It follows from equation (2.13) that $x_t^m = L_t$. Using this equality, the growth equation can be rewritten as

$$\frac{\dot{Y}}{Y_t} = d\,l_t \left[L_t^a + \left(\frac{a}{1-a} \right) \left(1 - L_t - x_t^a \right) \right] \qquad (2.23)$$

The growth rate of output depends positively on the learning coefficient in manufacturing, δ, and on the foreign capital's share in total output, λ, but negatively on output in the agricultural sector. The larger the proportion of foreign capital, the higher the growth rate.

Learning is assumed not to be subject to decreasing returns, and this implies unbounded productivity growth. LDCs face a technological frontier exogenously expanding as determined by research in the technologically developed countries.[7] Technology is embodied in imported capital, and since the LDCs never reach the frontier they escape decreasing returns.

The main theoretical implications of the model are that growth in LDCs depends on the human capital accumulation. The latter stems from specific training and on-the-job experience, captured by the learning coefficient in the manufacturing sector δ. An increase of foreign capital will raise human capital and, consequently, the productivity of labour. Therefore, policies which favour free trade and promote the import of foreign capital goods will help developing countries to close the technology gap and increase productivity growth. In the empirical analysis which follows, these gains will show up through an effect on the efficiency term in the stochastic frontier model.

