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Measuring Efficiency in Developing Countries

Camilla Mastromarco

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Department of Economics

University of Glasgow

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Contents

Introduction

One revealing way to consider the long-run evidence is to distinguish at any point in time between the country that is the "leader", that is, that has a highest level of productivity, and all other countries. Growth for a country that is not a leader will reflect at least in part the process of imitation and transmission of existing knowledge, whereas the growth rate of the leader gives some indication of growth at the frontier of knowledge

Paul M. Romer (1986)

Motivation and Thesis Structure

In the past, the literature on economic growth has focused on two issues: sustainability of growth in per capita income, and the possibility of income convergence across countries. Depending on technological assumptions, the theoretical models give different responses to these issues. The two key assumptions of neoclassical models concerning decreasing returns and the public good nature[1] of technology lead to the convergence result: decreasing returns imply that poorer countries have a greater incentive to save, and a

[1]Technology is a public good in the sense that the use by one country does not affect the supply available for other countries (Mas-Colell *et al.*, 1995, p.359).

higher rate of growth for a given investment share. In the long-term, growth is determined by exogenous technological change which is the same for all countries.

There is, however, a growing body of empirical evidence showing that divergence in per capita income is taking place between countries (Galor, 1996; Quah, 1996a,b, 1997; Bernard and Jones, 1996b; De La Fuente, 1997; Jones, 1997; Easterly and Levine, 2001). The observed divergence contrasts with the predictions of neoclassical growth models, and confirms the predictions of endogenous growth theory. This theory has explored the implications of increasing returns and the determinants of the rate of technological progress. In summary, endogenous growth theory identifies factors capable of explaining income differences across countries, and offers predictions that are consistent with the evidence. Although factor accumulation can be important for the developing process (De Long and Summers, 1993; Bosworth and Collins, 1996; Temple, 1998), the empirical importance of total factor productivity has been shown extensively. Easterly and Levine (2001) motivate the first of the two main topics of this thesis: "Economists should increase research on the "residual" determinants of growth and income, such as technology, externalities, etc. There is little doubt that technology is a formidable force".

In order to distinguish the sources of growth, it is desirable to incorporate the possibility of efficiency change. The use of the stochastic frontier approach allows the decomposition of growth into changes in input use, changes in technology (shift of production frontier) and changes in technical efficiency (movement toward the production frontier). This approach relates to the growth accounting literature, which decomposes output growth into two parts. One part 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 used in this thesis is that the residual can be decomposed into technical change, inefficiency and statistical noise. Efficiency measures describe the deviation from the best practice technology.

The econometric approach to the estimation of frontier models uses a parametric representation of the production function, along with a two-part composed error term. The first component of the error term represents technical inefficiency and the second represents a random error which captures uncertainty. The economic logic behind this specification can be illustrated using the example of a firm. The production process is subject to two economically distinguishable random disturbances: statistical noise, and technical inefficiency. The non-negativity of the technical inefficiency term reflects the fact that the firm will not produce at the maximum attainable level (along the production function). Any deviation below the frontier is the result of factors under the firm's control, but the frontier itself can vary across firms or over time for the same firm. This last consideration allows to say that the frontier is stochastic, with a random disturbance being positive or negative depending on favourable or unfavourable external events not under the firm's control. Differently, in the case of the deterministic frontier, it is assumed that the frontier cannot randomly vary across firms or over time. Estimation of the stochastic frontier allows an analysis of the factors which affect technical efficiency and, therefore, growth and convergence.

Countries in the early stage of industrialisation have limited innovative capabilities. It therefore becomes economically more convenient for them to import foreign technologies than to produce them domestically. The technological frontier is determined and expanded by research in developed countries. The adoption of new technologies through promoting the development of domestic innovative capabilities and increasing productivity helps the alleviation of the poverty problem in less developed countries (LDCs). There is a variety of channels through which new ideas and new technologies can be transmitted. Imports of high-technology products, adoption of foreign technology, and acquisition of human capital are certainly the most important channels for technology diffusion. Therefore, the exploration of the channels that enhance productivity by facilitating the catching-up of developing countries toward the technological frontier is an important area for examination. The catching-up effect represents an increase in efficiency that allows developing countries to close the gap with the technology frontier established by developed countries. The importance of trade channels to conduit technology through their effect on efficiency is the other focus of the thesis.

