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Decomposition of Labor Productivity Growth: A Multilateral Production Frontier Approach

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ABSTRACT

This paper develops a parametric decomposition framework of labor productivity growth relaxing the assumption of labor-specific efficiency. The decomposition analysis is applied to a sample of 52 developed and developing countries from 1965-90. A generalized Cobb-Douglas functional specification is used taking into account differences in technological structures across group of countries to approximate aggregate production technology using Jorgenson and Nishimizu (1978) bilateral model of production. Measurement of labor efficiency is based on Kopp's (1981) orthogonal non-radial index of factor-specific efficiency modified in a parametric frontier framework. The empirical results indicate that the weighted average annual rate of labor productivity growth was 1.43 per cent over the period analyzed. Technical change was found to be the driving force of labor productivity, while improvements in labor efficiency and human capital account approximately for the 22 per cent of that productivity growth.

Keywords: labor efficiency and productivity growth, multilateral production frontier.
JEL Classification: J24, O40, C23

DECOMPOSITION OF LABOR PRODUCTIVITY GROWTH: A MULTILATERAL PRODUCTION FRONTIER APPROACH

INTRODUCTION

The productivity fall observed in many developed and developing countries during the 60's and early 70's triggered an intense public debate aimed to unravel the internal mechanism of productivity growth. This heated debate had resulted to an enormous theoretical and empirical literature directed to the investigation of the proximate causes of the observed differences in per-capita income across developing and developed countries. Most researchers used the cross-sectional version of the familiar growth accounting framework of Solow (1957) to decompose country variations in the levels of output per worker into parts attributed to the variation in the factors of production and productivity growth. The results lead to the conclusion that the residual productivity rather than factor accumulation accounts for most of the income and growth differences across nations (see Caselli (2005) and the references cited therein). This finding although it uncovers the proximate causes of income differentials is unsatisfactory in the sense that the ultimate causes that lead to different levels of productivity are not explained. If we accept that productivity differences are large, then we are left with a shortage of convincing explanation for this result. The later is important as different sources of productivity differentials require different policy measures to enhance economic growth either in developed or developing nations (Prescott, 1988).

Since much of these productivity variations represents differences in technological structures, then there should be an adequate explanation why non-rival innovations do not diffuse across borders. And if they do, then why we still observe differences in measured productivity rates. If there is a uniform worldwide production frontier, then all of the observed differences in productivity reflect a gap from this frontier. Obviously there are strong barriers to adoption across countries related to the institutional and cultural environment preventing many countries from using that common technological structure. Olson (1982) and Krusell and Rios-Rull (1996) argue, that vested interest groups are lobbying for market power, protection from competition, limiting factor mobility and then blocking adoption of rival technologies through a political process. Parente and Prescott (1999) provide a theoretical model where the existence of monopoly power extend beyond the traditional deadweight loss affecting the adoption of new technologies as well as the appropriate use of technologies already adopted.

Relative recently economic growth literature questions the above perspective, recognizing that the technology frontier is not uniform. In other words, it admits that not every country face the same technological conditions. According to this perception countries choose the best production technologies available to them given their internal economic and structural conditions. Obviously factor endowments as well as the institutional and cultural environment affect these choices as some technologies may be less productive than others. For instance, ICT technologies enhance social welfare through structural transformation in production networks and social customs but at the same time require human capital, *i.e.*, high literacy rates, to function properly. Basu and Weil (1998) and Acemoglou and Zilibotti (2001), explored the appropriateness of technology paradigm to explain differences in income levels and economic convergence. They both conclude that developed countries invent new technologies that are compatible with their own resource endowments and these technologies do not work appropriately in developing countries with a different input mix. This implies that the adoption of a modern technology by poor countries do not raise their productivity levels as it is inappropriate to them. So the assumption of the same technological structure may not be adequate to explain productivity variations and empirical work should take that into account.

Under both paradigms, one would expect all countries to operate on their own or to the common technological frontier being thus fully efficient. Empirical evidence though suggest that rather the opposite is true. Several authors suggest that rarely countries are exploring fully the potential of the existing technology operating far from their respective production frontier (*e.g.*, Färe *et al.*, 1994; Kumar and Russell, 2002; Los and Timmer, 2005; Badunenko *et al.*, 2008). Theoretical models of explaining inefficiency in resource utilization, focus on the role of institutions and social structures to explain why the common or country-specific production technology is not utilized appropriately by individual countries. Apart of the availability of the technology, other factors must be present such as strong investment, a well trained work force, R&D activity, trading relationships, a receptive political structure that Abramovitz (1986) summarizes under the term *social capability*. However, all these elements of efficiency determination are not affecting the efficient use of all inputs in the same manner. For instance, lack of working experience affects rather more intensively labor efficiency than capital utilization. Nevertheless empirical studies, besides analyzing labor productivity differentials, they utilize an aggregate output or input inefficiency index. Important information, valuable from a policy perspective, can be gained by providing an empirical analysis focusing exclusively on labor-specific efficiency.

Probably the most important aspect related with resource utilization and therefore productivity differentials across countries, recognized by many researcher, is the role of human capital. Inspired by the early approaches on human capital theory (Schultz, 1961; Becker, 1975), many empirical researchers have focused on the important role played by educational levels in the efficiency of input utilization and hence on the growth process. In these early theoretical contributions schooling is viewed as an investment in skills having a direct effect on labor productivity as well as an indirect one through the improvement of worker's ability to work efficiently (Welch, 1970). Griliches (1970) and Jorgenson and Fraumeni (1993) found that a significant portion of differentials is attributed directly to increases in educational levels. On the other hand, Welch (1970) and Bartel and Lichtenberg (1987), among others, found that highly educated workers have a comparative advantage with regard to the implementation of new technologies exhibiting therefore higher efficiency levels. Recently the development of detailed educational data by Barro and Lee (1993; 2001) and the formulation of endogenous growth models by Lucas (1988) and Romer (1990), enabled the empirical analysis on the role of education in economic growth. All of these studies on growth accounting again indicated that a significant portion of measured productivity growth is attributed directly to increases in educational levels of the labor force (*e.g.*, Benhabib and Spiegel, 1994; O'Neil, 1995; Bils and Klenow, 2000). Regardless of the nature and the aims of these studies, they provided unshaken evidence about the important role played by human capital in the growth process, suggesting that it is an important element of any productivity decomposition analysis and it should be included in any empirical research.

Motivated by the works of Färe *et al.*, (1994), Kumar and Russell (2002) and Henderson and Russell (2005), we attempt in this paper to contribute in the relevant literature providing a theoretically consistent parametric decomposition of labor productivity growth. According to these studies labor productivity is decomposed into the rates of growth of factor intensities and TFP. However, shifts in relative capital-labor prices and the biases of technological change are also important possibilities for changes in the growth rate of factor intensities. Taking that into account, our decomposition framework provides a more detailed analysis of changes in labor productivity across countries. First, we focus on labor-specific inefficiency rather than an output efficiency measure which is more relevant when labor productivity growth is analyzed. The proposed index for measuring labor-specific technical and allocative efficiency is based on Kopp's (1981) orthogonal non-radial index of technical efficiency modified in a parametric frontier framework. Then the derived index of labor-specific efficiency is used to provide a complete decomposition framework of labor productivity growth.

Second, we dispense with the assumption of a common worldwide production technology in estimated parametrically the aggregate production frontier. Our empirical aggregate production frontier model is based on the generalized Cobb-Douglas functional specification suggested by Fan (1991) that accounts for biases in technical change, extended into a *multilateral* context in order to take into account differences in technological structures among countries in the sample using Jorgenson and Nishimizu (1978) bilateral production structure. In that way formal statistical testing can be used to examine the existence of a common worldwide technology utilized by all countries in the sample. The production frontier was estimated econometrically, incorporating human capital, using Cornwell *et al.*, (1990) fixed effects formulation that allows for country specific time varying inefficiencies. Following Griliches (1963), human capital is introduced as an augmenting factor of labor input using Hall and Jones (1999) construction, enabling thus the identification of both its direct and indirect role on measured labor productivity.

Using this general framework we provide a complete decomposition analysis of labor productivity growth in a sample of 52 developed and developing countries from 1965-90 drawn from *Penn World Tables*. Besides decomposing the growth of output per worker into technological change, technological catch-up and physical and human capital accumulation, our decomposition analysis accounts for the existence of variable returns to scale and for the labor biases of technical change due to changes in relative factor prices. The remaining paper is organized as follows. In the next section, we present the theoretical framework for measuring labor productivity growth in a parametric context. Next section 3 presents data description and describes the empirical model and estimation procedures. Section 4 discusses the empirical results while, the last section concludes the paper.

THEORETICAL FRAMEWORK

Let assume that countries in period t utilize labor, physical and human capital to produce a single aggregate output $y \in \Re_{+}$ through a well-behaved technology described by the following non-empty, closed set:

$$T^t = \{(k,l,\varepsilon,y) : y \le f(k,l,\varepsilon,t)\} \qquad (1)$$

where $k \in \Re_+$ denotes physical capital, $l \in \Re_+$ labor, $\varepsilon \in \Re_+$ human capital, $t \in \Re_+$ is a time index, and, $f(k,l,\varepsilon,t) : \Re_+^4 \to \Re_+$ is a strictly increasing, differentiable concave production function, representing the maximal output from physical capital and labor use given human capital and technological constraints. Using (1) we can define the input correspondence set as all the input combinations capable of producing $y \in \Re_+$ as: $L(y) = \{(k,l,\varepsilon) \in \Re_+^3 : (k,l,\varepsilon,y) \in T^t\}$. Given the assumptions made on $f(\bullet)$, the input correspondence set is a closed convex set satisfying strong disposability of labor and physical capital inputs.

Alternatively, aggregate production technology may be defined by the dual cost function $C(\mathbf{w},y,\varepsilon,t) : R(y) \times \Re_{++}^3 \to \Re_{++}^1$ as:

$$C(\mathbf{w},y,\varepsilon,t) = \min_{k,l} \{w_l l + w_k k : y \le f(k,l,\varepsilon,t)\} \qquad (2)$$

where $R(y) = \{y \in \Re_+ : L(y) \ne \varnothing\}$, $\mathbf{w} = \{w_l, w_k\} \in \Re_{++}^2$ are the strictly positive effective labor and capital prices. The cost function is differentiable in all its arguments, non-decreasing in $\mathbf{w}$ and y, non-increasing in ε and t, and homogeneous of degree one in $\mathbf{w}$.

At this point we may assume that the production of aggregate output may not be technical efficient, *i.e.*, countries are not able to minimize input use in the production of a given aggregate output in the light of the prevailing factor prices. Concentrating in labor input it should hold that $y = f\left(k, \theta^l \cdot l, \varepsilon, t\right)$ where θ^l is a measure of labor-specific technical efficiency indicating how much labor should be reduced still being able to produce the same level of aggregate output. Formally, θ^l may be defined according to Kopp's (1981) orthogonal non-radial index of input-specific technical efficiency:[1]

$$LTE^{KP} = \min_{\theta^l}\left\{\theta^l : \theta^l > 0,\ y \leq f\left(k, \theta^l \cdot l, \varepsilon, t\right)\right\} \tag{3}$$

which is bounded between zero and one, *i.e.*, $0 < LTE^{KP} \leq 1$. Graphically, the above definition is presented in Figure 1. Assuming that country *i* operates at point *A* in the graph utilizing l^0 quantity from labor and k^0 quantity from capital producing $\overline{y}$ level of aggregate output. Obviously the country in question is technically inefficient as it is possible to reduce input use moving on the respective isoquant and still being able to produce the same level of aggregate output. If inefficiency arises only from labor use then an obvious change would be the movement to point *B* on the graph, where capital use remains unchanged but labor quantity has been reduced to $l^1 = \theta^l l^0$.

