Decomposing Productivity Change in the Presence of Environmental Variables

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Abstract

This paper provides a decomposition of labor productivity growth into contributions associated with technical change, efficiency change, returns to scale, and environmental variables. The decomposition is based on parametric estimation of labor requirement functions. This approach is applied to a panel of Latin American distribution utilities between 1994 and 2001. The main results are a positive labor productivity growth averaging 7.5% per year, and that this is mainly due to a shift in the frontier.

Keywords: Productivity, Electricity Distribution, Labor Requirement Function, Efficiency.

An important assumption underlying frontier analysis is that all the firms in an industry share the same technology and face similar environmental conditions. However, this is not generally the case and, for the case of electricity distribution utilities, factors such as the demand structure may influence the performance measures obtained.

As pointed out by Coelli, Perelman, and Romano (1999), there are two alternative approaches to the problem of how to include environmental factors in a frontier model. One assumes that environmental factors influence the shape of the technology and hence they should be included as regressors (e.g., Good et al. 1993). The second approach assumes the environmental factors influence the degree of inefficiency (and not the shape of the technology) and hence that these factors should be modelled so that they directly influence the inefficiency term (e.g., Kumbhakar, Gosh, and McGuckin 1991; Battese and Coelli 1995).

In this paper I adopt the position of including the environmental variables as regressors in order to get efficiency measures that are net of their influences. When all environmental factors are taken into account, the net efficiency measure may be interpreted as a measure of managerial performance.

As observed by Kumbhakar and Hjalmarsson (1998), while productivity in electricity generation is to a large extent determined by technology, productivity in distribution is mainly determined by management and efficient labor use. Accordingly, this paper focuses on labor productivity, and the analysis is based on a translog labor requirement function (see Diewert 1974). A factor requirement function is particularly useful in industries producing multiple outputs by using one dominant input. The concept of efficiency used here is labor efficiency, according to which a firm is inefficient if, *ceteris paribus*, it uses more labor to produce a given bundle of outputs than an otherwise efficient firm would.

Based on the estimation of a parametric labor requirement frontier I show that labor productivity growth can be decomposed into four elements: technical change corresponding to shifts in the frontier, efficiency change corresponding to individual displacements with respect to the frontier (also called catching-up), a scale component, and a term related to the environmental variables. I take a total differential approach to the labor productivity decomposition (e.g., Bauer 1990; Kumbhakar and Lovell 2000). An alternative is the index number approach (Caves, Christensen, and Diewert 1982a, 1982b; Orea 2002). Diewert (2000) argues in favour of the index number approach because the total differential approach is an approximation to a continuous-time measure, which can take many values. However, as pointed out by Coelli et al. (2002), in most cases the two approaches provide similar estimates.

The methodology is applied to a panel of Latin American distribution utilities between 1994 and 2001, contributing to the literature on the sources of productivity change in electricity distribution (see Hjalmarsson and Veiderpass 1992; Førsund and Kittelsen 1998). By examining the elasticity of labor with respect to outputs and environmental variables, and the distribution of returns to scale, the paper also contributes to the empirical literature on the technology of electricity distribution (see Meyer 1975; Weiss 1975; Neuberg 1977; Huettner and Landon 1978; Salvanes and Tjøtta 1994; Pollitt 1995; Burns and Weyman-Jones 1996; Kumbhakar and Hjalmarsson 1998; Jamasb and Pollitt 2001).

1. Decomposition of Labor Productivity Change

I start with a general stochastic labor requirement frontier

$$l = f\left(y, z, t; \vartheta\right)\exp\left(\varepsilon\right). \tag{1}$$

where l is labor, $f\left(.\right)$ is an appropriate functional form, $y = \left(y_1, ..., y_K\right)$ is the output vector, $z = \left(z_1, ..., z_H\right)$ is the vector of control or environmental variables, t is the time trend, and ϑ is the vector of parameters to be estimated. The composite error term $\varepsilon = v + u$ allows for inefficiency in labor use $(u \geq 0)$ and for noise (v).

After taking logs to both sides of equation (1), totally differentiating with respect to time gives

(2) $$\frac{d\ Ln\ l}{dt} = \sum_{k=1}^{K} \frac{\partial\ Ln\, f(y,z,t;\vartheta)}{\partial y_k} \frac{dy_k}{dt} + \sum_{h=1}^{H} \frac{\partial\ Ln\, f(y,z,t;\vartheta)}{\partial z_h} \frac{dz_h}{dt} + \frac{\partial\ Ln\, f(y,z,t;\vartheta)}{\partial t} + \frac{du}{dt}.$$

Labor productivity change is defined as the difference between the rate of change of an output quantity index and the rate of change of labor. Thus,

(3) $$\dot{LP} = \dot{Y} - \dot{l}$$

where *LP* is labor productivity, *Y* is an index of outputs, and a dot over a variable indicates its rate of change $\left(\text{i.e., } \dot{l} = \frac{d\ Ln\ l}{dt}\right)$.

