$

$$a_{jj} \leq 0 \qquad , \; j = 1,4 \tag{19}$$

Restrictions (16) and (17) are necessary and sufficient to impose constant returns to scale on the translog, while (18) is necessary and sufficient to guarantee monotonicity at the approximation point. Assuming that (16), (17) and (18) hold, then (19) is both necessary and sufficient to guarantee global concavity. A proof of necessity and sufficiency of these conditions for global concavity of the translog was first advanced by Jorgenson and Fraumeni (1981). It relies on the one-to-one correspondence between the elements of the matrix of (constant) share elasticities A (see expression (15)) and those of its Cholesky decomposition. For global concavity it is necessary and sufficient that the diagonal elements of the Cholesky factorisation of A be non-positive, what in

[17]See Lau (1978), Christensen and Caves (1980), Jorgenson and Fraumeni (1981), Barnett and Lee (1985), Jorgenson (1986) and Diewert and Wales (1987) for discussions on concavity problems in flexible functional forms.

this case is equivalent to conditions (19).[18] It is worth pointing out, however, that attaining global concavity is not costless. In particular, as shown by Diewert and Wales (1987), there is a loss of flexibility and the risk of overestimating the elasticities of substitution between the inputs.

The maximization problems can now be redefined to incorporate all the above restrictions directly into the log likelihood functions. The deterministic frontier problem is then defined as that of finding a solution to:

$$\mathrm{Max}_{a,\tau,P}\ L^* = T\,[(\,P^2 + 2\,)\ \ln\tau^2 - \ln\Gamma(P^2 + 2)] + $$
$$+ [(P^2 + 2\,) - 1]\ \Sigma_i \ln(\epsilon_i) - \tau^2\,\Sigma_i\,\epsilon_i \quad (20)$$

while the stochastic frontier problem is defined as finding a solution to:

$$\mathrm{Max}_{a,\theta,\sigma}\ L^* = T\ \ln(2/\pi)/2 - T\ \ln(\sigma^2) + $$
$$+ \Sigma_i^T \ln[1 - \Phi(\epsilon_i\ \theta^2/\sigma^2)] - (1/2\sigma^4)\ \Sigma_i^T\ \epsilon_i^2 \quad (21)$$

Moreover, we have decided to estimate a corrected least squares (CLS) frontier by maximum likelihood, assuming that the error term is normally distributed. The problem in this case can be defined as finding a solution to:

$$\mathrm{Max}_{a,\sigma}\ L^* = T/2\ \ln(2/\pi) - T\ \ln(\sigma^2) - $$
$$- (1/2\sigma^4)\ \Sigma_i^T\ \epsilon_i^2 \quad (22)$$

In the three cases ϵ_i is defined by

$$\epsilon_i = a_o + \Sigma_j^4\ a^2_j\ .\ \ln(X_{ij}) + \Sigma_j^4\ \Sigma_{k>j}\ a_{jk}\ \ln(X_{ij})$$
$$\ln(X_{ik}) - 1/2\ \Sigma_k^4\ a^2_{kk}\ \ln(X_{ij})^2 - \ln Y_i \quad (23)$$

(16) and (17) are imposed by measuring output and inputs in per worker units.

To obtain a numerical solution to the maximization problems described by (20) to (23) the optimization software developed by Professors Richard Quandt and Stephen Goldfeld of Princeton University -- and in

[18]See Jorgenson (1986, p. 1859-1860) for a more detailed proof and Lau (1978) for a discussion on imposing and testing monotonicity and concavity using Cholesky decompositions. Note the particular role played by the constant returns to scale assumption.

particular its subroutine GRADX -- was used. The variance-covariance matrix of the asymptotic distribution was obtained from the inverse information matrix. Accuracy was fixed at 1^{-10}. The program converges in case one of the following is less than accuracy: (i) the attempted change in the value of each of the parameters, (ii) the norm of the gradient, and (iii) the relative improvement in the function value on any step. Convergence was achieved for 99 sectors in 1970 and 104 in 1980 for the deterministic frontier using the original working sample. No convergence was achieved for 8 sectors in 1970 and for 5 sectors in 1980. With the reduced sample, to be presently described, convergence occurred for 74 out of 82 sectors in 1970 and for 87 out of 97 sectors in 1980.

3. DATA BASE

The data used in the analysis comes from the Industrial Censuses of 1970 and 1980. The unit of observation in the Census is the establishment, defined as "the part of the organization that is in charge of the industrial activity and has installations and means to produce industrial goods." The working sample consists of all establishments with more than five employees and that had been active the entire year of the census. Furthermore, since we will be working with the logarithms of the variables, all establishments for which any of the inputs are equal to zero were deleted. Only sectors with more than 20 establishments were considered. This lower limit in the number of observations was imposed in order to allow for enough degrees of freedom. To control expenses with computer facilities, systematic samples were taken for all sectors with a large number of observations, setting an upper bound of around one thousand establishments in each sector.[19]

Four different inputs -- namely capital, labour, material inputs and energy inputs -- are considered. Output is defined as the current value of the goods and services produced by the establishment. The flow of capital services in each establishment is assumed to be proportional to its stock of machinery, equipment and installations, which is used to measure the capital input. Data for the number of employees in each

[19]Table 4.B.1 of Pinheiro (1989) lists the number of establishments in each sector before and after sampling. The last column of this table shows the number of establishments in the working sample with more than fifty employees and after eliminating outliers.

establishment come disaggregated according to sex, skills and whether employees work on or out of the production line. These figures, however, are available only for December of each year, and so had to be corrected to account for variations in the number of workers during the year. Our measure for the labour input in each sector tries to take into account the influence of different compositions according to skills and is defined by $L_l^{k,t} = \Sigma_h^H w_h^{k,t} L_{h,l}^{k,t}$, where $w_h^{k,t}$ is the average wage paid to workers of skill h, in sector k and year t, and $L_{h,l}^{k,t}$ is the corresponding figure for the number of employees in the establishment. Unfortunately there is no information for wages separately for male and female workers and so no distinction according to sex is made at this stage. The treatment dispensed to material inputs was much the same adopted for output, with the material input variable being measured by the value of goods and services consumed in production. No distinction was made between inputs that were domestically produced and those that were imported. Finally, the energy input was measured by the value of the establishment's expenses with electric energy and fuels.