However, still at point *B* country is not fully efficient. Although labor use is at its technical efficient point country fails to utilize an appropriate capital-labor mix given the input prices it faces. This is achieved at point *C* where cost of aggregate production is minimized given factor prices, human capital endowments and production technology. A measure of the extent for this allocation error is provided by the following ratio:

$$LAE = \frac{l^*\left(\mathbf{w}, y, \varepsilon, t\right)}{\theta^l l} \tag{4}$$

where $l^*(\mathbf{w}, y, \varepsilon, t)$ is the *Hicksian* constant output demand function for labor obtained from (2) through Shephard's lemma which is non-decreasing in *y* and w_k and non-increasing in w_l, *ε* and *t*. The above ratio may be viewed as an index of labor allocative efficiency which, contrary to its technical efficiency index, can take positive values below or above unity and it is equal to one when $\theta^l l = l^*(\mathrm{w}, y, \varepsilon, t)$. If it is greater (less) than one, labor is under- (over-) utilized at its technically efficient level given capital and labor prices. In developed countries that are abundant in capital input, labor allocative efficiency is expected to be greater than one whereas in developing countries that are abundant in labor input less than one assuming competitive factor prices.

Using (3) and (4) we may define overall labor efficiency by the product of labor technical and allocative efficiency or, equivalently, by the ratio of optimal to observed labor use as:

$$LOE = LTE^{KP} \times LAE = \frac{\theta^l l}{l} \times \frac{l^*(\mathbf{w}, y, \varepsilon, t)}{\theta^l l} = \frac{l^*(\mathbf{w}, y, \varepsilon, t)}{l} \tag{5}$$

which is equal to one when $l = l^*(\mathrm{w}, y, \varepsilon, t)$. When $LOE > 1$, individual country over-utilizes labor input at the observed point given the prevailing factor prices, whereas when $LOE < 1$ labor is under-utilized.

Taking the logarithms on the last equality of (5) and totally differentiating with respect to time we get:

$$\dot{LOE} = \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial \ln y}\dot{y} + e_{ll}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_l + e_{lk}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_k + e_{l\varepsilon}^d(\mathbf{w},y,\varepsilon,t)\dot{\varepsilon} + \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial t} - \dot{l} \qquad (6)$$

where a dot over a function or a variable indicates its time rate of change, $e_{ll}^d(\mathbf{w},y,\varepsilon,t) = \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial \ln w_l}$ and $e_{lk}^d(\mathbf{w},y,\varepsilon,t) = \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial \ln w_k}$ are the compensated own- and cross-price elasticities of labor demand, respectively and, $e_{l\varepsilon}^d(\mathbf{w},y,\varepsilon,t) = \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial \ln \varepsilon}$ is the compensated labor demand elasticity with respect to human capital. Then, using the conventional *divisia* index of labor productivity, *i.e.*, $\dot{LP} = \frac{d\ln(y/l)}{dt} = \dot{y} - \dot{l}$, the time rate of change of the first equality in (5), *i.e.*, $\dot{LOE} = \dot{LTE}^{KP} + \dot{LAE}$, and substituting them into (6), we obtain

$$\dot{LP} = \dot{LTE}^{KP} + \dot{LAE} + \left[1 - \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial \ln y}\right]\dot{y} - e_{ll}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_l - e_{lk}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_k - e_{l\varepsilon}^d(\mathbf{w},y,\varepsilon,t)\dot{\varepsilon} - \frac{\partial \ln l^*(\mathbf{w},y,\varepsilon,t)}{\partial t} \qquad (7)$$

decomposing, thus, labor productivity growth into a labor-specific technical and allocative inefficiency effect (first two terms), an output effect (third term), a substitution effect (fourth and fifth terms), a human capital effect (sixth term) and, a technological change effect (last term). Using the cost share equation of labor input, *i.e.*,

$\frac{\partial \ln C(\mathbf{w}, y, \varepsilon, t)}{\partial \ln w_l} = S_l(\mathbf{w}, y, \varepsilon, t) = \frac{w_l l^*(\mathbf{w}, y, \varepsilon, t)}{C(\mathbf{w}, y, \varepsilon, t)}$, taking logarithms and slightly rearranging terms we obtain:

$$\ln l^*(\mathbf{w}, y, \varepsilon, t) = \ln S_l(\mathbf{w}, y, \varepsilon, t) + \ln C(\mathbf{w}, y, \varepsilon, t) - \ln w_l \tag{8}$$

Then differentiating (8) with respect to aggregate output and time we can further decompose the output and technological change effect as (Kuroda, 1987; 1995):

$$\begin{aligned} \frac{\partial \ln l^*(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} &= \frac{\partial \ln S_l(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} + \frac{\partial \ln C(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} \\ &= \frac{1}{S_l(\mathbf{w}, y, \varepsilon, t)} \frac{\partial S_l(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} + \varepsilon_y^C(\mathbf{w}, y, \varepsilon, t) \end{aligned} \tag{9}$$

and

$$\begin{aligned} \frac{\partial \ln l^*(\mathbf{w}, y, \varepsilon, t)}{\partial t} &= \frac{\partial \ln S_l(\mathbf{w}, y, \varepsilon, t)}{\partial t} + \frac{\partial \ln C(\mathbf{w}, y, \varepsilon, t)}{\partial t} \\ &= \frac{1}{S_l(\mathbf{w}, y, \varepsilon, t)} \frac{\partial S_l(\mathbf{w}, y, \varepsilon, t)}{\partial t} + C^t(\mathbf{w}, y, \varepsilon, t) \end{aligned} \tag{10}$$

where $\varepsilon_y^C(\mathbf{w}, y, \varepsilon, t) = \frac{\partial \ln C(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y}$ is the output cost elasticity and, $-C^t(\mathbf{w}, y, \varepsilon, t) = \frac{\partial \ln C(\mathbf{w}, y, \varepsilon, t)}{\partial t}$ is the rate of cost diminution (*i.e.*, dual rate of technical change). Substituting equations (9) and (10) into (7) results in

$$\begin{aligned}\dot{LP} = & \underbrace{\dot{LTE}^{KP} + \dot{LAE}}_{\text{Efficiency effect}} + \underbrace{\left[1-\varepsilon_y^C\left(\mathbf{w},y,\varepsilon,t\right)\right]\dot{y}}_{\text{Scale effect}} - \underbrace{C^t\left(\mathbf{w},y,\varepsilon,t\right)}_{\substack{\text{Technological}\\ \text{change effect}}} - \underbrace{e_{l\varepsilon}^d\left(\mathbf{w},y,\varepsilon,t\right)\dot{\varepsilon}}_{\text{Human capital effect}} \\ & -\underbrace{e_{ll}^d\left(\mathbf{w},y,\varepsilon,t\right)\dot{w}_l - e_{lk}^d\left(\mathbf{w},y,\varepsilon,t\right)\dot{w}_k}_{\text{Price effect}} - \underbrace{\frac{1}{S_l\left(\mathbf{w},y,\varepsilon,t\right)}\left[\frac{\partial S_l\left(\mathbf{w},y,\varepsilon,t\right)}{\partial t} + \frac{\partial S_l\left(\mathbf{w},y,\varepsilon,t\right)}{\partial \ln y}\dot{y}\right]}_{\text{Extended labor biased techological change effect}}\end{aligned} \tag{11}$$

which is the final decomposition formula of labor productivity growth. Specifically, equation (11) attributes labor productivity growth into six sources. The first three terms accounts for changes in TFP which in turn is decomposed into changes in labor efficiency, the effect of scale economies and technological change. The first component of the right hand side of (11) indicates changes in labor-specific technical and allocative inefficiency over time. It is positive (negative) as labor technical and allocative efficiency increases (decreases) over time.[2] There is no *a priori* reason for both types of efficiency to increase or decrease simultaneously (Schmidt and Lovell, 1980) nor that their relative contribution should be of equal importance for productivity growth. More importantly, what really matters in productivity growth decomposition analysis is not the degree of efficiency itself, but its improvement over time. That is, even at low levels of overall efficiency, output gains may be achieved by improving either technical or allocative labor efficiency, or both. However, it seems difficult to achieve substantial rates of growth at very high levels of technical and/or allocative efficiency. The second term measures the relative contribution of scale economies to labor productivity growth. Under constant returns-to-scale, *i.e.*, $\varepsilon_y^C\left(\mathbf{w},y,\varepsilon,t\right)=1$, output growth or contraction makes no contribution to labor productivity change and therefore this term vanishes. It is positive (negative) under increasing (decreasing) returns-to-scale as long as aggregate output increases and *vice versa*. The third term refers to the dual rate of technical change, which is positive (negative) under progressive (regressive) technical change which can be further decomposed into a neutral and factor biased effect depending on the maintained assumption of the aggregate production technology. The fourth term is the effect of human capital accumulation on labor productivity growth. It is positive as an increase (decrease) in human capital affects negatively (positively) the optimal use of labor and it is zero if human capital remains constant over time.[3] The sum of the last three terms is the total substitution effect (*i.e.*, changes in factor intensities) which is decomposed into a price effect, a biased technological change effect and a non-homotheticity effect. The first term is the price effect of the labor demand due to changes in labor and capital prices. If the technology satisfies all neoclassical properties the own effect contributes positively (negatively) to labor productivity growth as long as the price of labor increases (decreases) over time whereas the cross demand effect is negative (positive) if capital prices increases (decreases). The price effect is zero when both labor and physical capital prices remain constant over time. The second term is the extended labor biased technical change effect (Blackorby *et al.*, 1976; Antle and Capalbo, 1988). Changes in relative prices of capital and labor induces changes in the individual factor cost shares as production is moved along the expansion path (first term in the last bracket). Further if the assumption of input homotheticity is not maintained an additional output effect is induced altering further factor proportions relative to their initial values (second term in the last bracket). If the technology is labor-saving (using) the extended labor biased technical change effect is positive (negative), whereas it is zero when technical change is extended *Hicks* neutral or if the production technology is linear homogeneous. In homothetic technologies the second term of the extended labor biased technical change effect vanishes as $\frac{\partial S_l(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} = 0$.

DATA AND EMPIRICAL MODEL

For the quantitative measurement and decomposition of labor productivity growth we utilized a balanced data set of 52 developed and developing countries covering the period from 1965 to 1990.[4] For aggregate output, physical capital and labor input we make use of the *Penn World Tables* (ver. 5.6).[5] For the calculation of capital and labor prices, following the approach suggested by Mamuneas *et al.*, (2006), we use the share of employee compensation in national income published by the *Total Economy Growth Accounting Database* of the Groningen Growth and Development Centre and *National Account Statistics* of the United Nations (UN).[6] Human capital was proxied using Barro and Lee (1993; 2001) educational data that are available for the same group of countries and for the same time period.[7,8] Following Henderson and Russell (2005), we adopt Hall and Jones (1999) construction where education appears as an augmentation factor for labor using an exponential specification, *i.e.*, $h(\varepsilon) = e^{\varphi(\varepsilon)}$ with $\varphi(\varepsilon)$ being a *Mincerian* piecewise linear function with zero intercept and slope that varies according to the time span.[9] Following Psacharopoulos (1994) survey on the evaluation of the returns to education, those parameters were defined as being 0.134 for the first four years, 0.101 for the next four years and 0.068 for education beyond the eight year.