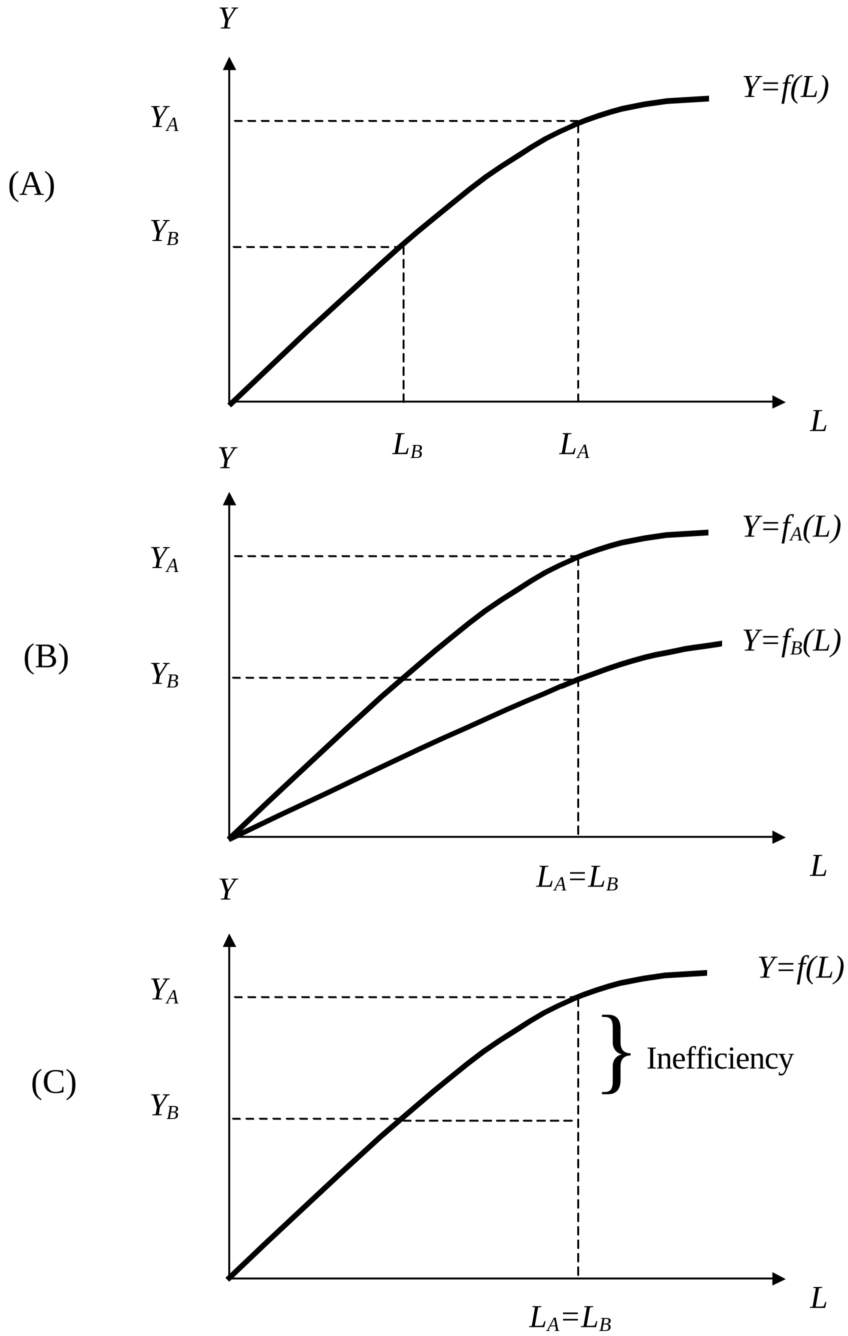
3. ECONOMETRIC METHODOLOGY

To test empirically the implications of the model requires a measure of technological progress, one widely used approach is a residual of the Abramovitz/Solow type, where output growth is decomposed into a weighted sum of input growth rates. The residuum, which represents the change in output that cannot be explained by input growth, is identified as technological progress. This measure is subject to criticism: the Solow residual ignores monopolistic markets, non-constant returns to scale (Hall, 1990) and variable factor utilisation over the cycle (Burnside *et al.*, 1995, Basu 1996).

A second approach is directly to estimate a production function, and to distinguish between technological change, or a shift in technological frontier, and efficiency, or a movement towards the technological frontier. To fix ideas, consider the example in Figure 1. It compares the output of two countries, *A* and *B*, as a function of labour, *L*. Given the same production technology, the higher output in country *A* than *B* can occur for four possible reasons. First, this difference can be due to differences in input levels, as is the case in panel (A). Second, technology acquisition may differ between countries or regions, with the consequence that for the same level of inputs different outputs result (panel (B)). Third, it might be that country *B* produces less efficiently than country *A*. In other words, both countries have the same frontier and the same input level, but output in *B* is lower (panel (C)). And fourth, differences could be due to some combination of the three causes. The Solow residual fails to discriminate between the second and the third possibility: efficiency is part of the residual. Stochastic frontier methodology, pioneered by Aigner, Lovell and Schmidt (1977) and by Meeusen and van den Broeck (1977), allows this important distinction.

[7] See Rauch and Weinhold (1997)

Figure 1: Production Functions



Assume the following common production frontier for the countries under analysis:

$$Y_{it} = f(X_{it}) t_{it} w_{it} \quad i = 1,......N; \; t = 1,....T \, . \tag{3.1}$$

where τ_{it} is the efficiency measure, with $0<\tau_{it} \leq 1$,[8] and ω_{it} captures the stochastic nature of the frontier. Assuming a production function of the Cobb-Douglas type, and writing it in log-linear form, we obtain

$$y_{it} = x_{it}^{'} b + v_{it} - u_{it} \, , \tag{3.2}$$

where $u_{it} = -\ln\tau_{it}$ is a non-negative variable. In matrix form, we obtain the basic panel data stochastic frontier model:

$$y_t = \mathbf{I}_{\mathrm{N}} a + \mathbf{x}_t b + \mathbf{v}_{\mathrm{t}} - \mathbf{u} \; ; \; \mathrm{t} = 1,\ldots,\mathrm{T}. \tag{3.3}$$

$$\mathbf{y}_{\mathrm{t}} = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ . \\ . \\ . \\ y_{N,t} \end{pmatrix}; \; \mathbf{x}_t = \begin{pmatrix} x_{1,1,t} & . & . & . & x_{1,k,t} \\ x_{2,1,t} & . & . & . & x_{2,k,t} \\ . & & & & \\ . & & & & \\ . & & & & \\ x_{N,1,t} & . & . & . & x_{N,k,t} \end{pmatrix} \; ; \tag{3.4}$$

$$\mathbf{v}_t = \begin{pmatrix} v_{1,t} \\ . \\ . \\ . \\ v_{N,t} \end{pmatrix}; \; \mathbf{u} = \begin{pmatrix} u_1 \\ . \\ . \\ . \\ u_N \end{pmatrix}.$$

In logarithmic specification, technical efficiency of country *i* is defined as

$$t_{it} = e^{-u_{it}} \quad . \tag{3.5}$$

Efficiency is ranked as $u_N \leq ... \leq u_2 \leq u_1$: Country *N* produces with maximum efficiency in the sample.

Jondrow *et al*. (1982) suggest a measure of efficiency. They show that the distribution of $u_i|e_i$ is normal with mean $m*_i = s_u^2 e_i (s_u^2 + s_v^2)^{-1}$ and variance $s_*^2 = s_u^2 s_v^2 (s_u^2 + s_v^2)^{-1}$.[9]

This measure of efficiency is based on the distribution of the inefficiency term conditional to the composite error term, $u_i|e_i$. The distribution contains all the information that e_i yields about u_i,. The expected value of the distribution can therefore be used as a point estimate of u_i. When the distribution of the inefficiency component is a truncated distribution, a point estimate for technical efficiency TE_i is given by

$$TE_i = E\left[\exp(-u_i)|e_i\right] = \frac{\left[1-\Phi(s_* - m*_i/s_*)\right]}{\left[1-\Phi(-m*_i/s_*)\right]} \exp\left[-m*_i + \frac{1}{2}s_*^2\right], \tag{3.6}$$

where $\Phi(\bullet)$ is the standard normal cumulative density function. To implement this procedure requires estimates of $m*_i$ and s_*^2. In other words, we need estimates of the variances of the inefficiency and random components and of the residuals $\hat{e}_i = y_i - \hat{a} - x_i\hat{b}$.