4. EMPIRICAL RESULTS

The results obtained from the estimation of the deterministic frontier production functions for 1970 and 1980 are reported in Pinheiro (1989). Two observations about these estimates are noteworthy. First, the hypothesis of a Cobb-Douglas specification for the frontier production function is rejected for almost all sectors, as most of them present second-order parameters that are statistically significant. In many cases, though, the parameters a_{ii} (i=1,4) are all not significantly different from zero and the concavity restrictions (19) are binding. This result reflects the difficulty to estimate the slope of isoquants when moving away from the approximation point, not an uncommon problem in the estimation of flexible functional forms. Second, the estimates for both P and the constant (a_0) are, for most sectors, much larger than expected. These results reflect the lack of asymmetry of the error distributions: as the value of P increases, the degree of skewness of the gamma distribution (that is equal to $2/\sqrt{P}$) declines [see Greene (1980<u>a</u>, p. 43-44)]. In fact, as P goes to infinite, the gamma distribution becomes symmetric, and the asymptotic efficiency gain of the maximum likelihood estimation diminishes considerably. The estimates obtained for the inefficiency term using the stochastic frontier also present this lack of skewness. In this case the value of θ -- that measures the ratio of the standard deviation of the inefficiency disturbance to that of the measurement error -- was of the order of magnitude of 10^{-4} for all sectors. From the analysis of Jondrow **et al.** (1982) it follows that $M(u|\epsilon)$ is of the order of magnitude of 10^{-8}.[20]

It is interesting to observe, in this regard, that similar results have been reported in other studies. Aigner, Lovell and Schmidt (1977) were not able to identify the technical inefficiency term in their analysis of the metals industry in the U.S. Comparable results were obtained by Lee and Tyler (1978) for two of the five sectors of the Colombian manufacturing industry they examined. Braga and Rossi (1986) obtained skewed error distributions for only one-third of the 136 sectors of the Brazilian manufacturing industry they studied. A relatively symmetric distribution is also reported by Alves (1987). Probably, equivalent (unreported) results were also obtained in an unknown number of studies using linear programming or COLS estimates.

The explanation for the large values obtained for the P parameter lies, therefore, in the lack of asymmetry of the distribution of the inefficiency error, which possibly results from two not necessarily mutually exclusive factors. First, best practice technology is used by just a few establishments, with most firms adopting average efficiency production techniques, and a small number of establishments being relatively inefficient. This scenario would reflect a slow diffusion of best practice techniques, as discussed by Salter (1966). Causes for that would stem from differences in firms' size and market shares, to education and training of managers, capital ownership, factor costs, and expectations about future demand.

A case could be made that the asymmetric distribution would describe the situation in mature economies and sectors with well-developed technologies. The symmetric profile, on the other hand, would apply to sectors or economies undergoing rapid structural change. This picture contrasts with the scenario inherent in the utilization of skewed distributions, which is characterized by a significant concentration of establishments close to the frontier, with a decaying number of firms adopting more and more inefficient techniques. It can be the case, therefore, that the symmetric distribution is caused by excessive heterogeneity of the firms in the sample: large and small firms may not use the same technology and have,

[20]As pointed out by Jondrow **et al.** (1982, p. 235), $M(u|\epsilon)$ can be interpreted as the maximum likelihood estimate of $u|\epsilon$, the conditional inefficiency error.

therefore, different frontiers. It would be a combination of these various frontiers that we would be actually measuring.

A second possible reason for a symmetric distribution of the residual term is that of an overwhelming measurement error that totally masks the nature of the inefficiency gap. The data covers a large number of different firms all over Brazil, and it would not be surprising if the variables used are not all perfectly measured, especially the capital input.

If those explanations actually hold, there is little justification for the use of frontiers rather than average production functions. Irrespective of the actual cause, however, it seems that the heterogeneity of the working sample may be an important fact contributing to the symmetrical distribution of ϵ. Trying to overcome this problem, the frontiers have been re-estimated using a reduced sample that includes only establishments with more than fifty employees. The assumption has been made that this would reduce heterogeneity across establishments and the significance of measurement errors. After estimating the frontier with this reduced sample, 5% of the establishments in each extreme of the distribution have been deleted to eliminate outliers and reduce measurement error. Then the deterministic frontier has been re-estimated once more with this reduced sample. With this procedure the degree of skewness increased for most sectors, although some of them continued to show symmetrical error distributions.

After estimating the frontier production functions we are able to measure the technical efficiency level of establishments and sectors. However, one of the consequences of the symmetric distribution of the error term has been that the resulting technical efficiency estimates lack economic sense for most sectors, both in the stochastic and the deterministic case.

For the stochastic frontier, average technical efficiency levels were equal to one for most sectors. Since technical efficiency is always nonnegative and less than or equal to one, this implies that individual establishments also have to be fully technically efficient. For the deterministic frontier, on the other hand, the opposite result was found. As the estimated error distribution becomes symmetric, its range of variation tends to $(-\infty, +\infty)$, since now both tails go to infinity. However, since by construction the error is always positive, it is necessary that the probability of the random variable ϵ lying on the negative half of the real line be very low, especially if the number of observations in the sample is reasonably large. A consequence of having a distribution for ϵ_i that is at the same time symmetric and concentrated in the positive half of the real line is a high positive correlation between the estimates of P and of the constant term a_0, which is actually observed empirically. A high value for the constant term implies that the technical efficiency levels for all establishments in the sector are close to zero. Then, for the deterministic case, technical efficiency for all establishments in sectors with symmetric error distributions is for all practical purposes equal to zero.

We are left with a problem very similar to that in the COLS estimation procedure: we do have the "correct" distribution of efficiencies, but it is "centred" around the wrong point. It seems reasonable to adopt some intercept correction to give economic meaning to the average technical efficiency measures. Table 1 reports the distribution of sectors in technical efficiency decils for three assumptions about the proportion of establishments above the frontier, for the stochastic and COLS frontiers, for alternative definitions of the average technical efficiency measure, and for different establishment samples.[21] When 5% of the observations are allowed to lie above the frontier, technical efficiency levels for the average establishment lie around 60% in 1970 and 55% in 1980 for most sectors.[22] In 1970 technical efficiency goes from a minimum of 31% to a maximum of 86%. These limits are 32% and 78%, respectively, in 1980 - Column (1), Table 1. Columns (2) and (3) summarize the results obtained for 1970 using alternative assumptions with respect to the distribution of the error term. Two remarkable facts deserve consideration. First, the technical efficiency levels obtained for the stochastic frontier are for most sectors almost the same found for the deterministic case. Second, when the error distribution is assumed to be normal, the resulting technical efficiency is significantly smaller for all sectors. The reason for these lower technical efficiency levels is the higher variance observed for the normally distributed error term. These rather unsettling results reinforce the point raised earlier

[21]The efficiency levels for each sector is reported in Pinheiro (1989).

[22]The average establishment is defined as a hypothetical firm that consumes sector average amounts of each of the inputs and produces sector average quantities of output.

that we know little of the distribution of the inefficiency error, beside that it should be one-sided.