Our empirical model for providing measurement of labor productivity growth is based on a *Cobb-Douglas* type of aggregate production frontier. Specifically, minimizing the cost on the flexibility of the functional specification, we adopt a generalized *Cobb-Douglas* (or quasi-translog) production frontier, proposed by Fan (1991). This functional specification, although not enough flexible like the translog, it allows for variable returns to scale, input-biased technical change, and time varying output and demand elasticities, but it restricts the latter to be unchanged over countries. It permits statistical testing for various features of the aggregate production technology, providing at the same time an analytical closed form solution for the corresponding dual cost frontier necessary to identify appropriately all terms in (11) (Fan and Pardey, 1997).

Since both developed and developing countries are included in the sample we should take into account technological differences among them. To lessen these potential biases in approximating production technology, we extent Jorgenson and Nishimizu (1978) "*bilateral*" production structure into a "*multilateral*" context within the generalized Cobb-Douglas production frontier model. Specifically, we distinguish six different groups of countries (*i.e.*, South and Central America, North America and Oceana, Europe, Asia, Africa and Asian Tigers) assuming that each one of those groups exhibit it's "own" technological structure. In that way, on the one hand, it is possible to identify differences in all terms appearing in (11) between group of countries that are assumed to exhibit different technological conditions, while on the other, we allow for more flexible patterns for technological features (*i.e.*, returns to scale, technological change, production and demand elasticities) between groups of countries lessened further the cost of choosing a less flexible functional specification for the approximation of the worldwide production technology.

In particular, the multilateral generalized *Cobb-Douglas* production frontier model, expressed in natural logarithms, has the following form:

$$\begin{aligned} ln\, y_{it} = \beta_{it}^{0} + \beta^{t} t + 0.5\beta^{tt} t^{2} + \beta_{j}^{l}\, ln\left(l_{it} \cdot e^{\varphi(\varepsilon_{it})}\right) \\ + \beta_{j}^{k}\, ln\, k_{it} + \beta_{j}^{lt}\, ln\left(l_{it} \cdot e^{\varphi(\varepsilon_{it})}\right) t + \beta_{j}^{kt}\, ln\, k_{it} t + v_{it} \end{aligned} \tag{12}$$

where $i = 1,\ldots,N$ are the countries in the sample, $t = 1,\ldots,T$ are the time periods, $j = 1,\ldots,J$ are the group of countries defined in the "multilateral" structure of the production technology, v_{it} depicts a symmetric and normally distributed error term, $v_{it} \sim N\left(0, \sigma_{v}^{2}\right)$, (*i.e.*, statistical noise), which represents left-out explanatory variables and measurement errors in the dependent variable and, $\beta_{j}^{l} = \beta^{l} D_{j}$, $\beta_{j}^{k} = \beta^{k} D_{j}$, $\beta_{j}^{lt} = \beta^{lt} D_{j}$ and, $\beta_{j}^{kt} = \beta^{kt} D_{j}$ with D being a dummy variable indicating the groups of countries, *i.e.*, $D_{j} = 1$ for country belonging in group j and $D_{j} = 0$ for every other country belonging to other groups. The above specification considers the data on inputs and aggregate output for each one of the countries in the sample belonging into different groups as a separate set of observations which are assumed to be generated by *multilateral* models of production. Hence, the presence of D_{j} as an argument in the production function above allows for different production technologies to be assigned into the different groups of countries.

Finally, $\beta_{it}^{0} = \beta^{0} - \xi_{it}$ are country- and period-specific intercepts introduced into (12) in order to capture temporal variations in output technical efficiency following

Cornwell *et al.*, (1990) fixed effects specification. According to this formulation output technical inefficiency is assumed to follow a quadratic pattern over time, *i.e.*,

$$\xi_{it} = \zeta_{i0} + \zeta_{i1}t + \zeta_{i2}t^2 \tag{13}$$

where, ζ_{i0}, ζ_{i1} and ζ_{i2} are the $(N \times 3)$ unknown parameters to be estimated. If $\zeta_{i1} = \zeta_{i2} = 0 \ \ \forall i$, then output technical efficiency is time-invariant, while when $\zeta_{i1} = \zeta_1$ and $\zeta_{i2} = \zeta_2 \ \forall i$ then output technical efficiency is time-varying following, however, the same pattern for all countries in the sample.[10]

The model in (12) and (13) can be estimated following either an one or a two step procedure by single-equation methods under the assumption of expected profit maximization. When N/T is relatively small, one can adopt an one-step procedure where ξ_{it} is included directly in (12) using dummy variables. However, in this case it is not possible to distinguish between technical change and time-varying technical efficiency if both are modeled via a simple time-trend (as in our case). In the two-step procedure, *OLS* estimates on the within group deviations are obtained for *β's* and then the residuals for each producer in the panel are regressed against time and time-squared as in (13) to obtain estimates of *ζ'*s for each country in the sample. In both cases time-varying output technical inefficiency is obtained following the normalization suggested by Schmidt and Sickles (1984). Specifically, define $\beta_t^0 = \max_i \{\xi_{it}\}$ as the estimated intercept of the production frontier in period *t*. Then output technical efficiency of each country in period *t* is estimated as $TE_{it}^O = exp(-\xi_{it})$, where $\xi_{it} = \left(\hat{\beta}_t^0 - \hat{\beta}_{it}\right)$.[11] The advantages of this specification are its parsimonious parameterization regardless of functional form, its straightforward estimation, its independence of distributional assumptions, and that it allows output technical inefficiency to vary across countries and time. Moreover, since the expression in (13) is linear to its parameters, the statistical properties of individual country-effects are not affected.

Under price uncertainty, expected profit maximization implies cost minimization allowing us to go back and forth between the production and cost functions in a theoretically consistent way (Batra and Ullah, 1974). Thus, solving the optimization problem in (2) using (12) we obtain the following dual to (12) cost function in a logarithmic form:

$$\begin{aligned} ln\,C_{it} = \delta_{jt}^{0} + \delta_{j}^{t} t + 0.5\delta_{j}^{tt} t^{2} + \delta_{j}^{y}\, ln\, y + \delta_{j}^{l}\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) \\ + \delta_{j}^{k}\, ln\, w_{kit} + \delta_{j}^{lt}\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) t + \delta_{j}^{kt}\, ln\, w_{kit} t \end{aligned} \tag{14}$$

where

$$\begin{aligned} &\delta_{jt}^{0} = ln\left(\frac{E_{j}}{\beta_{j}^{l} + \beta_{j}^{lt} t}\right) - \frac{1}{E_{j}}\left[\left(\beta_{j}^{k} + \beta_{j}^{kt} t\right) ln\left(\frac{\beta_{j}^{k} + \beta_{j}^{kt} t}{\beta_{j}^{l} + \beta_{j}^{lt} t}\right) + \beta^{0}\right], \\ &E_{j} = \beta_{j}^{l} + \beta_{j}^{k} + \beta_{j}^{lt} t + \beta_{j}^{kt} t\,,\ \delta_{j}^{t} = -\beta^{t}\delta_{j}^{y}\,,\ \delta_{j}^{tt} = -\beta^{tt}\delta_{j}^{y}\,, \\ &\delta_{j}^{l} = \beta_{j}^{l}\delta_{j}^{y}\,,\ \delta_{j}^{k} = \beta_{j}^{k}\delta_{j}^{y}\,,\ \delta_{j}^{lt} = \beta_{j}^{lt}\delta_{j}^{y}\,,\ \delta^{kt} = \beta_{j}^{kt}\delta_{j}^{y}\,,\ \delta_{j}^{y} = 1/E_{j} \end{aligned} \tag{15}$$

Then, using (14) we can derive the optimal demand function for labor input as:

$$ln\, l_{it}^{*} = ln\left(\frac{\delta_j^l + \delta_j^{lt} t}{w_{lit}}\right) + \delta_{jt}^0 + \delta_j^t t + 0.5\delta_j^{tt} t^2 + \delta_j^y \, ln\, y + \delta_j^k \, ln\, w_{kit} + \delta_j^l \, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) + \delta_j^{lt} \, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) t + \delta_j^{kt} \, ln\, w_{kit} t \tag{16}$$

From (16) we can derive the compensated own- and cross-price elasticities of labor demand, *i.e.*,

$$e_{ll}^d = \frac{\partial\, ln\, l_{it}^*}{\partial\, ln\, w_{lit}} = \delta_j^l + \delta_j^{lt} t - 1 \tag{17}$$

and

$$e_{lk}^d = \frac{\partial\, ln\, l_{it}^*}{\partial\, ln\, w_{kit}} = \delta_j^k + \delta_j^{kt} t \tag{18}$$

which are necessary for the estimation of the fifth term in (11). These demand elasticities are both group and time-specific. Similarly the labor demand elasticity with respect to human capital is obtained from:

$$e_{l\varepsilon}^d = \frac{\partial\, ln\, l_{it}^*}{\partial\, ln\, \varepsilon_{lit}} = -\left(\delta_j^l + \delta_j^{lt} t\right) \frac{\partial \varphi\left(\varepsilon_{it}\right)}{\partial \varepsilon_{it}} \varepsilon_{it} \tag{19}$$

that provides estimates of the fourth term in (11). The output cost elasticity necessary for the estimation of the scale effect is obtained from:

$$\varepsilon_y^C = \frac{\partial ln C_{it}}{\partial ln y_{it}} = \delta_j^y \tag{20}$$

The hypothesis of constant returns-to-scale can be statistically tested by imposing the restriction that $\delta_j^y = 1, \forall j$ which is equivalent with imposing linear homogeneity in the aggregate production frontier given the restrictions in (15), *i.e.*, $\beta_j^l + \beta_j^k = 1$ and $\beta_j^{lt} + \beta_j^{kt} = 0 \ \forall j$. If this hypothesis cannot be rejected then the underlying technology exhibits constant returns-to-scale and the second term in (11) vanishes.

For the estimation the technological change effects (third and last terms in (11)) we need to compute the rate of cost diminution and the labor share equation. The former under the multilateral generalized Cobb-Douglas specification in (14) is obtained,

$$-C_{it}^t = \frac{\partial ln C_{it}}{\partial t} = \delta_j^t + \delta_j^{tt} t + \delta_j^{lt} ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) + \delta_j^{kt} ln\, w_{kit} \tag{21}$$

The hypothesis of *Hicks*-neutral and zero technical change involves the following parameter restrictions in (21): $\delta_j^{lt} = \delta_j^{kt} = 0$ and $\delta_j^t = \delta_j^{tt} = \delta_j^{lt} = \delta_j^{kt} = 0 \quad \forall j$, respectively.[12] Accordingly, using the optimal labor share equation, *i.e.*,

$$S_{lit} = \frac{\partial ln C_{it}}{\partial ln w_{lit}} = \delta_j^l + \delta_j^{lt} t \tag{22}$$

we can compute the extended labor biased technical change effect as:

$$\frac{1}{S_{lit}}\frac{\partial S_{lit}}{\partial t}=\frac{\delta_j^{lt}}{\delta_j^l+\delta_j^{lt}t} \tag{23}$$

Since the multilateral generalized Cobb-Douglas aggregate production model is homothetic the second term in the extended labor biased technological change effect is zero and therefore it does not contribute in labor productivity growth. If the underlying aggregate production technology exhibits zero technical change then the third and the last terms in (11) are zero and labor productivity growth is affected only from the remaining four terms. If, however, technical progress is Hicks-neutral then only the extended labor biased technical change effect vanishes. Finally, if the underlying technology is neutral with respect to labor use, *i.e.*, $\delta_j^{lt}=0\ \forall j$, then again the final term in labor productivity decomposition formula vanishes[13].