To make equation (3) operational, one must specify a form for the time rate of change of aggregate output. I will assume that

(4) $$\dot{Y} = \sum_{k=1}^{K} \frac{\varepsilon_k^y}{\varepsilon} \dot{y}_k$$

where $\varepsilon_k^y = \frac{\partial\ Ln\, f\left(y,z,t;\vartheta\right)}{\partial\ Ln\ y_k}$ is the elasticity of labor with respect to output *k* and $\varepsilon = \sum_{k}^{K} \varepsilon_k^y$. A measure of returns to scale is given by ε^{-1}.

Inserting (2) and (4) in (3) yields

(5) $$\dot{LP} = \left(\frac{1-\varepsilon}{\varepsilon}\right) \sum_{k=1}^{K} \frac{\varepsilon_k^y}{\varepsilon} \dot{y}_k + T\Delta + TE\Delta - \sum_{h=1}^{H} \varepsilon_h^z \dot{z}.$$

The first term on the right hand side of equation (5) is a scale component, the second term provides a measure of the rate of technical change, $T\Delta = -\frac{\partial\ Ln\, f(y,z,t;\vartheta)}{\partial t}$, the third term provides a measure of the rate of change of labor efficiency, $TE\Delta = -\frac{du}{dt}$, and the last term accounts for the contribution of the environmental variables.

The scale term depends on the degree of local returns to scale and on changes in output quantities. In particular, the scale term vanishes under constant returns to scale or constant output quantities.

Technical change accounts for shifts in the labor requirement function, and labor efficiency change accounts for catching-up effects. If either production technology or labor efficiency is time invariant, then it makes no contribution to labor productivity change.

The last term depends on the labor elasticity with respect to the environmental variables and on changes in these environmental factors. A particular environmental variable has not effect on productivity growth if the corresponding elasticity is equal to zero or if the environmental factor is constant over time.

2. Model Specification of Electricity Distribution in Latin America

The electricity distribution model includes one endogenous input (the number of employees); four exogenous outputs (number of final customers, total energy supplied to final customers, service area, and kilometers of distribution network); and two environmental variables (residential sales' share and GNP per capita).

Because a finer disaggregation was not available, I use the number of employees as the measure of labor input. Ideally, labor input should be divided into various categories (unskilled labor, skilled labor, management). As Coelli et al. (2002) note, measuring labor in a single aggregate variable implicitly assumes uniform skills distributions across firms. This is usually a reasonable assumption within one country, but it could be problematic in cross-country comparisons. As discussed below, I try to control for the differences in skills distributions across countries by including GNP per capita as an environmental variable.

Given that most Latin American electricity distribution firms have the obligation to meet demand, I consider the amount of electricity supplied to final customers (in gigawatt hours, GWh) and the number of final customers served as exogenous outputs in electricity distribution. I include service area (in square kilometers) as an output, since an increase in the service area either increases the use of resources or reduces the supply of other products (Førsund and Kittelsen 1998). Although there is an occasional redrawing of boundaries due to merger and takeover, for practical purposes the firm has little direct control over the size of its service territory, and hence service area can be considered an exogenous variable.

As Kumbakhar and Hjalmarsson (1998) note, the extent to which distributors have control over the length of distribution lines is limited since the amount of capital in the form of network reflects geographical dispersion of customers rather than differences in productive efficiency. Therefore, network capital is referred to the output side rather than the input side, leaving labor as the dominant input.

The model also includes two environmental variables: residential sales' share and GNP per capita. The proportion of total energy delivered that is distributed to residential customers captures the effect of delivering energy at different voltages required by different customers. It is included as an environmental variable, since the resources needed to deliver *E* units of medium voltage electricity to one customer are not the same as those needed to supply *E*/1,000 units of low voltage electricity to 1,000 households. GNP per capita (in purchasing power parity units) is included to control for differences in the socioeconomic environment in which firms operate in each country. It can capture, for example, differences in the quality of the labor input across countries.