In columns (4) and (5) an attempt is made at gauging the sensitiveness of the results to alternative definitions of average sector technical efficiency. While still keeping 5% of the establishments above the frontier, the geometric (EFG) and the arithmetic (EFA) average technical efficiency levels were estimated. EFG is on average closer to our basic estimate, whereas EFA tends to surpass it. In both cases the range of variation is narrower than that observed for the average establishment. In columns (6) and (7) an effort is made to evaluate the impact of allowing different proportions of the firms to lie beyond the frontier. As would be expected, while technical efficiency increases with the percentage of super-efficient establishments, the cross-sector variance is significantly reduced. Two other points seem worth calling attention to. First, in sectors with few establishments, there is very little or no difference between the 0% and the 1% measures, which seems to be an argument in favour of using the 5% measure. Second, for sectors in which the error distribution is asymmetric, relatively small differences arise when using the 0% or the 5% measure.

Table 1: DISTRIBUTION OF AVERAGE SECTOR TECHNICAL EFFICIENCY
1970

INTERVAL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.0-0.1			0.09			0.10		
0.1-0.2			0.23			0.19	0.04	
0.2-0.3			0.38			0.17	0.13	
0.3-0.4	0.03	0.04	0.24			0.23	0.21	
0.4-0.5	0.08	0.09	0.04	0.11	0.04	0.17	0.36	0.03
0.5-0.6	0.28	0.28		0.28	0.24	0.07	0.19	0.08
0.6-0.7	0.46	0.46	0.01	0.55	0.59	0.05	0.05	0.31
0.7-0.8	0.11	0.10		0.06	0.13	0.01	0.01	0.49
0.8-0.9	0.03	0.03						0.09
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minimum	0.31	0.31	0.00	0.40	0.45	0.03	0.12	0.48
Average	0.61	0.61	0.24	0.60	0.63	0.32	0.42	0.70
Weight Avg	0.58	0.60	0.26	0.57	0.61	0.20	0.37	0.71
Maximum	0.86	0.87	0.67	0.75	0.76	0.71	0.71	0.86

(continua)

1980

INTERVAL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.0-0.1						0.20		
0.1-0.2						0.18	0.04	
0.2-0.3						0.34	0.24	
0.3-0.4	0.06					0.14	0.38	0.01
0.4-0.5	0.19			0.27	0.07	0.08	0.25	0.05
0.5-0.6	0.45			0.51	0.51	0.02	0.05	0.23
0.6-0.7	0.28			0.20	0.38	0.04	0.04	0.49
0.7-0.8	0.02			0.02	0.03			0.20
0.8-0.9					0.01			0.02
Total	1.00			1.00	1.00	1.00	1.00	1.00
Minimum	0.32			0.42	0.45	0.02	0.13	0.40
Average	0.55			0.55	0.59	0.24	0.36	0.64
Weight Avg	0.56			0.55	0.60	0.18	0.34	0.64
Maximum	0.78			0.78	0.80	0.68	0.68	0.85

(1), (2) and (3), respectively, deterministic, stochastic and CLS frontiers, with 5% of the establishments above frontier (4) and (5), deterministic frontier, 5% of the establishments above frontier, geometric and arithmetic averages, respectively. (6) and (7), deterministic frontier, 0% and 1% of the establishments above frontier, respectively. (8) Deterministic frontier, 5% of the establishments above frontier, reduced sample (>50 employees).

Using the reduced sample (>50 employees) frontiers and letting 5% of the observations be above the frontier, one obtains that sector technical efficiency averaged 70% in 1970 and 64% in 1980 - Column (8) of Table 1. The variances of the error term for the reduced sample are considerably smaller than the ones observed for the original sample (>5 employees). This result is consistent with the assumption of higher homogeneity among larger firms and with the idea that, on average, larger firms tend to be closer to the frontier.

Table 2 reports the values of average technical efficiency for each sector and the main industrial complexes in Brazilian manufacturing industry.[23] It is

[23]"Any segment of the economy forms an industrial complex when it comprises a set of industries that are technologically interdependent, that are regulated by a common set of rules or that produce goods that are highly complementary in consumption." [Araújo Jr. **et al.** (1990, p. 9)].

clear that average technical efficiency declined in most sectors from 1970 to 1980 (see also Graph 1). On average, this decline amounted to -0.7% p.a. for the complete sample and to -0.9% for the large firm sample. For individual sectors, however, the annual rate of change varied from -4.2% to 1.9% for the complete sample, and from -4.9% to 1.7% for the reduced sample.

Two observations about the results in Table 2 are noteworthy. First, they are similar to the ones presented by Nishimizu and Page Jr. (1982) for Yugoslavia, by Handoussa, Nishimizu and Page Jr. (1986) for Egypt, and by Noh (1987) for the iron and steel sectors in Japan and Korea. In all cases there was a general decline in technical efficiency. Second, these results should not be interpreted as indicating that firms in Brazil became less efficient from 1970 to 1980. Average technical efficiency in this type of methodology is narrow defined to evaluate relative cross-firm variance, and not absolute levels of productivity. The interpretation here is very similar to the one with Kuznets's U curve for income distribution: as some firms adopt new technologies and others do not, variance increases and so does inefficiency. That does not mean we are worse off or that firms now misuse the technology they control. It is important to note that firms may decide not to adopt best-practice technologies for several reasons -- such as the existence of quasi-fixed inputs.[24] This is a shortcoming of our methodology, and the correct interpretation of average sector technical efficiency has to be kept in mind when analyzing the results.

Average technical efficiency levels were rather similar for all complexes, varying from 56% to 63% in 1970 and between 51% and 57% in 1980, except for paper and printing in 1980 with an average technical efficiency of 63.5%. For the reduced sample the intervals are [63%, 76%] and [63%, 73%], respectively. Technical efficiency levels decreased for the construction, metal-mechanic, textile and footwear and agroindustrial complexes, remained about the same for the chemical complex and increase for paper and printing.

[24]See Salter (1966) for a discussion of this issue.