Finally, for the estimation of the first term in (11) we need to compute labor technical efficiency. For doing so we use Reinhard, Lovell and Thijssen (1999) approach in the context of the multilateral generalized *Cobb-Douglas* production frontier.[14] Conceptually, measurement of LTE_{it}^{KP} requires an estimate for the quantity $\tilde{l}_{it}=\theta_l\cdot l_{it}$ which is not observed. Substituting this into the aggregate production function model in (12) and by noticing that the labor-specific technical efficient point lies on the frontier, *i.e.*, $\xi_{it}=0$, relation (12) may be rewritten as:

$$\begin{aligned} ln\, y_{it} &= \beta_t^0+\beta^t t+0.5\beta^{tt}t^2+\beta_j^l\, ln\left(\tilde{l}_{it}\cdot e^{\varphi(\varepsilon_{it})}\right) \\ &\quad + \beta_j^k\, ln\, k_{it}+\beta_j^{lt}\, ln\left(\tilde{l}_{it}\cdot e^{\varphi(\varepsilon_{it})}\right)t+\beta_j^{kt}\, ln\, k_{it}t+v_{it} \end{aligned} \tag{24}$$

Since under weak monotonicity, output technical efficiency should imply and must be implied by labor-specific technical efficiency, we can set the input specification in (24) equal to the output-oriented specification in (12). Then, using the parameter estimates obtained from the econometric estimation of the multilateral generalized Cobb-Douglas production model and solving for $\tilde{l}_{it}$, we can derive a measure of Kopp's (1981) non-radial labor-specific technical efficiency from the following relation (Reinhard Lovell and Thijssen, 1999):[15]

$$LTE_{it}^{KP} = exp\left(-\frac{\xi_{it}}{\beta_j^l + \beta_j^{lt} t} \right) \tag{25}$$

which is always different than zero as long as farms are technically inefficient from an output-oriented perspective, *i.e.*, $\xi_{it} \neq 0$ or $\zeta_{i0} \neq 0, \zeta_{i1} \neq 0, \zeta_{i2} \neq 0 \quad \forall i$. Using (13) and (25) the time rate of change of labor technical efficiency is computed from:

$$\dot{LTE}_{it}^{KP} = -\frac{\zeta_{i1} + 2\zeta_{i2} t}{\beta_j^l + \beta_j^{lt} t} + \frac{\left(\zeta_{i0} + \zeta_{i1} t + \zeta_{i2} t^2\right) \beta_j^{lt}}{\left(\beta_j^l + \beta_j^{lt} t\right)^2} \tag{26}$$

It is time-invariant if also output technical efficiency is time-invariant, *i.e.*, $\zeta_{i1} = \zeta_{i2} = 0$ $\forall i$ and biased technical change is labor neutral, *i.e.*, $\beta_j^{lt} = 0$. It's temporal pattern is common across countries if $\zeta_{i1} = \zeta_1$, $\zeta_{i2} = \zeta_2$ $\forall i$, $\beta_j^l = \beta^l$ and $\beta_j^{lt} = \beta^{lt}$ $\forall j$.

Labor allocative efficiency is then computed using the derived demand for labor input in (16) and the labor technical efficient use, *i.e.*, $\tilde{l}_{it} = LTE_{it}^{KP} \times l_{it}$, as:

$$LAE_{it} = l_{it}^{*}\left(\mathbf{w}, y, \varepsilon, t\right)\left[exp\left(-\frac{\xi_{it}}{\beta_j^l + \beta_j^{lt} t}\right) \times l_{it}\right]^{-1} \tag{27}$$

and it's time rate of change is then computed using the time derivative of (16) and relation (26) above as:

$$\dot{LAE}_{it} = \frac{\partial\, ln\, l_{it}^{*}\left(\mathbf{w}, y, \varepsilon, t\right)}{\partial t} - \frac{\partial\, ln\left(LTE_{it}^{KP} \times l_{it}\right)}{\partial t} \tag{28}$$

In effect it remains constant over time under zero technical change and time invariant labor technical inefficiency, *i.e.*, $\zeta_{i1} = \zeta_{i2} = 0 \;\wedge\; \beta_j^{lt} = 0 \;\forall j$ and $\beta^{t} = \beta^{tt} = \beta_j^{lt} = \beta_j^{kt} = 0 \;\forall j$, while it's temporal pattern is common across countries if $\zeta_{i1} = \zeta_1 \wedge \zeta_{i2} = \zeta_2 \;\forall i$ and $\beta_j^l = \beta^l$, $\beta_j^k = \beta^k$, $\beta_j^{lt} = \beta^{lt}$, $\beta_j^{kt} = \beta^{kt} \;\forall j$.

EMPIRICAL RESULTS

The fixed effects parameter estimates of the multilateral aggregate Cobb-Douglas production frontier model in (12) are presented in Table 1 along with their corresponding standard errors. The majority of the estimated parameters (except of two) were found to be statistically significant at the 1 or 5 per cent level. All parameters have the anticipated positive sign, while their magnitudes are bounded between 0 and 1 indicating that the bordered *Hessian* matrix of first- and second-order partial derivatives is negative semi-definite. This implies that all regularity conditions hold at the point of approximation, *i.e.*, positive and diminishing marginal productivities. In the lower panel of Table 1 are also reported the country and time specific parameters of Cornwell *et al.*, inefficiency effects model in (13) for the country with the maximum efficiency score in each one of the six groups. For the majority of the countries in the sample all parameters were found to be positive (except of some African countries) implying improvements in output technical efficiency over time (this finding is statistically examined next).[16]

Several hypotheses concerning the multilateral structure of the aggregate production frontier model were tested using the generalized likelihood-ratio test statistic[17] and the results are presented in the upper panel of Table 2. First, the hypothesis that the imposed multilateral structure of the aggregate production frontier model in (12) is not valid is rejected at the 5 per cent significance level (first hypothesis in table 2). Further, the assumption that only the biases of technical change are similar across group of countries is also rejected (second hypothesis in table 2). The same is true for the marginal productivities of physical capital and labor inputs (third hypothesis in table 2). Statistical testing results in the same conclusion when each one of the estimated coefficients is tested separately (last four hypotheses). Hence, indeed data on inputs and aggregate output in our sample are generated by multilateral models of production supporting our initial hypothesis for approximating the worldwide production technology. There are significant differences across group of countries in their respective choice of production technology which should be taken into account in labor productivity growth decomposition. Basu and Weil (1998) and Acemoglou and Zilibotti (2001), appropriateness of technology paradigm is verified by the econometric estimation of our aggregate production frontier.

The next set of hypotheses testing concerns the structure of technology, *i.e.*, returns-to-scale and technical change. The results are presented in the middle panel of Table 2. First, it seems that for every country group, the aggregate production technology is not characterized by constant returns-to-scale as the relevant hypothesis was rejected at the 5 per cent level, *i.e.*, $\beta_j^l + \beta_j^k = 1$ and $\beta_j^{lt} + \beta_j^{kt} = 0$. This implies that the scale effect is present constituting an important source of labor productivity growth. Average country and time estimates of scale coefficients were found to be increasing for South and Central American (1.0925), North America and Oceana (1.0412), Asian Tigers (1.2080) and Europe (1.0141). On the other hand, African and Asian countries exhibit decreasing returns as the relevant point estimates were found 0.9572 and 0.9573, respectively. This implies that less developed countries in these two continents (*i.e.*, Africa and Asia) have gone beyond the potential capabilities of their aggregate own production technology.

The hypotheses of zero technical change *i.e.*, $\beta_T = \beta_{TT} = \beta_j^{lt} = \beta_j^{kt} = 0$ and *Hicks*-neutral technical change *i.e.*, $\beta_j^{lt} = \beta_j^{kt} = 0, \forall j$ were also rejected at the 5 per cent significance level. On the average technical change was found progressive in all country groups with the highest value being for Asian Tigers, 1.001 per cent. For North America and Oceania the corresponding figure was 0.6076, for European countries 0.6909, for South and Central American countries 0.5979, for African countries 0.6138 and for Asian countries 0.7559. The parameters related with the neutral technical change, *i.e.*, β^t and β^{tt}, were found to be positive and statistically significant at the 1 per cent level, implying that technical change was constantly progressive for the time period under consideration. The second order parameters related with the biased part of technological change, *i.e.*, β_j^{lt} and β_j^{kt} were found to vary among the different groups of countries. Specifically, technical change was found to be labor using in North America and Oceania and labor saving in South and Central America, Africa, Asia and Asian Tigers, while the corresponding parameter was found positive for Europe but statistically insignificant. On the other hand, technical change was capital using in South and Central America, Africa, and Asian Tigers and capital saving in Europe and North America and Oceania. The relative parameter for Asia was found statistically insignificant. We have further examined the hypothesis of labor-neutral technical change using the LR-test. The results are in favour of labor-biased technical change rejecting the relevant hypothesis (last hypothesis in the middle panel of table 2). Thus, the labor biased technical change effect, *i.e.*, first term in the last parenthesis in relation (11) is present and it should be taken into consideration in the decomposition analysis of labor productivity growth.

The final set of statistical testing refers to the specification of labor technical and allocative efficiency and it's temporal pattern. First, countries in the sample are indeed not exploiting full the potential of their aggregate production technology exhibiting inefficiencies in resource utilization. These inefficiencies in labor use should be taken into account when labor productivity growth is to be analyzed. Specifically the hypothesis that all ζ parameters are jointly equal to zero is rejected at the 5 per cent level of significance (first hypothesis in the lower panel of table 2). Further, labor technical efficiency was found to be time varying during the 1965-90 period as the hypothesis that $\zeta_{i1} = \zeta_{i2} = 0$ and $\beta_j^{lt} = 0$ is also rejected at the same significance level (2nd hypothesis in the lower panel). This temporal pattern of labor technical efficiency is not common across countries in the sample, implying differences between countries in movements towards their respective aggregate production frontier. Specifically the hypothesis that $\zeta_{i1} = \zeta_1$, $\zeta_{i2} = \zeta_2$ $\forall i$ and $\beta_j^l = \beta^l \wedge$ $\beta_j^{lt} = \beta^{lt}$ $\forall j$ is rejected from the generalized LR-test (3rd hypothesis in the lower panel of the table). Concerning labor allocative inefficiency, statistical testing implies that there are time varying labor utilization mistakes at its technically efficient point. Finally, indeed countries in the sample are making adjustments towards better utilization of labor under the prevailing factor prices which are not common across countries in the sample (last two hypotheses in table 2).