Differently from growth accounting, technological change is not forced to be neutral in the stochastic production frontier approach. Moreover, this method solves the problem, emphasised by Islam (1995) and Temple (1999), of the possible spurious correlations due to the omission of initial efficiency. Alcalá and Ciccone (2004) underline that the positive effect of trade on productivity may depend on correlated omitted variables. These omitted variables are characteristics of countries, and include institutional quality, which has been shown to play a key role for productivity (Hall and Jones, 1999; Acemoglu *et al.*, 2001). If these unobservable variables are omitted and are correlated with trade, the coefficient which relates trade to productivity is biased upward. Islam (1995) states "the panel data framework makes it possible to correct this bias. From growth theory's point of view, the panel approach allows us to isolate the effect of "capital deepening" on the one hand and technological and institutional differences on the other, in the process of convergence" (Islam, 1995, p.1128). He adds that the individual term "reflects not just technology but resources endowments, climate, institutions, and so on" (Islam, 1995, p.1133).

The stochastic frontier model goes a step further. Clearly distinguishing between technological shifts and efficiency allows the isolation of three different sources of the convergence process: factor accumulation, efficiency and technological change. Moreover, it permits the analysis of the factors that drive the catching-up effect, viz. efficiency. Efficiency is the most important growth component for convergence analysis of countries that are below the technological frontier because it reflects "the process of imitation and transmission of existing knowledge" (Romer, 1986).

Survey of Empirical Literature

Identifying stylised facts which are at odds with the implications of the neoclassical growth model, Easterly and Levine (2001) state that they hope their study "... stimulates researchers to develop models more in line with the evidence and to provide more empirical content to the term *total factor productivity*". The widely used measure for total factor productivity (TFP) goes back to the seminal work of Solow (1956), who constructs a growth model with two inputs, labour and capital, and assumes constant returns to scale and diminishing returns to each input. He argues that the main determinant of growth is exogenous technical progress. Abramovitz (1956) and Solow (1956) identify the "residual" as the difference in the growth of output and the contribution of the inputs, weighted by their respective factor shares in value added. In these early growth accounting studies the residual has been named "total factor productivity growth" (Solow residual) and has been equated with neutral technical change. This means that the residual accounts just for parallel shifts in production technology. Important extensions of the measure incorporate vintage effects and quality adjusted input factors (Kendrick, 1961, 1976), as well as economies of scale (Denison, 1962, 1979, 1985).[2]

Instead of imposing factor shares and calculating TFP growth as a residual, the growth regression approach estimates the parameters of the production function directly, as introduced by Mankiw *et al.* (1992).[3] Barro (1991) and Benhabib and Spiegel (1994) are famous contributions in this line of research. Temple (1999) lists among the problems of this approach parameter heterogeneity, outliers, model uncertainty, endogeneity, measurement errors, error correlations, and regional spillovers. Some of these issues can be alleviated using panel data, as it is done in this thesis. However, the problem with the identification of TFP components remains.

For many years econometricians have estimated average production functions by using regression techniques which gave mean (as opposite to maximum) output for a given set of inputs.[4] It has only been since the pioneering work of Farrell (1957) that serious consideration has been given to the possibility of estimating frontier production functions. Farrell shows how to decompose cost efficiency into technical and allocative efficiency, drawing inspiration from the work of Koopmans (1951) and Debreu (1951). The former introduced a definition of technical efficiency; Debreu (1951) and Shephard (1953) proposed distance functions as a way of modelling multiple output technology. Following the seminal papers by Aigner and Chu (1968), Seitz

[2]See Chapter 1 for a discussion of the more recent extensions by Hall (1990) and Basu (1996).

[3]See Durlauf and Quah (1999) and Sachs and Warner (1997) for an overview of the methodology.

[4]For a survey of these studies see Farrell (1957).

(1971), Timmer (1971), Afriat (1972), Richmond (1974), and Farrell (1957) estimate a deterministic production frontier for the US agricultural sector by linear programming techniques and modifications of least squares techniques.

Applications can be found both in a microeconomic and in a macroeconomic context. Examples are the estimation of inefficiencies in the public sector, or, allowing for multiple output technologies, the estimation of inefficiency in pollutant firms (where one of the outputs is pollution). A major field in macroeconomics is the application of this technique to cross-country productivity analysis. The introduction of efficiency change as a source of productivity change was pioneered by Nishimizu and Page (1982), who use a deterministic translog production frontier to decompose productivity change in Yugoslavia manufacturing industries into technical change and technical efficiency change. They analyse TFP growth, technological progress and efficiency change among the manufacturing industries in Yugoslavia 1965-78. The main finding of their paper is that changes throughout the period 1965-70 in technical efficiency dominated technological progress in Yugoslavia. Furthermore, the slowdown in total factor productivity growth in Yugoslavia in the 1970s was due to the deterioration in technical efficiency.