Table 2: Average Technical Efficiency by Sector

Sector	# EMPLOYEES > 5 1970	# EMPLOYEES > 5 1980	# EMPLOYEES > 5 RATE OF CHANGE	# EMPLOYEES > 50 1970	# EMPLOYEES > 50 1980	# EMPLOYEES > 50 RATE OF CHANGE
CONSTRUCTION COMPLEX						
Stones for Construction	48.6	43.8	-1.03	58 1	56.0	-0.38
Lime	43.4	32.2	-2.99	65.4	39.9	-4.93
Ceramics	44.8	53.0	1.69	67.9	63.5	-0.67
Cement	59.8	39.3	-4.21	68.0	51.2	-2.84
Cement Products & Artefacts	62.4	53.6	-1.53	67.7	58.5	-1.46
Glass	60.2	48.1	-2.24	71.7	58.4	-2.06
Processed Non-Metallic Minerals	37.1	36.6	-0.15		45.1	
Misc. Prod. of Non-metallic Miner.	68.0	48.2	-3.44		69.7	
Wood	58.1	51.1	-1.29	66.2	55.9	-1.70
Wood Furniture	62.9	64.0	0.18	74.2	75.5	0.17
Metallic Furniture	68.7	59.2	-1.48	70.4	70.3	-0.02
Upholstery	72.5	66.0	-0.95		68.4	
Complex Average	57.7	51.0	-1.23	68.3	59.8	-1.33
METAL-MECHANIC COMPLEX						
Iron and Steel	63.0	53.5	-1.62	66.3	60.7	-0.88
Nonferrous Metals	59.2	54.6	-0.81	66.7	65.9	-0.12
Metallic Structures		55.8		63.1	62.6	-0.09
Iron and Steel Artef.	64.4	59.2	-0.83	76.0	67.3	-1.22
Metal Stamping	56.5			73.3	64.7	-1.24
Metal Tanks & Recipients	69.2	60.5	-1.34	71.4	69.1	-0.33
Cutlery/Hand Tools/Hardware & Guns	71.2	59.6	-1.78	72.8	61.7	-1.66
Special Ind. Machin.	60.8	48.6	-2.23	69.2	60.0	-1.42
Ind. Mach. for Hidr.&Termic Inst.	67.4	56.7	-1.73	75.3	62.1	-1.92
General Industrial Machinery		48.1		65.6	59.9	-0.91
Machin.& Equip. for Agriculture	54.7	56.6	0.33	75.6	65.3	-1.46
Home & Office Machin.& Equip.	55.3	55.9	0.10	65.3	60.9	-0.70
Clocks, Whatches & Cronometers		44.0				
Tractors & Earth-Moving Machines	55.2	54.8	-0.08	59.4	66.9	1.20
Equip. for Electrical Energy	61.9	59.0	-0.48	80.5	64.2	-2.27
Electrical Material (a)	61.6	56.8	-0.81	66.0	63.7	-0.36
Lamps		69.8				
Electr. Material for Vehicules (b)	61.1	63.8	0.44	71.5	67.9	-0.51
Electrical Appliances	66.9	58.3	-1.38	75.9		
Electronic Material	55.3	51.1	-0.77	77.8	59.3	-2.72
Communication Equipment	55.0	58.5	0.62	67.0	62.1	-0.77
Naval Industry	44.6			57.1	57.8	0.13
Railway Stock		47.1		50.7	55.8	0.96
Autom. Vehicules & Parts	65.6	56.9	-1.42	74.1	63.1	-1.61
Bicycles	82.6	67.5	-2.03		64.6	
Aircrafts		43.7				
Other Vehicules	66.6	53.3	-2.22			
Complex Average	62.1	55.2	-1.19	69.3	62.5	-1.02

(continua)

Sector	# EMPLOYEES > 5 1970	# EMPLOYEES > 5 1980	# EMPLOYEES > 5 RATE OF CHANGE	# EMPLOYEES > 50 1970	# EMPLOYEES > 50 1980	# EMPLOYEES > 50 RATE OF CHANGE
PAPER AND PRINTING						
Paper	64.7			73.3	70.6	-0.38
Paper Products	58.8	62.2	0.55	75.1	69.5	-0.78
Newsp., Books, Manuals & Period.	57.1	56.4	-0.13	66.2		
Teaching/Ind./Comm. Printed Matter	64.7	78.4	1.92	71.9	85.2	1.70
Other Print. & Publish. Services	54.9	45.0	-2.01		48.8	
Complex Average	61.0	63.5	0.39	71.2	72.3	0.15
CHEMICAL COMPLEX						
Rubber	74.6	59.2	-2.31		70.2	
Chemical Elem. & Compositions	30.9	33.0	0.64	48.1	45.8	-0.50
Oil-Refining & Petrochem.	51.4	58.0	1.22	59.9	65.4	0.88
Artific. Threads & Resins		56.8			68.8	
Raw Vegetable Oils	57.2	50.3	-1.30	74.1	69.4	-0.65
Aromatic Concentrates	72.6	58.8	-2.11			
House Clean. Prod. & Pesticides	60.4	61.7	0.22	61.7	70.8	1.38
Pigments, Paints & Solvents	63.3	56.1	-1.21	65.1	60.3	-0.75
Fertilizers	65.2	58.8	-1.02		75.5	
Other Chemical Products		54.6		62.0	67.0	0.78
Pharmaceuticals	53.2					
Perfumery	56.4	54.2	-0.40		51.5	
Soaps		59.4		86.2	60.7	-3.50
Candles	57.6	64.4	1.10			
Plastic Sheets	64.6	54.1	-1.77	67.4	63.1	-0.67
Plastics for Industrial Use	64.2	55.5	-1.46	71.6		
Plastics for Domestic Use		74.3			69.1	
Complex Average	56.6	56.3	-0.06	63.8	65.8	0.31
TEXTILE AND FOOTWEAR COMPLEX						
Leather and Hides	66.2	60.7	-0.86		75.2	
Spinning and Weaving	52.1	47.2	-1.00	73.2	60.6	-1.89
Other Textile Artifacts	55.5	49.8	-1.09	70.9	64.5	-0.95
Special Textile Products	68.0	51.9	-2.70		58.4	
Clothing	64.9	62.4	-0.39	76.5	62.5	-2.02
Hats	58.0	54.9	-0.55		68.8	
Footwear	74.5	63.3	-1.63	86.4	71.1	-1.96
Other Clothing Products	72.0	56.7	-2.40		62.5	
Complex Average	57.8	54.2	-0.65	75.1	63.3	-1.71

(continua)

Sector	# EMPLOYEES > 5 1970	1980	RATE OF CHANGE	# EMPLOYEES > 50 1970	1980	RATE OF CHANGE
AGROINDUSTRIAL COMPLEX						
Agroindustry	63.2	59.2	-0.65	76.2	66.9	-1.30
Canned & Preserved Fruits & Veget.	61.5	62.4	0.15	81.3	70.5	-1.42
Meat Products & Animal Fats	54.8	50.2	-0.88	78.8	77.4	-0.18
Fish & Other Sea Products	63.7	42.8	-3.99	74.8	69.5	-0.74
Candies & Chocolates	73.9	61.2	-1.89		70.6	
Bakery Products	67.6	56.0	-1.89	65.0	47.4	-3.16
Pasta & Cookies	76.4	60.3	-2.36	83.2	68.3	-1.98
Veget. Oil&Fats & Misc. Food Prod.	48.7	50.1	0.28	66.5	68.0	0.22
Alcoholic Beverages	64.7	61.7	-0.48	72.1	69.7	-0.34
Nonalcoholic Beverages	54.8	56.2	0.26	68.7		
Tobacco	71.6	65.9	-0.83	73.0	55.2	-2.80
TOTAL	60.5	55.3	-0.89	74.6	69.4	-0.73

(a) Exclusive Vehicules
(b) Excluding Train Engines.