Estimates of both labor technical and allocative efficiency in the form of frequency distribution are reported in Table 3 for each group of countries. Estimated mean labor technical efficiency over both countries and time was found to be 66.4 per cent. This figure implies that the same level of aggregate output could have been produced on the average, under the current technological conditions and physical capital use, if labor use was decreased almost by 34 per cent. There is a notable difference on the average efficiency scores between rich and poor group of countries. The most labor technically efficient group was found to be Asian Tigers (87.81 per cent) followed by North America and Oceania (79.42 per cent), and Europe (68.23 per cent). On the other hand, the less labor technically efficient groups were South and Central America (63.88 per cent), Asia (61.12 per cent) and Africa (44.75 per cent). Some of the Asian Tigers exhibit the highest mean technical efficiency values (Thailand 90.59 per cent, Korea Rep 89.68 per cent, Japan 87.64 per cent and Hong Kong 84.31 per cent) whereas African countries have the lowest ones (Zambia 44.35 per cent, Zimbabwe 45.89 per cent, Malawi 45.38 per cent and Mauritius 47.04 per cent).

On the other hand, estimates of labor allocative efficiency further confirm this divergence among poor and rich countries. In all three groups of developed countries mean labor allocative efficiency is greater than unity indicating that labor is under-utilized at its technical efficiency point compared with the groups of developing countries where the corresponding figure is below one. Specifically, mean labor allocative efficiency is 1.12 for North America and Oceania, 1.25 for Europe, and 1.32 for Asian Tigers. Contrary, in South and Central America the corresponding figure is 0.66, 0.57 in Africa and 0.67 in Asia. Israel and most European countries are underutilizing labor at its technical efficient point having mean values well above unity (Israel 1.53, Belgium 1.56, Ireland 1.40 and Denmark 1.41). On the other hand, India (0.34), Malawi (0.39), Turkey (0.47) and Sri Lanka (0.47) seem to over-utilize extensively labor input.

Concerning the temporal pattern of these efficiency measures, the three less efficient groups (South and Central America, Asia and Africa) were found to follow a quite similar temporal pattern. As far as labor technical efficiency, all three groups were found to follow an ascending path until 1975, followed by a constant decrease -except of some slight upward variations- after this year. Only South and Central American countries were found to present small improvements in their labor efficiency score at the end of the period under consideration. The picture is different as regard allocative efficiency scores. All three countries were found to follow an ascending temporal pattern which was constantly sharper for Asian countries. On the other hand, North America and Oceania and Europe were found to follow approximately a common path until the second half of 70’s when European countries experienced a decrease in their labor technical efficiency score. In the beginning of 80’s, North America and Oceania countries overcame slightly the corresponding technical efficiency score of the European countries, following however approximately a common path after this year. The results for the two groups are similar, regarding labor allocative efficiency. Finally, Asian Tigers were found to experience an increase in their labor technical efficiency score until 1975 which is though lower than those of Europe and North America and Oceania. After a small decrease in the second half of 70’s, Asian Tigers experienced an increase in labor technical efficiency which was about two times higher than those of the other two developed country-groups. As far as allocative efficiency, Asian Tigers were found to follow a slightly descending path during the first five years, followed by a constant increase until the end of the period. The highest rates of these improvements are observed in the second half of 80’s.

Developing countries with low capital-labor mix seems to utilize more inefficiently labor input compared with developed countries not exploring full the advantage of their technological conditions. The appropriate technology paradigm of Basu and Weil (1998) explains differences in the gap from the frontier among developed and developing countries, but in a competitive economic environment exchange rate misalignments, institutional features (*e.g.*, rigidities in product and labor markets) and competitive pressures affect the overall performance of individual economies. Further, the abundance of labor input in developing countries results in over-utilization of its use in the production process creating further inefficiency problems (*e.g.*, India, Turkey and Malawi). Finally, it is notable the fact that the variation on average labor technical efficiency is higher for the groups of developing countries. It seems that some "rich" developing countries have passed over some factor ratios and improved the technologies specific to these ratios enhancing the utilization of their stock of labor (*i.e.*, Mexico, Colombia, Paraguay). This is also indicated by estimated mean labor allocative efficiency values in Africa and South and Central America.

Table 4, reports the average values over countries and time of labor productivity growth and it's decomposition using relation (11). These figures are the weighted averages computed following Olley and Pakes (1996) aggregation scheme. This is actually a weighted average measure of worldwide labor productivity growth, using countries' output shares as weights. During the 1965-1990 time period, the weighted average labor productivity growth was 1.431 per cent annually. The greatest part of that labor productivity growth was due to TFP growth (75.76 per cent) and to a lesser extent due to changes in factor intensities (15.45 per cent) and human capital accumulation (8.79 per cent). This finding is in accordance with the relevant literature that also attributes the greatest share of productivity changes to TFP growth. Concerning the sources of TFP growth, changes in the available technology (48.83 per cent) driven mainly by neutral technical changes (45.04 per cent) and to a lesser extent due to factor biases (3.40 per cent) are the most important factor accounting for that productivity growth. The effect of scale economies and efficiency changes on labor productivity growth was found to be of equal importance accounting for the 13.51 and 13.43 per cent of it, respectively. Improvements in labor technical efficiency were more important indicating a trend towards the respective technological frontier in each country. Still, however, the majority of countries experienced a shift of the frontier rather than growth of their efficiency scores.

In total, substitution effects (*i.e.*, changes in capital-labor mix) were the second highest source of that productivity growth accounting for the 15.45 per cent of it. Shifts in relative capital-labor prices and the biases of technological change are important possibilities for changes in the growth rate of factor intensities and the accumulation of physical capital. The labor price effect (5.66 per cent) and the biased labor saving effect (7.33 per cent) are dominant. The bias of technological change towards saving labor and using capital is associated with the rising trend of labor price and the decline in the price of capital. In this sense, the bias of technological change is consistent with the induced innovation hypothesis (Hayami and Ruttan, 1970). Finally, human capital accumulation accounts on the average for the 8.79 per cent of measured productivity growth. This is mainly due to the high rates of growth in educational levels during 70's in both developed and developing countries.

Besides these average values it is also important to see the decomposition results for each group of countries separately. Tables 5a and 5b present the decomposition of labor productivity growth per group of country for the five sub-periods. The values reported therein are the within groups weighted average for each sub-period. According to these results Asian Tigers experienced the higher labor productivity growth during 1965-90 time period, 2.564 per cent, that is almost two times higher than the next two groups of developed countries, namely North America and Oceania (1.352 per cent) and Europe (1.218 per cent). South and Central America also experienced a high average annual labor productivity growth, 1.232 per cent, driven mainly by scale economies and technological improvements. On the other tail of the productivity distribution are African and Asian countries that exhibit significant lower values, 0.886 and 1.004, per cent respectively. Concerning the composition of these average values, productivity changes rather than changes in factor intensities seems to dominate measured labor productivity growth. There is only the exception of African countries where the contribution of productivity changes accounts for the 52.60 per cent of that growth. Changes in relative factor prices resulted to significant labor-saving technological improvements in these countries given their input-mix which was abundant in labor input. Thus, the percentage contribution of the extended labor saving technological change effect was the highest among all groups of countries accounting for the 22.12 per cent of labor productivity growth.

In Asian Tigers TFP accounts approximately for the 84.98 per cent of total labor productivity changes whereas substitution effect only for the 11.43 per cent. The contribution of human capital changes was the lowest among all groups of countries, 3.63 per cent (this figure is higher in Taiwan and Korea Rep.). These high TFP growth was due to technological advances, 39.04 per cent, and the effect of scale economies, 39.47 per cent, (that was the highest scale effect among all groups). Korea Rep. and Taiwan exhibit a very strong scale effect, whereas technological changes were significant in Thailand, Japan and Korea Rep (see tables 6a and 6b). Given their factor endowments, Asian Tigers seems to benefit a lot from exploring further the potential of their technological conditions. They operate far below their minimum efficient size where the average productivity of their resource endowments is maximized. Efficiency improvements played an important role only in Japan, Taiwan and Thailand indicating that only in these three countries significant movements towards the technological frontier are observed. On the average improvements in labor technical and allocative efficiency accounts only for the 6.48 per cent of productivity growth. Finally, changes in factor intensities were also minor in labor productivity improvements, accounting for the 11.43 per cent.

In North America and Oceania changes in factor intensities and human capital accumulation have a greater contribution in measured labor productivity growth. Still, however, TFP changes account for the 71.60 per cent of labor productivity improvements. Specifically, the human capital effect accounts for the 13.39 per cent of measured productivity growth whereas the substitution effect for the 15.16 per cent. Improvements in technical rather than in allocative efficiency are explaining the 12.80 per cent of total labor productivity (labor allocative accounts only for the 4.22 per cent of total LP growth). Scale economies also have a minor contribution, 9.62 per cent, as all countries operate close to maximizing average ray productivity. USA and Canada have the highest annual productivity improvements, 1.370 and 1.323 per cent, respectively (see tables 6a and 6b). In both countries, improvements in labor technical efficiency, human capital accumulation and technological advances are the foremost important reasons of the observed labor productivity growth.

Labor technical efficiency improvements are also important factor of labor productivity growth for European countries. On the average labor technical efficiency accounts for the 12.81 per cent of productivity improvements, while the corresponding figure of labor allocative efficiency is only 2.22 per cent. In Switzerland, Denmark and Netherlands technical efficiency changes are even higher than group average (see tables

6a and 6b). Given the input mix which is in favor of physical capital, developed countries in both continents moved closer to their respective frontier as more cost effective ways of improving their overall productivity rates. Still, however, technological innovations account for the 56.73 per cent of total productivity rates, whereas the effect of scale economies is also low, 3.53 per cent. In total TFP growth accounts for the 75.29 per cent of total labor productivity with insignificant variations among countries in the group. On the other hand human capital accumulation accounts only for the 4.93 per cent, whereas changes in factor intensities are significant as they contribute by 19.79 per cent to total labor productivity growth. Changes in relative factor prices are the more important source for the substitution effect. Netherlands, Austria and Sweden exhibit the highest productivity rates among all European countries (1.454, 1.423 and 1.409, respectively), whereas Italy (1.067 per cent), Germany (1.129 per cent) and UK (1.149 per cent) the lowest.

South and Central American countries present a similar picture in their decomposition analysis. Specifically, the 74.35 per cent of measured labor productivity is due to TFP, the 13.07 per cent to changes in factor intensities and the 12.66 per cent to human capital accumulation. The latter is the third highest among all groups of countries in the sample. The contribution of labor efficiency accounts for the 11.12 per cent with both indices having and equal magnitude, 5.93 and 5.19 per cent for technical and allocative efficiency, respectively. The effect of scale economies accounts for the 14.69 per cent of total labor productivity, higher than the European and North American and Oceania countries. Caribbean and Central American countries exhibit the highest productivity rates, Dominican Rep. 1.393 per cent, Guatemala 1.265 per cent, Honduras

1.321 per cent and Panama 1.243 per cent. In these countries, improvements in allocative efficiency are more important than those of technical efficiency indicating better adjustments of input mix relative to factor prices. This is in accordance with the substitution effect whose contribution is increased for the countries with the highest productivity rates in the group. Finally, no significant variation is observed on the importance of technological innovations among South and Central American countries.