Much later there were many microeconomic studies which used the frontier model on different aggregation levels to analyse efficiency. Important influential contributions are the papers by Greene (1993) and Horrace and Schmidt (1996). The topics of these studies vary from efficiency comparisons of airlines in the United States (Schmidt and Sickles, 1984; Greene, 1993) to agricultural issues such as the production of rice in Indonesia (Horrace and Schmidt 1996, based on the work by Lee and Schmidt 1993). Coelli (1997) uses the stochastic frontier approach to highlight the technical and efficient components of productivity change in Australian coal-fired electricity generation industries. Other studies which decompose productivity into its components and taking into account technical eficiciency are Tybout and Westbrook (1995), Chang and Luh (1999), and Suhariyanto and Thirtle (2001).

In the following, the discussion turns to the main microeconomic studies on technological diffusion, using the frontier technique. Handoussa *et al.* (1986) show that the large increase in productivity in Egypt is due to the fact that firms closed the gap between themselves in terms of efficiency. On the contrary, the most efficiency firms within the country did not improve their own productivity. It is therefore possible to interpret productivity growth in Egypt as efficiency change. Havrylyshyn (1990) examines the empirical literature concerning the correlation between trade liberalisation and increases in capacity utilisation, economies of scale and efficiency. He arrives at the important conclusion that the studies which yield more statistically reliable results are the ones which use the efficiency-production methodology.

Tybout (2000) presents a survey of firm and plant level econometric studies over the past decade, to show how openness through technological diffusion in LDCs fosters productivity growth. He shows that the econometric evidence of technological diffusion in LDCs is limited. Comparing results from LDCs with those from industrialised countries he shows that the cross-firm variance in productivity levels is often high in developing countries.[5] Nonetheless, the average deviations from the efficient frontier are not typically larger than what is observed in industrialised countries. The standard methodology, when it "works", yields mean technical efficiency levels around 60 and 70 percent of the best practice frontier in both regions. Hence it is hard to reconcile the studies surveyed with the view that LDC markets are

[5]See Pack (1988), Evenson and Westphal (1995), and Blomstrom and Kokko (1997).

relatively tolerant of inefficient firms. When trade liberalisation improves productive efficiency, it is probably due to intra-plant improvements that are unrelated to internal or external scale economies. The elimination of waste, reductions in managerial inefficiency, incentives for technological catch-up, and access to better intermediate and capital goods are all possible explanations, but there is little direct evidence on their importance. The most promising direction for further research on this topic seems to be a detailed analysis of task-level efficiency and technological choice within narrowly defined industries before and after a major change in trade policy. The evidence on openness and productivity growth suggests that openness allows access to the international knowledge stock. This is in contrast to some studies which suggest that learning by doing among domestic firms is important (Evenson and Westphal, 1995; Basant and Fikkert, 1996). Therefore, the case for fostering growth by protecting learning industries seems weak. An interesting point emphasised by Tybout is that imported capital and intermediate goods may be the most important channel through which trade diffuses technology, but there is no evidence on this issue. Therefore, frontier methodology could be applied to address this interesting question, that is how factors such as imported machinery and equipment and foreign direct investments can affect productivity dispersion in LDCs.

Piesse and Thirtle (2000) use firm level accounting data, from 1985 to 1991, to study productive efficiency of Hungarian manufacturing and agricultural enterprises. They find materials and labour account for most of the output, while capital and energy do not contribute. They provide evidence of low elasticity of substitution that, they argue, may cause inefficiency as firms are constrained by little opportunity to respond to changing economic conditions. Inefficiency is found to depend on overcapitalization, subsidies and management costs. However, they underline that efficiency changes are dominated by technological regress. This finding leads to the conclusion that policy makers should try to reverse the technological decline rather than improving technical or scale inefficiencies.

The concept used in all these studies can easily be extended to the macro level. To date, there are only few macroeconomic studies: Koop *et al.* (1999), Koop *et al.* (2000a), Koop *et al.* (2000b), and Koop (2001).[6] Koop *et al.* (1999) apply a Bayesian stochastic production frontier model to decompose the output changes in technical, efficiency and input change to a sample of seventeen OECD countries over the period 1979-1988. All these countries are assumed to have the same technology, so that each country faces the same production frontier. They estimate the contributions of these three components and find that technological change plays a dominant role in explaining output changes, although efficiency and input changes were also found to be important in several special cases. Koop *et al.* (1999) use the Bayesian approach to stochastic frontier analysis for several reasons. One of the most important is that the Bayesian technique is particularly appropriate when the data set is small. Moreover, through deriving the full posterior distribution of the efficiency term, this technique allows calculation of standard deviations and the making of inference about differences in efficiency. It is also possible to account for uncertainty in the estimation of efficiency. Finally, it is especially easy to impose economic regularity conditions on the production function. The same technique is adopted by Koop *et al.* (2000a). They use Bayesian stochastic frontier methodology and data for 20 West-