A correlation analysis between average technical efficiency levels and a set of variables reflecting sector characteristics seems to confirm that low or decreasing technical efficiency is associated with technological progress (Table 3). For both 1970 and 1980 a negative and significant association is obtained between technical efficiency and different measures of capital intensity (the ratio of total capital stock to output (CS/OUT) and to value added (CS/VA) and the ratio of the stock of machinery to these two variables (M&EQ/OUT and M&EQ/VA)). Negative correlations are also observed in both years between technical efficiency and the shares of direct exports in output (SHDEX) and of imports in material inputs (SHIMI), the average establishment size (SIZE), and the share of less-than-five-year-old establishments in production (AGE). None of these correlations is, however, significant. On the other hand, positive and significant correlations result for the rates of return on the stock of total capital (RRCS) and on the stock of machinery (RRM&EQ) in 1980. For the investment-capital ratios (IL for total stock and ILM for the stock of machinery), the composition of the stock of capital (M&EQ/CS) and the degree of industrial concentration (IC) the correlations are positive and nonsignificant for 1970 and 1980.[25] For the male participation in the labour force (MP), the degree of capital utilization (CU), and the share of skilled workers in total labour force in production (SW) correlations are negative. They are significant in 1970 for the first two and in 1980 for the latter. Finally, for the share of imports in investment in machinery (SHINV), for the ratio of royalties to profits (ROY) and for profitability (PROF) the correlations are nonsignificant and of different signs in the two years.

Table 3: Correlations with Average Sector Technical efficiency

	Correlations with Average Sector Technical efficiency		Correlations with Changes in Technical efficiency Levels			
VARIABLE	1970	1980	1970	1980	RATE OF CHANGE	ABSOLUTE CHANGE
SHDEX	-0.012	-0.149	-0.186	-0.170	-0.061	-0.096
SHIMI	-0.034	-0.060	0.137	0.163	-0.333**	0.097
SHINV	-0.103	0.061	0.045	-0.087	0.007	-0.107
ROY	-0.055	0.077	-0.015	-0.004		0.012
M	-0.195	-0.325**	0.025	-0.037	-0.211*	-0.188
SW	-0.241**	-0.113	0.234*	0.085*	-0.012	-0.163*
M&EQ/CS	0.034	0.014	0.047	0.021	-0.040	-0.041
M&EQ/VA	-0.352**	-0.501**	0.083	-0.070	-0.243**	-0.194
CS/VA	-0.425**	-0.525**	0.047	-0.113	-0.252**	-0.222*
M&EQ/OUT	-0.38**	-0.473**	0.040	-0.003	-0.150	-0.055
CS/OUT	-0.451**	-0.502**	-0.007	-0.035	-0.159	-0.055
RRCS	0.270**	0.297**	-0.045	0.151	0.296**	0.233*
RRM&EQ	0.191	0.228**	-0.043	0.113	0.283**	0.194
ILM	-0.027	-0.021	-0.245**	0.011		
IL	-0.029	0.054	-0.278**	0.002		
SIZE	-0.089	-0.010	-0.039	0.103	0.141	
CU	-0.175	-0.248**	-0.128	0.054	0.247**	0.162
AGE	-0.151	-0.173	-0.083	0.113	0.089	0.167
IC	0.115	0.100	-0.132	-0.089*	0.106	0.094
PROF	0.013	-0.008	-0.181	0.122	0.300**	0.304**

* Significant at 10% level.
** Significant at 5% level.

Results for the change in technical efficiency levels also seem to confirm that technological change takes place more fast then technological diffusion. Sectors

[25]This last result differs from that of Rossi(1984), who found a positive and significant correlation between industrial concentration and sector efficiency.

in which technical efficiency increased were the ones that in 1970 had lower ratios of investment to capital stock and larger shares of skilled workers in production. Average technical efficiency increased with the rate of return to capital and profitability, and decreased with capital intensity, male participation in the labour force, and the share of imports in the consumption of material inputs.

The methodology of section 2 and the estimates of average technical efficiency can now be combined to decompose the rate of TFP change from t-1 to t into movements of the frontier production function (technological progress) and changes in the technical efficiency with which the available technology is used (technical efficiency change). Recall from expression (6) that:

$$TFPC_P = \ln [Y(1,t) / Y(1,t-1)] - \{ \ln F[x(1,t); 1, t-1] - \ln F[x(1,t-1); 1,t-1]\} = \ln F[x(1,t);1,t] - \ln F[x(1,t);1,t-1] + \ln e(1,t) - \ln e(1,t-1) \qquad (6)$$

Since different frontiers have been estimated for each census, it is necessary to choose a point of comparison to derive meaningful results from the decomposition. The natural choice is the average establishment, which is not only representative but also allows the comparison between the results of this paper and the nonparametric estimates of TFP change obtained by Pinheiro (1989).[26] Note that the estimates to be obtained for TFP change using the parametric approach will probably differ from those estimated using index numbers. To understand why recall the expression for the translog index of (nonparametric) TPF change from t-1 to t:

$$TFP_{NP} = \ln [Y(k,t)/Y(k,t-1)] - \Sigma_j^J v_j [\ln(X_j(k,t)/X_j(k,t-1))] \qquad (24)$$

[26]Note also that constant returns to scale imply the rates of TFPC for the sector and for the average establishment are the same. To see that, define TFPC for the average establishment,

$$TFPC_{AV} = \ln[(Y^t/T^t)/(Y^{t-1}/T^{t-1})] - \Sigma_n^N v_n \ln[(X^t/T^t)/(X^{t-1}/T^{t-1})] = \ln[Y^t/Y^{t-1}] - \Sigma_n^N v_n \ln[X^t/X^{t-1}] + (T^t/T^{t-1}) - \Sigma_n^N v_n \ln[T^t/T^{t-1}] = \ln[Y^t/Y^{t-1}] - \Sigma_n^N v_n \ln[X^t/X^{t-1}] = TFPC$$

where T_t is equal to the number of establishments in t; v_n is the average elasticity of output with respect to input n; and TFPC and $TFPC_{AV}$ are the rates of TFP change for the sector and the average establishment, respectively.

where,

$v_j = [v_j(k,t) + v_j(k,t-1))/2$

$v_j(k,t)$ = the share of input X_j in the output of the average establishment of sector k in period t.