The effect of human capital accumulation was the highest in the group of Asian countries accounting for the 15.94 per cent of total labor productivity. Still TFP accounts for the 70.42 per cent and the substitution effect for the 13.75 per cent. Also changes in input mix are towards improving allocation of physical capital and labor given the prevailing factor prices as labor allocative efficiency has been considerably improved over the period. On the average the effect of labor allocative efficiency accounts for the 11.65 per cent of measured productivity growth. This is the highest figure among all groups. On the other hand movements towards the aggregate production frontier were rather minor as the technically efficient effect was the 1.79 per cent of total labor productivity. Finally, scale diseconomies combined with increased input use resulted in a decrease of productivity rates by 18.33 per cent.

Finally, African countries exhibit the lowest labor productivity rates among all groups with an average annual rate of only 0.886 per cent. Only the 52.60 per cent of it arises from TFP growth and the 36.23 per cent from changes in factor intensities. Mauritius and Malawi have the lowest productivity rates of 0.771 and 0.772 per cent, respectively. On the other hand, Zambia and surprisingly Sierra Leone have the highest mean values of 1.052 and 1.171 per cent, respectively. Like Asian countries, the scale diseconomies accounted for a 17.72 per cent labor productivity slowdown during the 1965-90 period. It seems that both group of countries have gone beyond the potential capabilities of their aggregate own production technology given their input-mix and endowments. The striking result is that labor technical efficiency was deteriorated during the period analyzed accounting for the 1.47 per cent productivity slowdown. However, African countries seems to achieve a better input-mix given relative factor prices. Finally, human capital accumulation is rather important indicating the gap of educational levels in these countries.

Table 7 shows the decomposition of the average of labor productivity growth across countries during the 1965-90 period. Labor productivity growth is following an increasing pattern over time, experiencing however three falling sub-periods during 1970-71, 1974-75 and 1981-1983 which were due to decreases in scale effect and human capital effect that took place in these periods. The decreases in scale effect were caused mainly by decreases in the relative output growth of many countries during the above-mentioned periods which more or less coincide with the first oil crises. Moreover, as it was expected, technical change was found to be constantly progressive over time, while labor technical efficiency effect and substitution effect do not appear significant variations during the period analyzed. The evolution of labor productivity growth for the different groups of countries is illustrated in Figure 2. As we can observe, all groups seem to have similar variations in labor productivity growth following an increasing trend. However, we can notice two sharp decreases in labor productivity growth during the years 1971 and 1975. The fall of labor productivity was found to be more intense for Asian Tigers and African countries, while Asian countries seem to not have been affected. During the first fifteen years, North America and Oceania group was found to achieve greater labor productivity growth than Europe but after the early 80's the corresponding scores for the two groups were found to be quite similar.

CONCLUDING REMARKS

Motivated by the works of Färe *et al.*, (1994), Kumar and Russell (2002) and Henderson and Russell (2005), we provide a theoretically consistent parametric decomposition of labor productivity growth. Relaxing the restrictive assumption of labor-specific technical efficiency and incorporating human capital into our decomposition analysis we present a detailed decomposition of labor productivity growth for a sample of developed and developing countries drawn from *Penn World Tables*. Our empirical aggregate production frontier model was based on the generalized Cobb-Douglas functional specification suggested by Fan (1991) and was extended into a *multilateral* production structure using Jorgenson and Nishimizu (1978) context of bilateral production functions. The measurement of labor efficiency was based on Kopp's (1981) orthogonal non-radial index of factor-specific technical efficiency modified in a parametric frontier framework. Finally, following Griliches (1963), human capital proxied by Hall and Jones (1999) construction was introduced into the analysis as a multiplicative augmentation of labor input.

Our empirical results confirms that Basu and Weil (1998) and Acemoglou and Zilibotti (2001) appropriateness of technology paradigm as the hypothesis of a common worldwide aggregate production technology does not fit data of our sampled countries. Each continent seems to have different technological conditions that should be taken into account in productivity analysis. TFP growth accounts for the greatest share of labor productivity with significant variations though among group of countries. On the average countries in the sample experienced an average labor productivity growth of 1.4309 per cent annually. Asian Tigers, North America and Oceania and Europe exhibit the highest labor productivity changes whereas, for African and Asian countries the corresponding figures were significantly lower. In developed countries, changes in labor efficiency seems to be important source explaining that productivity differentials, while human capital accumulation had an important effect in developing countries productivity improvements. In African countries labor utilization have been deteriorated as technical efficiency of labor was decreased over time. Still changes in technological conditions are the foremost important sources of productivity growth mainly in developing countries that accounted approximately for the 65 per cent of that growth.

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Figure 1. Measurement of Labor Specific Technical and Allocative Efficiency.

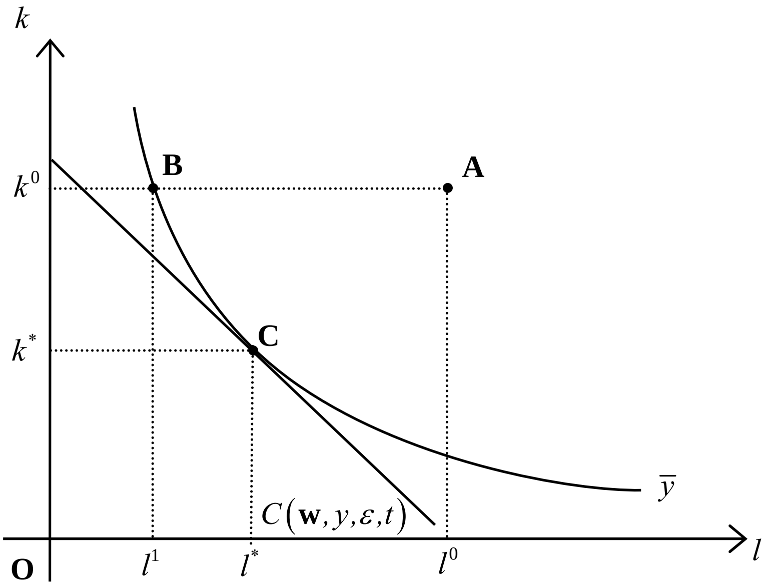

Table 1. Parameter Estimates of the Multilateral Cobb-Douglas Production Frontier.

Par.	N. America&Oceania		S.&C. America		Europe		Africa		Asia		Asian Tigers	
						Estimate	StdError					
Common Coefficient Estimates												
β^0						0.6469	$(0.0350)^{*}$					
β^t						0.1250	$(0.0151)^{*}$					
β^{tt}						0.0356	$(0.0042)^{*}$					
	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError
Multilateral Structure												
β^l	0.4234	$(0.1879)^{*}$	0.5783	$(0.3408)^{**}$	0.3943	$(0.0478)^{*}$	0.4627	$(0.0428)^{*}$	0.5768	$(0.0742)^{*}$	0.7403	$(0.0814)^{*}$
β^k	0.6182	$(0.1500)^{*}$	0.5138	$(0.0256)^{*}$	0.6162	$(0.0278)^{*}$	0.4921	$(0.0213)^{*}$	0.3728	$(0.0520)^{*}$	0.4848	$(0.0343)^{*}$
β^{lt}	0.2795	$(0.0540)^{*}$	-0.0240	$(0.0114)^{*}$	0.0060	(0.0092)	-0.0772	$(0.0416)^{**}$	-0.0457	$(0.0094)^{*}$	-0.0849	$(0.0161)^{*}$
β^{kt}	-0.2780	$(0.0542)^{*}$	0.0226	$(0.0075)^{*}$	-0.0203	$(0.0083)^{*}$	0.0673	$(0.0260)^{*}$	0.0144	(0.0133)	0.1542	$(0.0112)^{*}$
ζ_{i0}	0.9523	$(0.0180)^{*}$	0.9070	$(0.0148)^{*}$	0.9798	(0.0160)*	0.7928	$(0.0207)^{*}$	0.9107	$(0.0496)^{*}$	0.9205	$(0.0199)^{*}$
ζ_{i1}	0.6439	$(0.0156)^{*}$	0.6854	$(0.0288)^{*}$	0.6568	(0.0118)*	0.6310	$(0.0402)^{*}$	0.6360	$(0.0187)^{*}$	0.5636	$(0.0192)^{*}$
ζ_{i2}	0.3563	$(0.0088)^{*}$	0.3149	$(0.0163)^{*}$	0.3434	(0.0066)*	0.3694	$(0.0227)^{*}$	0.3644	$(0.0105)^{*}$	0.3374	$(0.0108)^{*}$
$\bar{R}^2$							0.4690					

Note: l refers to labor, c to capital and, t to time. In the lower panel of the table are reported the ζ parameters of the country with the maximum efficiency score. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively.

Table 2. Model Specification Tests.

Hypothesis	LR-test	Critical Value (a=0.05)
Multilateral Structure Testing		
$\beta_j^l = \beta^l$, $\beta_j^k = \beta^k$, $\beta_j^{lt} = \beta^{lt}$ and $\beta_j^{kt} = \beta^{kt}$	37.61	$\chi_4^2 = 9.49$
$\beta_j^{lt} = \beta^{lt}$ and $\beta_j^{kt} = \beta^{kt}$	25.69	$\chi_2^2 = 5.99$
$\beta_j^l = \beta^l$ and $\beta_j^k = \beta^k$	23.40	$\chi_2^2 = 5.99$
$\beta_j^l = \beta^l$	14.26	$\chi_1^2 = 3.84$
$\beta_j^k = \beta^k$	16.30	$\chi_1^2 = 3.84$
$\beta_j^{lt} = \beta^{lt}$	12.55	$\chi_1^2 = 3.84$
$\beta_j^{kt} = \beta^{kt}$	13.21	$\chi_1^2 = 3.84$
Technological Specification		
Constant returns-to-scale: $\beta_j^l + \beta_j^k = 1 \wedge \beta_j^{lt} + \beta_j^{kt} = 0 \ \forall j$	64.20	$\chi_2^2 = 5.99$
Hicks-neutral technical change: $\beta_j^{lt} = \beta_j^{kt} = 0 \ \forall j$	49.28	$\chi_2^2 = 5.99$
Zero-technical change: $\beta^t = \beta^{tt} = \beta_j^{lt} = \beta_j^{kt} = 0 \ \forall j$	75.60	$\chi_4^2 = 9.49$
Labor-neutral technical change: $\beta_j^{lt} = 0 \ \forall j$	13.78	$\chi_1^2 = 3.84$
Inefficiency Specification		
Existence of inefficiency: $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0 \ \forall i$	144.58	$\chi_{156}^2 \approx 71.52$
Time-invariant labor technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0 \ \wedge \ \beta_j^{lt} = 0 \ \forall j$	123.21	$\chi_{105}^2 \approx 69.92$
Common temporal pattern of labor technical efficiency across countries: $\zeta_{i1} = \zeta_1 \wedge \zeta_{i2} = \zeta_2 \ \forall i$ and $\beta_j^l = \beta^l \wedge \ \beta_j^{lt} = \beta^{lt} \ \forall j$	106.37	$\chi_{106}^2 \approx 70.34$
Time-invariant labor allocative efficiency: $\zeta_{i1} = \zeta_{i2} = 0 \ \wedge \ \beta_j^{lt} = 0 \ \forall j$ and $\beta^t = \beta^{tt} = \beta_j^{lt} = \beta_j^{kt} = 0 \ \forall j$	198.42	$\chi_{109}^2 \approx 71.33$
Common temporal pattern of labor allocative efficiency across countries: $\zeta_{i1} = \zeta_1 \wedge \zeta_{i2} = \zeta_2 \ \forall i$ and $\beta_j^l = \beta^l$, $\beta_j^k = \beta^k$, $\beta_j^{lt} = \beta^{lt}$, $\beta_j^{kt} = \beta^{kt} \ \forall j$	174.57	$\chi_{108}^2 \approx 71.05$

Table 3. Frequency Distribution of Labor-Specific Technical and Allocative Efficiency.