If the distribution of the inefficiency component follows a half-normal distribution (with $m*_i = 0$), the point estimate of technical efficiency will take the more simple form

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[8] When τ_i=1 there is full efficiency, in this case the country i produces on the efficiency frontier.

[9] The following assumptions must hold : (i) the v_i are iid $N(0, s_v^2)$, (ii) x_i and v_j are independent, (iii) u_i is independent of *x* and *v*, and (iv) u_i follows a one-sided normal distribution (e.g. truncated or half-normal).

$$TE_i = E\left[\exp(-u_i)\middle|e_i\right] = 2\left[1-\Phi(s_*)\right]\exp\left[\frac{1}{2}s_*^2\right], \quad (3.7)$$

where Φ(•) is the cumulative distribution function.

Often studies estimate the stochastic frontier and calculate the efficiency term according to equation (3.6), and, as a second step, they regress predicted efficiency on specific variables to study the factors which determine efficiency. But such a two-stage procedure is logically flawed. It requires a first-stage assumption that the inefficiencies are independent and identically distributed. Kumbhakar, Ghosh and McGukin (1991) and Reifschneider and Stevenson (1991) address this issue by proposing a single-stage Maximum Likelihood procedure. I use this approach, but in the modified form suggested by Battese and Coelli (1995). They propose an extended version of the model of Kumbhakar, Ghosh and McGuckin (1991) to allow the use of panel data[10]. Battese and Coelli (1995) specify inefficiency as

$$u_{it} = z_{it}\,\delta \quad , \quad (3.8)$$

where u_{it} are technical inefficiency effects in the stochastic frontier model that are assumed to be independently but not identically distributed, z_{it} is vector of variables which influence efficiencies, and δ is the vector of coefficients to be estimated.

Since this article aims to analyse the effect of foreign direct investment and imports of machinery and equipment, equation (3.8) specifies these as exogenous variables. Maximum likelihood estimation is used to take into consideration the asymmetric distribution of the inefficiency term. Greene (1980) argues that the only distribution which provides a maximum likelihood estimator with all desirable properties is the Gamma distribution. However, following van den Broeck et al (1994), the truncated distribution function is preferred, which better distinguishes between statistical noise and inefficiency terms.

The approach used here relates to the growth accounting literature, but goes beyond it. Growth accounting decomposes increases in output into two parts. One is explained by input changes and the other, calculated as a residual, as “technical change”. Interpretation of the unexplained residual as technical change is reasonable only if all countries are producing on their frontier. The strength of the stochastic frontier model in this article is that the residual can be decomposed into technical change, inefficiency and statistical noise. Efficiency measures describe the deviation from the best practice technology.[11] Estimation of the stochastic frontier allows an analysis of the factors which affect technical efficiency.

4. RESULTS

Empirical results derive from a panel for 57 developing countries for the period 1960-90.[12] The dependent variable is the log of real GDP, and the independent variables the log of the labour force and physical capital. Explanatory variables for the efficiency term are import of machinery and transport equipment, the inflow of FDI, and human capital.[13] Data are from the World Bank CD-ROM (1999), except for real physical capital (physical capital at market prices, Nehru and Dhareshwar, 1993) and labour (calculated from GDP per worker series in the Penn World Table, 5.6).

The empirical model is a translog production function with regional dummy

[10] See also Koop *et al*. (1997).
[11] For a detailed treatment of this argument see Maddala (1994).
[12] The countries are: Algeria, Argentina, Bangladesh, Bolivia, Cameroon, Chile, Colombia, Costa Rica, Cote d'Ivoire, Cyprus, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Ghana, Guatemala, Haiti, Honduras, India, Indonesia, Iran, Jamaica, Jordan, Kenya, Korea, Rep., Madagascar, Malawi, Malaysia, Mali, Malta, Mauritius, Mexico, Morocco, Mozambique, Myanmar, Pakistan, Panama, Paraguay, Peru, Philippines, Rwanda, Senegal, Sierra Leone, Singapore, Sri Lanka, Sudan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Uruguay, Venezuela, Zambia, Zimbabwe.
[13] Human capital takes the role of a control variable. It accounts for the part of the learning-by-doing effect which is not due to trade related influences. The measure is from Collins and Bosworth (1996), and is a weighted average of the percentage of a country’s population attained 7 levels of schooling (1: no schooling to 7: beyond secondary completed). The weights are estimated returns to each level of schooling.