Then:

$$TFPC_{NP} - TFPC_P = \ln F[X(k,t);k,t-1] - \ln F[X(k,t-1);k,t-1] - \Sigma_j^J v_j [\ln(X_j(k,t) - \ln X_j(k,t-1)] \quad (25)$$

Then, the parametric and the nonparametric measures of TFP change may differ due to: (i) the use of cost shares to approximate output elasticities with respect to the inputs; and (ii) the fact that the elasticities for "interior" establishments, for which the shares provide estimates, may differ from those for establishments at the frontier production function used in the parametric estimation.[27]

In Table 5 the values of $TFPC_P$, the two terms of the decomposition yielded by (6) for the 1970-80 period, using the deterministic frontier estimates, the error term defined by (25), and the value of $TFPC_{NP}$, are reported for each sector. Results are somewhat mixed with respect to the difference between the rates of $TFPC_P$ and $TFPC_{NP}$, as can also be seen in Graph 2. In most cases the two measures are close, although for extreme observations significant discrepancies arise. It seems important to stress, though, that these differences are of the same order of magnitude of the ones reported for Yugoslavia [Nishimizu and Page Jr. (1982)], and for Korea and Japan [Noh (1987)].

TFP growth resulted in most sectors from technological progress (advances in the frontier production function) - and/or, for that matter, from increases in the absolute technical efficiency of the most productive firms. While parametric TFP change averaged 2.56% p.a. in the 1970-80 period -- very close, therefore, to the nonparametric estimate of 2.6% p.a. obtained by Pinheiro (1989) -- best practice TFP advanced at about 3.3% p.a., whereas technical efficiency declined annually at a rate of 0.7%. Technological progress was more important in the paper and printing (4.2% p.a.), construction (4.2% p.a.), chemical (3.7% p.a.) complexes, and stayed below average for the textile and

[27]If, however, inefficiency arises only from a difference in the values of the intercept terms of the average and the frontier production functions, then this second term will vanish.

footwear (3.1% p.a.), metal-mechanic (3.0% p.a.) and agroindustrial (3.0% p.a.) complexes.

The remarkable productivity growth (2.9% p.a.) and technological progress (4.2% p.a.) in the construction complex during the seventies resulted to a large extent from the performance of the cement and glass sectors, with high rates of productivity growth (4.1 and 5.6% p.a., respectively) and technological progress (8.4 and 7.7% p.a., respectively). On the other hand, the ceramics and the wood sectors acted to slow down the complex's performance, with low rates of productivity growth and technological progress. Both the cement and the glass sectors expanded their output substantially during the seventies, as a response to the construction boom that took place at the residential and public works segments, and invested in reducing the consumption of energy after the oil shock. The two sectors are highly concentrated, the second with a significant share of output in the hands of transnational corporations, in contrast with the ceramics and wood sectors, in which a large number of small national enterprises compete among themselves. No state enterprises are present in any of the four sectors, that together answer for 60.3% of the complex's output.

Two sectors alone answer for 45% of the metal-mechanic complex's output, the most important of the six we consider here: the iron and steel sector and the automobile vehicules and parts sector (25% and 20% of the complex's output, respectively). Most of the output from the iron and steel sector comes from state enterprises, that received large investments during the seventies, which explain the relatively high growth rates of average and best practice productivity. The automobile sector experienced a more modest expansion in productivity and in the technological frontier. The naval industry presented the highest rate of productivity growth in the transport equipment segment. The mechanic and electrical equipment segments also revealed positive advances with the exceptions of tractors and earth-moving machinery in the first and of communication equipment in the second. In the electrical equipment segment technological diffusion was more significant than in other parts of the complex.

The paper and printing complex experience the highest rates of productivity growth, technological progress and diffusion. Only one sector, other printing and publishing services, showed a significant reduction in average efficiency. On the average, the printing industry revealed a more positive performance than the paper industry.

The highly favourable performance of the chemical complex was pulled by four of its more important sectors: rubber, chemical elements and composites, oil refining and petrochemicals, and pharmaceuticals, responsible for 58% of the complex's output. The negligible loss of efficiency in the complex, by its turn, resulted from the very positive performance in the oil refining and petrochemical sectors, that answers for about a third of the chemical complex's output. Possibly, the dominance of the sector by a single enterprise (Petrobrás) explains why technological diffusion was so well succeeded.

The textile and footwear complex was characterized in the seventies by a high rate of technological progress and a slower rate of technological diffusion, resulting in a combination of a 2.4% annual rate of TFP growth and a 1.0% annual rate of efficiency loss. Three sectors answer for almost 90% of the complex's output: spinning and weaving (58%), clothing (20%) and footwear (11%). While the first and the last presented low rates of productivity growth and below average rates of technological progress, the clothing sector showed rapid change in average and best practice TFP.

In the agroindustrial complex, the three main sectors -- agroindustry, meat products&animal fats and vegetable oils & miscellaneous food products, with 25%, 26% and 16% of output, respectively -- showed a similar performance in the 1970-80 period, with a rate of TFP annual growth in the 2.3% - 2.8% interval and of technological progress in the 2.4% - 3.5% range. More positive results were accomplished by the beverage sector, both alcoholic and nonalcoholic, with above average rates of average and best practice TFP growth.

The results from the decomposition of productivity growth confirm the point made earlier that when structural change is significant TFP change is caused mainly by the adoption of new technologies. Technological diffusion takes place at a slower pace, increasing cross-firm heterogeneity and average sector inefficiency. However, in the case of Brazil, unlike Yugoslavia, a significant number of important firms adopted best-practice technology, with technical advance exceeding by far the loss in technical efficiency.

Table 5: Decomposition of Total Factor Productivity Change (% per year)