%	N. America&Oceania	S.&C. America	Europe	Africa	Asia	Asian Tigers	All Countries
Labor Specific Technical Efficiency							
<40	0	0	0	0	0	0	0
40-50	0	0	0	6	0	0	6
50-60	0	1	1	0	3	0	5
60-70	0	12	12	0	2	0	26
70-80	1	0	5	0	1	0	7
80-90	3	0	0	0	0	4	7
90>	0	0	0	0	0	1	1
Mean	79.4	63.9	68.2	44.9	61.1	87.8	66.4
Min	72.3	58.9	56.1	44.3	51.2	84.3	44.3
Max	83.5	69.9	74.8	47.0	74.9	90.6	90.6
Labor Specific Allocative Efficiency							
<0.5	0	0	0	1	4	0	5
0.5-0.75	0	12	1	4	0	0	17
0.75-1.0	1	1	0	1	1	0	4
1.0-1.25	1	0	6	0	0	1	8
1.25-1.5	2	0	10	0	0	4	16
1.5>	0	0	1	0	1	0	2
Mean	1.12	0.66	1.25	0.57	0.67	1.32	0.95
Min	0.81	0.51	0.56	0.40	0.35	1.23	0.35
Max	1.31	0.80	1.56	0.75	1.53	1.45	1.56
N	4	13	18	6	6	5	52

Table 4. Decomposition of Labor Productivity Growth (average values over countries and time).

	Annual Rate	(%)
Labor Productivity Growth	1.431	(100.0)
Changes in Labor Technical Efficiency	0.140	(9.80)
Changes in Allocative Efficiency	0.052	(3.63)
Scale Effect	0.193	(13.51)
Rate of Technical Change:	0.699	(48.83)
Autonomous Part	0.647	(45.04)
Biased Part	0.052	(3.40)
Human Capital Effect	0.126	(8.79)
Substitution Effect:	0.221	(15.45)
Price Effect:	0.116	(8.12)
Physical Capital	0.035	(2.46)
Labor	0.081	(5.66)
Extended Labor Biased TC Effect	0.105	(7.33)

Note: The average rate of labor productivity change was calculated using Olley and Pakes (1996) output share weighting. The values in parenthesis indicate the percentage contribution of each effect to labor productivity change.

Table 5a. Decomposition of Labor Productivity Growth per group of Countries.

	1966-70	1971-75	1976-80	1981-85	1986-90	1966-90
North America & Oceania						
LP Change	1.079	1.364	1.355	1.274	1.689	1.352
LTE	0.215	0.428	0.013	0.069	0.138	0.173
LAE	0.019	0.020	0.035	0.103	0.106	0.057
SE	0.129	0.086	0.184	0.124	0.125	0.130
TC	0.318	0.465	0.576	0.739	0.941	0.608
HC	0.171	0.136	0.378	0.056	0.165	0.181
PE	0.154	0.134	0.116	0.100	0.086	0.118
ELBTC	0.074	0.094	0.054	0.084	0.128	0.087
Europe						
LP Change	0.912	1.242	1.115	1.249	1.570	1.218
LTE	0.195	0.415	-0.016	0.034	0.151	0.156
LAE	0.018	0.016	0.060	0.025	0.018	0.027
SE	0.084	0.056	0.032	0.017	0.025	0.043
TC	0.330	0.511	0.693	0.868	1.053	0.691
HC	0.071	0.004	0.091	0.067	0.069	0.060
PE	0.127	0.153	0.167	0.150	0.167	0.153
ELBTC	0.088	0.087	0.088	0.088	0.088	0.088
Asian Tigers						
LP Change	2.331	2.270	2.521	2.458	3.243	2.564
LTE	0.140	0.114	-0.033	0.102	0.237	0.112
LAE	-0.018	0.089	0.095	0.003	0.101	0.054
SE	1.269	0.760	0.991	0.860	1.178	1.012
TC	0.768	0.883	1.007	1.103	1.246	1.001
HC	-0.060	0.142	0.177	0.084	0.124	0.093
PE	0.047	0.058	0.075	0.076	0.098	0.071
ELBTC	0.186	0.224	0.210	0.231	0.258	0.222

Note: LP column refers to labor productivity changes, LTE to labor technical efficiency changes, LAE to labor allocative efficiency change, SE to scale effect, TC to technical change, HC to human capital effect, PE to price effect, and ELBTC to extended labor biased technological change effect. All values in the table were calculated using Olley and Pakes (1996) output share weighting.

Table 5b. Decomposition of Labor Productivity Growth per group of Countries.

	1966-70	1971-75	1976-80	1981-85	1986-90	1966-90
South and Central America						
LP Change	0.961	1.053	1.291	1.242	1.614	1.232
LTE	0.111	0.245	-0.012	-0.018	0.037	0.073
LAE	0.062	0.038	0.072	0.067	0.081	0.064
SE	0.157	0.078	0.303	0.192	0.176	0.181
TC	0.267	0.433	0.599	0.763	0.928	0.598
HC	0.202	0.083	0.158	0.081	0.258	0.156
PE	0.111	0.125	0.121	0.102	0.081	0.108
ELBTC	0.052	0.052	0.051	0.055	0.054	0.053
Africa						
LP Change	0.529	0.669	0.950	0.994	1.290	0.886
LTE	0.058	0.080	-0.083	-0.079	-0.042	-0.013
LAE	0.030	0.021	0.006	0.031	0.022	0.022
SE	-0.120	-0.198	-0.156	-0.125	-0.184	-0.157
TC	0.205	0.406	0.624	0.814	1.021	0.614
HC	0.061	0.057	0.227	0.022	0.133	0.100
PE	0.122	0.131	0.145	0.113	0.113	0.125
ELBTC	0.175	0.173	0.187	0.217	0.227	0.196
Asia						
LP Change	0.762	0.935	0.925	1.079	1.320	1.004
LTE	0.141	0.121	-0.088	-0.064	-0.022	0.018
LAE	0.113	0.091	0.119	0.124	0.139	0.117
SE	-0.135	-0.130	-0.153	-0.224	-0.279	-0.184
TC	0.368	0.557	0.749	0.951	1.156	0.756
HC	0.151	0.151	0.162	0.152	0.185	0.160
PE	0.027	0.036	0.035	0.033	0.030	0.032
ELBTC	0.098	0.109	0.102	0.108	0.113	0.106

Note: LP column refers to labor productivity changes, LTE to labor technical efficiency changes, LAE to labor allocative efficiency change, SE to scale effect, TC to technical change, HC to human capital effect, PE to price effect, and ELBTC to extended labor biased technological change effect. All values in the table were calculated using Olley and Pakes (1996) output share weighting.

Figure 2. Annual Labor Productivity Growth per Group of Countries.

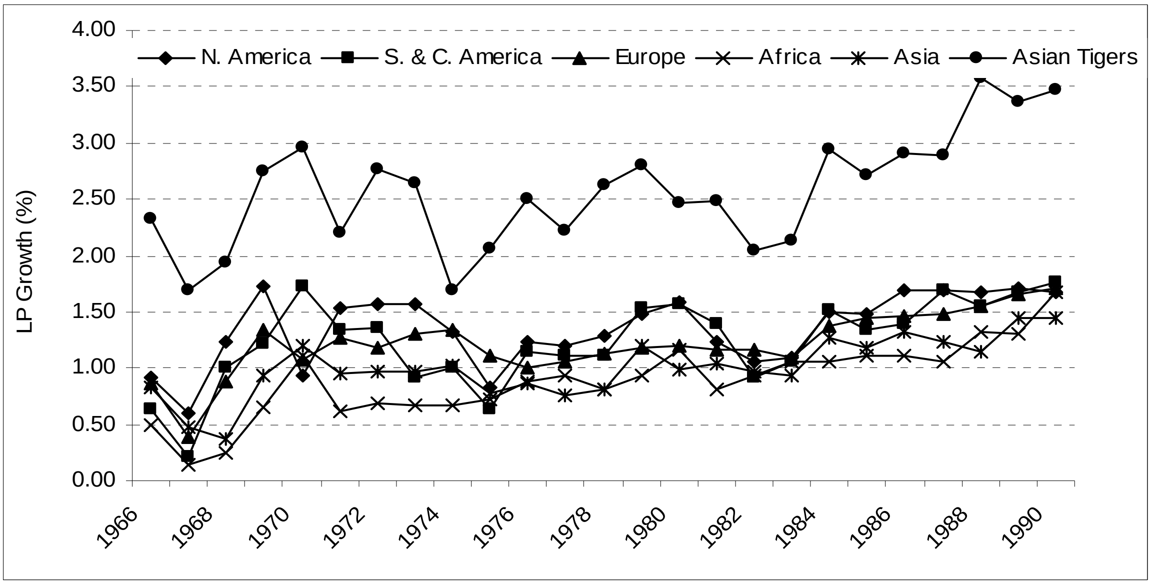

Table 6a. Decomposition of Labor Productivity Growth for Each Country (average values over the 1965-90 time period).

Countries	LP	LTE	LAE	SE	TC	HC	PE	ELBTC
Argentina	1.267	0.045	0.119	0.166	0.607	0.129	0.149	0.053
Australia	1.061	0.104	0.034	0.141	0.622	0.053	0.053	0.053
Austria	1.423	0.184	0.095	0.047	0.685	0.036	0.287	0.088
Belgium	1.295	0.059	0.108	0.044	0.683	0.014	0.298	0.088
Bolivia	1.153	0.060	0.114	0.218	0.574	0.046	0.088	0.053
Canada	1.323	0.129	0.011	0.132	0.660	0.125	0.144	0.123
Chile	1.179	0.086	0.111	0.213	0.578	0.119	0.020	0.053
Columbia	1.226	0.027	0.119	0.226	0.596	0.110	0.095	0.053
Denmark	1.355	0.188	0.094	0.036	0.684	0.033	0.233	0.088
Dominican Reb	1.393	0.062	0.112	0.249	0.569	0.129	0.219	0.053
Ecuador	1.304	0.053	0.112	0.200	0.566	0.173	0.147	0.053
Finland	1.328	0.153	0.024	0.035	0.681	0.112	0.234	0.088
France	1.243	0.148	0.073	0.043	0.694	0.065	0.132	0.088
Germany	1.129	0.200	-0.025	0.034	0.695	0.016	0.121	0.088
Greece	1.314	0.133	0.099	0.049	0.683	0.105	0.157	0.088
Guatemala	1.265	0.074	0.111	0.184	0.571	0.083	0.189	0.053
Honduras	1.321	0.039	0.113	0.227	0.571	0.147	0.170	0.053
Hong Kong	2.777	0.022	0.070	1.325	0.802	0.171	0.168	0.221
Iceland	1.378	0.192	0.002	0.050	0.669	0.078	0.299	0.088
India	1.077	0.006	0.157	-0.195	0.819	0.164	0.020	0.106
Ireland	1.237	0.121	0.006	0.047	0.677	0.071	0.227	0.088
Israel	0.693	0.075	-0.020	-0.199	0.489	0.106	0.137	0.106
Italy	1.067	0.050	0.004	0.055	0.691	0.053	0.127	0.088
Jamaica	1.137	0.052	0.113	0.156	0.564	0.119	0.079	0.053
Japan	2.458	0.130	0.045	0.895	1.031	0.069	0.066	0.221
Kenya	0.787	-0.011	-0.029	-0.183	0.642	0.106	0.067	0.196

Note: LP column refers to labor productivity changes, LTE to labor technical efficiency changes, LAE to labor allocative efficiency change, SE to scale effect, TC to technical change, HC to human capital effect, PE to price effect, and ELBTC to extended labor biased technological change effect.