The electricity distribution data used in this study include information on 142 Latin American firms between 1994 and 2001. The data were constructed on the basis of the Regional Electric Integration Commission (CIER) reports, which are based on surveys answered by the firms. Given the obvious danger that only the most successful utilities would answer the survey, I took great care to assemble the largest possible sample of firms, complementing CIER's reports with information provided by regulators and governmental agencies.

The sample is representative of the electricity distribution sector in the region. It covers the following countries: Argentina (34 firms that supply electricity to 83% of the total number of customers in the country), Bolivia (3, 34%), Brazil (47, 76%), Chile (3, 20%), Colombia (5, 34%), Costa Rica (8, 100%), Ecuador (13, 62%), El Salvador (5, 100%), Mexico (1, 79%), Panama (1, 62%), Paraguay (1, 100%), Peru (12, 99%), Uruguay (1, 100%), and Venezuela (8, 92%). Summary statistics of the unbalanced panel are presented in table 1. A total of 593 observations are available for estimation. The trend variable is defined as $t = 1,...,8$.

The purchasing power parity figures of GNP per capita were obtained from the World Bank database. I use purchasing power parity in order to correct for international differences in relative prices (for details, see the technical notes to the *World Development Reports*).

3. Econometric Model

The translog stochastic labor requirement frontier model with four outputs and two environmental variables, for a panel of $i = 1,...,N$ producers observed over $t = 1,...,T$ periods may be specified as

(6)
$$\begin{aligned} Ln\ l^{i,t} &= \beta_0 + \sum_{k=1}^{4}\beta_k Ln\ y_k^{i,t} + \frac{1}{2}\sum_{k=1}^{4}\sum_{n=1}^{4}\beta_{kn} Ln\ y_k^{i,t} Ln\ y_n^{i,t} \\ &+ \sum_{h=1}^{2}\psi_h Ln\ z_h^{i,t} + \frac{1}{2}\sum_{h=1}^{2}\sum_{m=1}^{2}\psi_{hm} Ln\ z_h^{i,t} Ln\ z_m^{i,t} + \sum_{h=1}^{2}\sum_{k=1}^{4}\zeta_{hk} Ln\ z_h^{i,t} Ln\ \mathrm{y}_k^{i,t} \\ &+ \theta_t t + \frac{1}{2}\theta_{tt} t^2 + \sum_{k=1}^{4}\theta_{kt} Ln\ y_k^{i,t} t + \sum_{k=1}^{2}\theta_{ht} Ln\ \mathrm{z}_h^{i,t} t + u^{i,t} + v^{i,t}. \end{aligned}$$

where $Ln\ l$, $Ln\ y_1$, $Ln\ y_2$, $Ln\ y_3$, $Ln\ y_4$, $Ln\ z_1$, and $Ln\ z_2$ are the natural logarithms of labor, sales, customers, area, lines, residential sales' share, and GNP per capita.

The time-trend variable appears in a second order polynomial in *t* and interacting with outputs and environmental variables. These terms introduce second order flexibility in the translog labor requirement function and will be used to identify technical change over time, which can vary from firm to firm and from one period to the next. An alternative specification for technical change would consist of introducing T-1 dummy variables instead of a trend variable (Baltagi and Griffin 1988). The alternative approach, however, has the disadvantage of being high in consuming degrees of freedom.

In the model in equation (6), technical change is neutral with respect to outputs and environmental variables if, and only if, $H_0 : \theta_{kt} = \theta_{ht} = 0 \ \forall h, k$, and absent if, and only if, $H_0 : \theta_t = \theta_{tt} = \theta_{kt} = \theta_{ht} = 0 \ \forall h, k.$

The labor requirement frontier is given by equation (6) when $u = 0$. Thus, the frontier gives the minimum amounts of labor required to produce a given level of outputs, *ceteris paribus*, and inefficiency can be interpreted as the percentage increase in labor for a firm that is not operating on the frontier.

Estimation of the parameters and firm-specific inefficiency in the above model requires distributional assumptions on the noise and inefficiency terms. The noise term is assumed to be independent and identically distributed $N\left(0, \sigma_v^2\right)$. The $u^{i,t}s$ are non-negative random variables representing technical inefficiency, and are assumed to be independently and identically distributed defined as the truncation (at zero) of the $N(\mu, \sigma_u^2)$ distribution. The Battese and Coelli (1992) representation is used for the evolution over time of the technical efficiency term, $u^{i,t} = u^i \exp\left[-\eta(t-T)\right]$, where η is a parameter to be estimated. If η is positive inefficiency is decreasing, if η is negative inefficiency is increasing, and if it is equal to zero then inefficiency is constant over time.