Sector	TFPCp	TECHN. PROGRESS	EFFIC. CHANGE	TFPCnp - TFPCp	TFPCnp
CONSTRUCTION COMPLEX					
Stones for Construction	6.40	7.24	-1.03	-1.32	5.08
Lime	4.97	7.89	-2.99	-8.17	-3.20
Ceramics	1.59	-0.10	1.69	-0.23	1.35
Cement	4.13	8.35	-4.21	-0.23	3.90
Cement Products & Artefacts	0.11	1.65	-1.53	-0.28	-0.17
Glass	5.58	7.70	-2.24	1.39	6.97
Processed Non-Metallic Minerals	13.39	12.72	-0.15	-4.99	8.40
Misc. Prod. of Non-metallic Miner.	0.83	4.33	-3.44	-1.22	-0.39
Wood	0.93	2.22	-1.29	-2.22	-1.29
Wood Furniture	3.40	3.16	0.18	-1.61	1.79
Metallic Furniture	3.98	5.40	-1.48	0.56	4.55
Upholstery	4.77	5.61	-0.95	0.52	5.29
Complex Average	2.87	4.15	-1.23	-1.11	1.75
METAL-MECHANIC COMPLEX					
Iron and Steel	2.31	3.92	-1.62	-0.77	1.55
Nonferrous Metals	1.09	1.90	-0.81	2.07	3.17
Metallic Structures					2.17
Iron and Steel Artef.	0.31	1.15	-0.83	0.02	0.33
Metal Stamping	0.68			0.35	1.03
Metal Tanks & Recipients	2.92	4.24	-1.34	0.25	3.18
Cutlery/Hand Tools/Hardware & Guns	1.01	2.79	-1.78	0.93	1.94
Special Ind. Machin.	2.22	4.45	-2.23	-0.03	2.19
Ind. Mach. for Hidr.&Termic Inst.	3.04	4.74	-1.73	-1.03	2.01
General Industrial Machinery					1.56
Machin.& Equip. for Agriculture	1.75	1.40	0.33	1.01	2.76
Home & Office Machin.& Equip.	2.63	2.50	0.10	2.68	5.31
Clocks, Whatches & Cronometers					6.10
Tractors & Earth-Moving Machines	-2.25	-2.19	-0.08	8.32	6.07
Equip. for Electrical Energy	2.28	2.73	-0.48	0.79	3.08
Electrical Material (a)	6.22	6.85	-0.81	0.76	6.98
Lamps					5.50
Electr. Material for Vehicules (b)	3.89	3.38	0.44	4.35	8.23
Electrical Appliances	2.86	4.21	-1.38	2.97	5.83
Electronic Material	1.01	1.78	-0.77	2.72	3.73
Communication Equipment	-2.24	-2.89	0.62	1.54	-0.70
Naval Industry	6.03			3.19	9.22
Railway Stock					4.70
Autom. Vehicules & Parts	0.93	2.36	-1.42	2.10	3.03
Bycicles	0.99	3.03	-2.03	0.15	1.14
Aircrafts					14.50
Other Vehicules	2.20	4.42	-2.22	2.20	4.40
Complex Average	1.77	2.99	-1.19	1.12	2.89

(continua)

Sector	TFPCp	TECHN. PROGRESS	EFFIC. CHANGE	TFPCnp - TFPCp	TFPCnp
PAPER AND PRINTING					
Paper	0.36			2.58	2.94
Paper Products	5.86	5.15	0.55	0.29	6.15
Newsp., Books, Manuals & Period.	6.10	6.05	-0.13	-0.51	5.59
Teaching/Ind./Comm. Printed Matter	7.33	5.17	1.92	-0.39	6.94
Other Print. & Publish. Services	2.82	4.81	-2.01	-0.94	1.87
Complex Average	4.59	4.18	0.39	0.55	5.14
CHEMICAL COMPLEX					
Rubber	3.69	5.96	-2.31	-0.54	3.15
Chemical Elem.&Composit.	3.00	2.32	0.64	-3.23	-0.23
Oil-Refining & Petrochem.	4.35	3.05	1.22	-1.58	2.77
Artific. Threads & Resins					1.59
Raw Vegetable Oils	0.75	2.06	-1.30	0.56	1.31
Aromatic Concentrates	-2.29	-0.18	-2.11	5.72	3.43
House Clean. Prod. & Pesticides	8.10	7.57	0.22	-1.34	6.75
Pigments, Paints & Solvents	1.02	2.23	-1.21	3.24	4.26
Fertilizers	0.81	1.83	-1.02	1.83	2.64
Other Chemical Products					3.00
Pharmaceuticals	3.11			3.50	6.61
Perfumary	0.68	1.07	-0.40	1.65	2.33
Soaps					2.29
Candles	6.64	5.33	1.10	0.81	7.45
Plastic Sheets	3.14	4.88	-1.77	0.12	3.26
Plastics for Industrial Use	4.33	5.71	-1.46	-0.29	4.04
Plastics for Domestic Use					-0.07
Complex Average	3.61	3.67	-0.06	-0.65	2.96
TEXTILE AND FOOTWEAR COMPLEX					
Leather and Hides	-2.04	-1.20	-0.86	0.50	-1.55
Spinning and Weaving	1.46	2.45	-1.00	-0.46	1.00
Other Textile Artifacts	7.03	7.89	-1.09	-0.52	6.52
Special Textile Products	2.83	5.53	-2.70	1.97	4.80
Clothing	7.12	7.27	-0.39	-1.40	5.72
Hats	4.58	5.03	-0.55	-0.46	4.12
Footwear	0.48	2.12	-1.63	0.07	0.55
Other Clothing Products	-1.00	1.42	-2.40	-0.31	-1.30
Complex Average	2.38	3.05	-0.65	-0.49	1.89

(continua)

Sector	TFPCp	TECHN. PROGRESS	EFFIC. CHANGE	TFPCnp - TFPCp	TFPCnp
AGROINDUSTRIAL COMPLEX					
Agroindustry	2.84	3.46	-0.65	0.05	2.89
Canned & Preserved Fruits & Veget.	1.00	0.85	0.15	-1.39	-0.39
Meat Products & Animal Fats	2.28	3.14	-0.88	-1.02	1.26
Fish & Other Sea Products	-0.43	3.64	-3.99	0.91	0.48
Candies & Chocolates	-1.70	0.20	-1.89	-0.21	-1.90
Bakery Products	-3.24	-1.39	-1.89	0.60	-2.65
Pasta & Cookies	-0.14	2.24	-2.36	0.80	0.66
Veget. Oil&Fats & Misc. Food Prod.	2.67	2.35	0.28	-0.44	2.23
Alcoholic Beverages	3.85	4.26	-0.48	-2.85	0.99
Nonalcoholic Beverages	7.40	6.88	0.26	-2.25	5.15
Tobacco	-0.11	0.73	-0.83	2.03	1.91
Complex Average	2.03	2.95	-0.89	-0.48	1.55