Table 6b. Decomposition of Labor Productivity Growth for Each Country (average values over the 1965-90 time period).

Countries	LP	LTE	LAE	SE	TC	HC	PE	ELBTC
Korea Rep	3.028	0.035	0.027	1.552	0.903	0.221	0.070	0.221
Malawi	0.772	-0.039	0.037	-0.175	0.619	0.055	0.079	0.196
Mauritius	0.771	-0.029	0.072	-0.124	0.534	0.104	0.018	0.196
Mexico	1.180	0.096	0.012	0.142	0.605	0.192	0.081	0.052
Netherlands	1.454	0.218	0.060	0.046	0.686	0.113	0.244	0.088
New Zealand	1.314	0.216	0.055	0.079	0.640	0.174	0.023	0.128
Norway	1.298	0.104	0.001	0.048	0.684	0.146	0.227	0.088
Panama	1.243	0.079	0.026	0.173	0.550	0.160	0.203	0.052
Paraguay	1.165	0.090	0.032	0.134	0.571	0.136	0.150	0.052
Peru	1.312	0.086	0.043	0.227	0.590	0.165	0.149	0.052
Philippines	0.907	0.005	0.063	-0.140	0.671	0.165	0.038	0.106
Portugal	1.350	0.176	0.006	0.055	0.683	0.100	0.243	0.088
Sierra Leone	1.171	-0.031	0.022	-0.079	0.661	0.044	0.356	0.196
Spain	1.370	0.263	0.033	0.050	0.685	0.093	0.157	0.088
Sri Lanka	0.775	-0.007	0.049	-0.148	0.609	0.097	0.070	0.106
Sweden	1.409	0.182	0.038	0.039	0.688	0.048	0.327	0.088
Switzerland	1.331	0.267	0.037	0.031	0.684	0.069	0.155	0.088
Syria	0.837	0.000	0.005	-0.111	0.503	0.217	0.118	0.106
Taiwan	3.017	0.037	0.142	1.430	0.851	0.204	0.130	0.221
Thailand	2.692	0.056	0.125	1.160	0.959	0.131	0.040	0.221
Turkey	0.869	0.080	0.028	-0.167	0.645	0.141	0.036	0.106
UK	1.149	0.138	0.006	0.036	0.695	0.075	0.111	0.088
USA	1.370	0.180	0.062	0.129	0.602	0.193	0.120	0.084
Yugoslavia	1.277	0.141	0.098	0.053	0.688	0.097	0.113	0.088
Zambia	1.052	0.016	0.047	-0.095	0.580	0.128	0.179	0.196
Zimbabwe	0.939	-0.004	0.061	-0.162	0.604	0.113	0.131	0.196
Mean	1.431	0.140	0.052	0.193	0.699	0.126	0.116	0.105

Note: LP column refers to labor productivity changes, LTE to labor technical efficiency changes, LAE to labor allocative efficiency change, SE to scale effect, TC to technical change, HC to human capital effect, PE to price effect, and ELBTC to extended labor biased technological change effect.

Table 7. Annual Decomposition of Labor Productivity Growth (weighted average over countries)

Year	LP	LTE	LAE	SE	TC	HC	PE	ELBTC
1966	1.002	0.209	0.036	0.179	0.298	0.114	0.123	0.043
1967	0.600	-0.192	0.006	0.150	0.333	0.114	0.122	0.068
1968	1.104	0.104	0.025	0.251	0.368	0.112	0.121	0.123
1969	1.603	0.530	0.054	0.248	0.404	0.111	0.121	0.135
1970	1.287	0.287	0.001	0.247	0.440	0.109	0.119	0.085
1971	1.458	0.456	0.056	0.169	0.469	0.088	0.120	0.102
1972	1.515	0.387	0.004	0.262	0.503	0.088	0.122	0.149
1973	1.512	0.385	0.026	0.249	0.542	0.088	0.127	0.097
1974	1.335	0.404	0.053	0.004	0.571	0.088	0.127	0.090
1975	1.064	0.110	0.032	0.021	0.598	0.088	0.121	0.095
1976	1.276	-0.072	0.072	0.220	0.619	0.219	0.120	0.098
1977	1.240	-0.040	0.005	0.207	0.654	0.220	0.119	0.074
1978	1.354	-0.018	0.037	0.223	0.691	0.221	0.121	0.078
1979	1.534	0.026	0.094	0.242	0.724	0.220	0.124	0.103
1980	1.522	0.035	0.095	0.198	0.755	0.218	0.124	0.097
1981	1.376	0.042	0.074	0.168	0.786	0.073	0.116	0.117
1982	1.217	0.050	0.044	0.017	0.816	0.074	0.109	0.109
1983	1.230	-0.131	0.054	0.177	0.854	0.074	0.105	0.097
1984	1.652	0.127	0.083	0.267	0.890	0.074	0.104	0.109
1985	1.615	0.130	0.055	0.223	0.928	0.074	0.101	0.104
1986	1.747	0.149	0.066	0.185	0.968	0.136	0.106	0.139
1987	1.766	0.130	0.029	0.232	1.007	0.136	0.108	0.124
1988	1.873	0.137	0.061	0.266	1.047	0.136	0.110	0.116
1989	1.933	0.130	0.110	0.231	1.082	0.136	0.108	0.136
1990	1.968	0.130	0.128	0.208	1.120	0.136	0.108	0.137
Mean	1.431	0.140	0.052	0.193	0.699	0.126	0.116	0.105

Note: LP column refers to labor productivity changes, LTE to labor technical efficiency changes, LAE to labor allocative efficiency change, SE to scale effect, TC to technical change, HC to human capital effect, PE to price effect, and ELBTC to extended labor biased technological change effect. All values in the table were calculated using Olley and Pakes (1996) output share weighting.

ENDNOTES

[1] Labor-specific technical efficiency as defined in (3), has an input conserving interpretation, which however cannot be converted into a cost-saving measure due to its non-radial nature. Akridge (1989) based on Kopp's (1981) theoretical framework incorporated factor prices suggesting a single factor technical cost efficiency index which measures the potential cost savings that can be realized by adjusting single factor use.

[2] If labor input is under-utilized at it's technical efficient point, the second term of the efficiency effect is positive (negative) as labor allocative efficiency decreases (increases) over time. In this case in the measurement of labor productivity growth the correct direction has been accounted for.

[3] The maintained assumption that derived demand for labor is non-increasing in ε, implies that human capital and labor inputs are substitutes in the production of aggregate output (Griliches, 1964).

[4] Our data set is the same with that used by Henderson and Russell (2005) and to some extent with Kumar and Russell (2002) and so our results are comparable with those reported by these two studies.

[5] Aggregate output is real gross domestic product multiplied by population while capital stock and labor inputs were retrieved from capital stock per worker and real GDP per worker. All variables are measured in 1985 international prices.

[6] Data obtained by *National Account Statistics* of the UN do not take into consideration self-employment. To deal with this, the number of self employed workers was computed as a proportion of the total number of employees, and then labor compensation was calculated by assuming that employees and self-employed workers receive the same wages on average (Gollin, 2002). Then we calculated labor compensation by multiplying the share of employee compensation, *i.e.*, s_l, in national income with the product of GDP price *i.e.*, P_Y, times the GDP. The remaining portion of this

product, *i.e.*, $(1-s_l)\times(P_Y \times GDP)$, was the corresponding value for physical capital. Then, we constructed a price index for labor by dividing labor compensation by the number of workers from *Penn World Tables*, *i.e.*, $w_l = \left[s_l \times (P_Y \times GDP)\right]/l$. The constructed price index for labor was converted to constant 1985 US dollars using PPP for labor in each country which was computed by dividing the labor cost per worker at the base year by the corresponding value in the US. The same approach was conducted for the calculation of the price of capital at constant 1985 US dollars.

[7] Using the years of schooling for adult population is a good proxy for human capital given the difficulties of alternative data source. As Griliches (1963) pointed out the use of "specific" or more elegant variables does not alter significantly the econometric results as all these variables are highly correlated with years of schooling.

[8] Given that Barro and Lee (1993; 2001) data are available in five years intervals while the rest of out data are on annual basis, we assume a constant annual rate of growth for human capital within each interval.

[9] This specification implicitly imposes perfect substitutability between human capital and physical labor (Acemoglou and Zilboti, 2001). Alternatively we could have follow Welch (1970) approach treating human capital as a separate factor of production. Following Griliches (1970) we used formal statistical testing to examine both hypotheses. In doing so the production frontier model in (12) was estimated using human capital as a separate factor of production. Then using a simple *t*-test we examined the hypothesis that the coefficients of human capital and labor are equal. The result rejects the alternative hypothesis validating our choice of using education as an augmentation factor for physical labor in the production frontier model.

[10] We have tried to introduce the multilateral structure into the temporal pattern of output technical inefficiency, but unfortunately we couldn't obtain statistical significant estimates.

[11] This means that in each period at least one country is fully efficient, although the identity of this country may vary through years.

[12] Given (15) this is equivalent by testing the hypotheses that $\beta_j^{lt} = \beta_j^{kt} = 0$ and $\beta_j^{t} = \beta_j^{tt} = \beta_j^{lt} = \beta_j^{kt} = 0 \ \forall j$ in the aggregate production function in (12).

[13] Again given (15) this is equivalent by testing the hypotheses that $\beta_j^{lt} = 0$ in the aggregate production function in (12).

[14] In fact Ray (1998) based on Atkinson and Cornwell's (1998) findings suggested a similar approach with Reinhard Lovell and Thijssen (1999) for the estimation of input specific technical efficiency.

[15] Reinhard, Lovell and Thijssen (1999) in developing their approach of measuring Kopp's (1981) orthogonal input-specific technical efficiency correctly argued that under a *Cobb-Douglas* specification of the production function, both indices will exhibit the same ranking for countries in the sample. However, this is not true with the multilateral generalized *Cobb-Douglas* production model utilized herein which allows for different temporal patterns among the two efficiency measures for countries belonging to different groups as well as across time.

[16] The complete set of parameter estimates for the Cornwell *et al.*, (1990) inefficiency effects model are available upon request.

[17] The generalized likelihood-ratio test statistic is computed as: $LR = -2\left\{ln\,L\left(H_0\right) - ln\,L\left(H_1\right)\right\}$, where $L\left(H_0\right)$ and $L\left(H_1\right)$ denote the values of the likelihood function under the null $\left(H_0\right)$ and the alternative $\left(H_1\right)$ hypothesis, respectively.