Labor efficiency of the *i*-th producer at time *t* is given by $TE^{i,t} = \exp\left(u^{i,t}\right)$. The prediction of labor efficiencies is based on conditional expectations (see Battese and Coelli 1993).

4. Empirical Results

Maximum likelihood estimates of the stochastic labor requirement model are presented in table 2. To derive the likelihood function, I use the parameterization proposed by Battese and Corra (1977): $\gamma = \sigma_u^2 / \left(\sigma_v^2 + \sigma_u^2\right)$. The parameter γ must lie between zero and one, where zero indicates that the deviations from the frontier are due entirely to noise. All estimates were performed using the computer program FRONTIER 4.1 (Coelli 1996). As usual for translog function approximations, the variables are expressed in deviations with respect to average values.

The first-order output coefficients have the expected signs regarding economic behavior and suggest that labor use is mainly driven by the GWh sold and the number of customers. Since a translog form is only a local second-order approximation about a point of expansion the properties required from economic theory must be checked for every observation point, not just the sample mean. Non-decreasing use of labor in output levels is checked by calculating the labor elasticities with respect to output levels y_1, y_2, y_3, and y_4. The estimated labor elasticities with respect to GWh sold, number of customers, service area, and distribution lines are positive for 81%, 84%, 82%, and 58% of the observations.

The first-order output coefficients sum to 0.82, implying an approximate scale elasticity of 1.22 at the sample mean values. To assess the returns to scale characteristics of the industry in more detail, I evaluate returns to scale at every observation point. Inspection of the distribution of the scale elasticity reveals that 98% of the observations exhibit increasing returns to scale, 55% have scale elasticity greater than 1.2, 18% of the observations display scale elasticity greater than 1.35, and 6% of the observations have scale elasticity greater than 1.5.

I also calculate average returns to scale by firm size quartile, using the number of customers as the proxy for firm size. The first quartile consists of firms with less than 55,090 customers; the second between 55,408 and 157,894; the third between 158,830 and 558,297; and the fourth greater than 558,528.Returns to scale are 1.41, 1.24, 1.19, and 1.10, for the first, second, third and fourth quartiles. This suggests that productivity gains are possible through increasing the size of the firms, especially in below average size firms.

The coefficient of GNP per capita is negative and significant, implying that firms in countries with higher per capita income use less labor, *ceteris paribus*. The coefficient of residential sales' share is very small relative to its estimated standard error.

Formal tests of hypotheses associated with the translog average labor requirement model are reported in table 3.Labor inefficiency is correctly identified within the composed error term: the likelihood ratio test on the one-sided error is highly significant, the share of labor-inefficiency in total variance is high $\hat{\gamma} = 0.94$, and it appears to have a truncated normal distribution with $\hat{\mu} = 0.99$. I cannot reject the hypothesis that labor efficiency is time invariant at any of the usual levels of significance, thus suggesting that there are no catching-up effects in the period.

The hypothesis that there is no technical change is rejected at the 1% level. The null hypothesis of neutral technical change is also rejected at the 1% level, even when I use the small sample correction to the likelihood ratio statistic proposed by Mizon (1977).

Table 4 reports the annual decomposition of labor productivity growth, together with an overall year average. The main results are a positive labor productivity growth averaging nearly 7.5% per year, and that this is mainly due to a shift in the frontier.

It is interesting to compare these results with related studies on the sources of productivity change in electricity distribution. Hjalmarsson and Veiderpass (1992) find that the average annual productivity growth in Swedish electricity distribution sector, over the period 1970-1986, has been about 5%. The primary source of productivity growth is returns to network density, i.e., the economies of increasing the amount of electricity supplied when the network is held constant. They find no evidence of catching-up effects. Førsund and Kittelsen (1998) examine Norwegian electricity distribution utilities finding that total productivity growth is nearly 2% per year and that this is mainly due to frontier technology shift. As in Hjalmarsson and Veiderpass's study, there is no tendency for the least efficient firms to catch-up with the more efficient ones.

5. Concluding Remarks

In this paper I decompose labor productivity growth into contributions associated with technical change, efficiency change, returns to scale, and environmental variables. The methodology is illustrated with an application to Latin American electricity distribution utilities. The following main conclusions can be drawn from the empirical results: (i) there is an important labor productivity growth averaging nearly 7.5% per year; (ii) most of labor productivity growth is due to a shift in the labor requirement frontier; (iii) there are small but positive effects of the scale and environmental variables component, and there are no catching-up effects; and (iv) there are increasing returns to scale in electricity distribution in Latin America, which are higher for small firms.