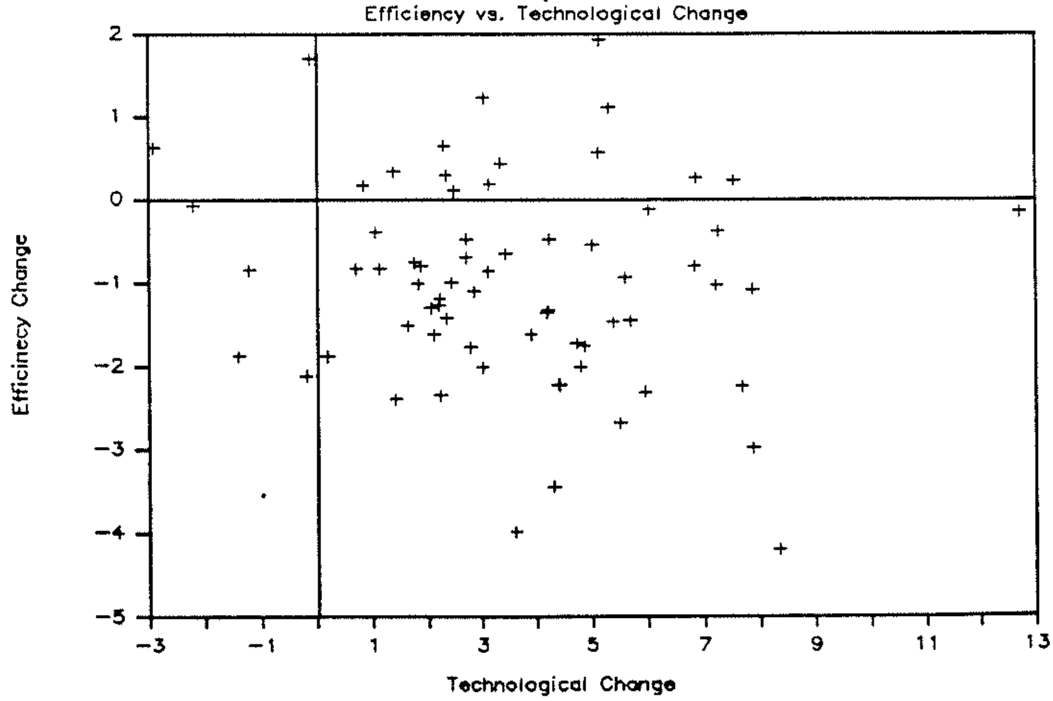
Note: See text for description of variables.

(a) Exclusive Vehicules.

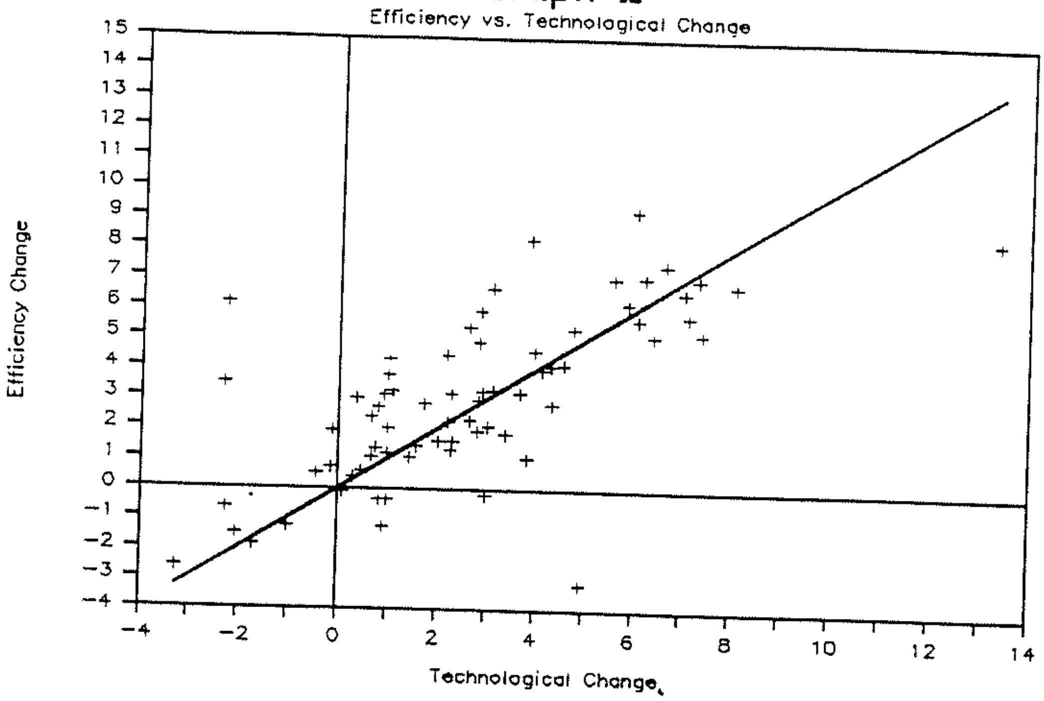
(b) Excluding Train Engines.

Graph 1

Efficiency vs. Technological Change



Graph 2



5. FINAL REMARKS

In this paper data at establishment level was used to estimate frontier production functions for each sector of Brazilian manufacturing in 1970 and 1980, which were then used to measure the rate of TFP change in each sector. TFP change measures growth of production that is not accounted for by changes in the quantities of the inputs consumed. Shifts of the average production function are associated with index number measures of TFP change. Best-practice TFP change reflects technological progress; that is, shifts in the frontier production function not explained by changes in the consumption of inputs. The difference between the two is given by the change in the average technical efficiency with which known technology is used. The second step in the paper was to decompose TFP change into its two components.

Results for the frontiers were somewhat frustrating. Error distribution was found to be symmetric for most sectors, contrary to prior expectations, with three important consequences. First, this fact reduced significantly the technical efficiency gains we had expected to achieve using the more expensive maximum-likelihood estimators. Second, it made the results for the deterministic and the stochastic frontiers very much alike, but for the average value of the distributions. Few of the insights we had anticipated gaining by comparing the two methodologies were attained.

In order to mitigate the effects of heterogeneity among establishments, deterministic frontiers were re-estimated for a reduced sample. Only establishments with more than fifty employees were considered in this second run, with 5% of the firms in each tail being eliminated before a third estimation was conducted. Results showed that our correction was in the right direction. Skewness of the error distribution was increased for most sectors, with asymmetric distributions arising for several of them. For many sectors, however, results changed little.

Our basic estimates revealed average sector technical efficiency to have been around 60% in 1970 and 55% in 1980. For the reduced sample of larger firms these estimates were 70% and 64%, respectively. On average technical efficiency declined 0.7% p.a in the seventies for establishments with more than five employees and 0.9% for those with more than 50 employees.

Correlation analyses for both the levels and the rates of change of technical efficiency revealed little with respect to what drives technical efficiency levels. A negative and significant correlation was obtained for capital intensity, and it seems also to have been the case that sectors that experienced increases in technical efficiency reduced the participation of men in the labour force.

Not very significant differences were observed between the parametric and the nonparametric (index number) measures of TFP change. On average, the two measures yield the same growth rate for the 1970's -- about 2.6% p.a.. Although important in some extreme sectors, the differences between the two measures were of the same order of magnitude of similar results reported elsewhere.

Our results are consistent with those in the literature for the decomposition of the rates of total factor productivity change. While best-practice TFP advanced almost 3.3% annually, technical efficiency declined for most sectors. These empirical findings seem to support the conclusion that during periods of rapid structural change it is ordinary that the main source of TFP growth be rapid technological progress. It is important to stress, however, that the argument refers to relative, rather than absolute technical efficiency. In this way, reductions on average technical efficiency open new perspectives for policies targeted at the diffusion and adaptation of best practice techniques among industrial establishments.

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