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Table 1: Sample Summary Statistics

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Outputs				
Sales (in GWh)	5,485	18,348	11	175,498
Number of customers	694,224	2,071,978	3,323	19,760,000
Service area (in km^2)	88,954	248,551	32	1,889,910
Distribution lines (in km)	22,292	70,931	76	595,170
Input				
Number of employees	1,564	4,699	12	41,063
Environmental variables				
Residential sales/total sales	0.40	0.11	0.11	0.97
GNP per capita (in PPP units)	7,252	2,621	2,193	12,890

Table 2: Maximum Likelihood Estimates

	Variable	*Coefficient*	*Standard error*
	Intercept	-0.996	0.071
Outputs	Ln y_1	0.317	0.057
	Ln y_2	0.396	0.071
	Ln y_3	0.080	0.024
	Ln y_4	0.025	0.053
	$(\text{Ln } y_1)^2$	-0.271	0.077
	$(\text{Ln } y_2)^2$	-0.061	0.183
	$(\text{Ln } y_3)^2$	-0.015	0.017
	$(\text{Ln } y_4)^2$	0.032	0.104
	(Ln y_1)(Ln y_2)	0.237	0.106
	(Ln y_1)(Ln y_3)	0.076	0.035
	(Ln y_1)(Ln y_4)	-0.029	0.082
	(Ln y_2)(Ln y_3)	-0.047	0.046
	(Ln y_2)(Ln y_4)	-0.064	0.108
	(Ln y_3)(Ln y_4)	0.004	0.036
Control	Ln z_1	-0.023	0.072
Variables	Ln z_2	-0.175	0.064
	$(\text{Ln } z_1)^2$	0.426	0.332
	$(\text{Ln } z_2)^2$	0.149	0.148
	(Ln z_1)(Ln z_2)	-0.626	0.189
Control variables -outputs	(Ln z_1)(Ln y_1)	0.272	0.128
	(Ln z_1)(Ln y_2)	-0.190	0.202
	(Ln z_1)(Ln y_3)	-0.024	0.047
	(Ln z_1)(Ln y_4)	-0.064	0.146
	(Ln z_2)(Ln y_1)	-0.229	0.130
	(Ln z_2)(Ln y_2)	0.371	0.194
	(Ln z_2)(Ln y_3)	-0.067	0.035
	(Ln z_2)(Ln y_4)	-0.094	0.107
Technical	Time	-0.058	0.008
Change	$(\text{Time})^2$	-0.002	0.003
	Time* Ln y_1	0.067	0.010
	Time* Ln y_2	-0.107	0.014
	Time* Ln y_3	-0.010	0.003
	Time* Ln y_4	0.037	0.010
	Time* Ln z_1	0.051	0.015
	Time* Ln z_2	0.016	0.011
ML Parameters	γ	0.937	0.005
	μ	0.987	0.073
	η	-0.007	0.007
	Log likelihood	103.93	

Table 3: Specification Tests

Null hypothesis	Test statistic[a]	Small sample statistic[B]
$H_0 : \gamma = \mu = \eta = 0$	880.77***	823.58***
$H_0 : \mu = 0$	29.14***	27.20***
$H_0 : \eta = 0$	1.15	1.07
$H_0 : \theta_t = \theta_{tt} = \theta_{kt} = \theta_{ht} = 0 \ \forall h, k$	122.20***	114.78***
$H_0 : \theta_{kt} = \theta_{ht} = 0 \ \forall h, k$	79.67***	74.70***

*The null hypothesis is rejected at the 10 percent level.

**The null hypothesis is rejected at the 5 percent level.

***The null hypothesis is rejected at the 1 percent level.

[a] Critical values are obtained from the appropriate chi-square distribution, except for the tests of hypotheses involving $\gamma = 0$ (Kodde and Palm 1986, Table 1).

[b] Small sample correction of the likelihood ratio test proposed by Mizon (1977).

Table 4: Decomposition of Labor Productivity Change

Period	*Technical change*	*Efficiency change*	*Scale component*	*Environmental variables component*	*Labor productivity change*
1995	0.065	0	0.004	-0.002	0.067
1996	0.062	0	0.006	0.024	0.093
1997	0.063	0	0.009	0.010	0.082
1998	0.071	0	0.004	0.007	0.082
1999	0.058	0	0.008	0.000	0.065
2000	0.054	0	0.006	0.015	0.075
2001	0.048	0	0.007	-0.001	0.054
Average	0.060	0	0.006	0.008	0.074