[6]On a more disaggregated level Coelli *et al.* (2003a), using data for 16 regions in their frontier study of Bangladesh crop agriculture, find that the decline in TFP is caused by a combined effect of slow technical progress and fall in efficiency. Thus, Bangladesh government needs to promote new technologies and improve efficiency.

ern economies and also Poland and Yugoslavia (1980-1990) to measure the productivity gap between Poland and western countries before the beginning of the Polish economic reform. The main finding is that increasing output through efficiency change may explain Poland's growth in recent years. Koop *et al.* (2000b) use an extension of the Bayesian stochastic production frontier model for the decomposition of output change into input, efficiency and technical change of 44 countries over the period 1965-1990. The three important extensions of their approach are to incorporate "effective-factor correction", to allow for the efficiency distribution to depend on exogenous variables and to allow for regional differences in the production frontier. In particular they stress that as it is unreasonable to assume that input quality is comparable across a set of countries with different levels of development. Since output depends on effective rather than actual inputs they specify a relationship between effective and actual factors. They correct the labour variable, which is measured as number of workers, for the level of skill.[7] The capital variable is corrected by making it depend on the percentage of labour force in agriculture and industrial sectors. They find that having a large percentage of the labour force engaged in agriculture has a significant negative effect on effective capital. This implies that countries with a large agricultural sector tend to have less productive capital. The second extension allows efficiency distribution to depend on observable variables. They analyse how macroeconomic factors, political instability and interference in markets cause a country to be inefficient given its stock of quality-corrected

[7]They argue, as Tallman and Wang (1994) do, that education affects growth through its effect on labour productivity. Differently, Mankiw *et al.* (1992) show that human capital (measured by education) acts on growth as a production factor. This was criticised by Nelson and Phelps (1966), and additionally the empirical study of Benhabib and Spiegel (1994) indicates that this is not the correct way to take account of the effect of human capital on income growth. To address this issue, the impact of human capital on both as a factor of production and as a determinant of efficiency will be analysed in Chapter 2.

inputs. Finally, the third extension, through accounting for regional frontier, allows investigation of convergence within the regional groups and they show evidence of catch up through a reduction of inefficiency. Koop (2001) applies the same methodology to analyse the output growth in six manufacturing sectors in eleven OECD countries during the period 1970-1988. He estimates the relative contribution of the three components of output growth: input, efficiency and technological change. He finds that technological change explains the major part of output growth, although efficiency and input change also play an important role. Moreover, he postulates that inefficiency tends to be weakly associated with slow growth phases of the business cycle. This finding can be explained by the fact that industries operate efficiently during high growth phases and during a slow growth phases they are inefficient because they are unable or unwilling to reduce factors of production (Koop, 2001).

The thesis contributes to the existing literature by analysing a panel of 55 developing countries in the period 1960-1990, thus adding further evidence on macro level efficiency measurement. Looking at the determinants of efficiency for developing countries helps to better understand the catch-up process. The panel data approach helps to address some of the issues raised by Temple (1999),[8] while the stochastic frontier methodology allows for a theory based empirical analysis of TFP components.

Thesis Structure

The thesis is divided into four chapters. The first chapter explains the stochastic frontier methodology. The second presents an empirical analy-

[8]For a detailed discussion of this point, see Section 2.3.

sis to find the best model to study technology diffusion. The third chapter examines the components of growth and their distributions. In the final chapter, a different specification of the empirical model allows to go more deeply into the analysis of the link between openness, human capital, and efficiency.

Chapter 1:

This chapter presents a critical and detailed review of the stochastic frontier methodology from a macro-data perspective. The advantages over the standard growth accounting approach are emphasised, and the main features of the translog production function, used throughout the thesis, are discussed.

On the macro level, TFP can be decomposed into the level of technical knowledge, technical efficiency, allocative efficiency, and returns to scale effects. Using TFP growth as a measure for technical change can be misleading in the presence of the other components. The "growth accounting" Solow residual widely used in the literature suffers from a number of shortcomings. It is based upon strong assumptions, such as constant returns to scale, perfect competition and no short-run fixities. Very often these assumptions are not representative of reality. In such a case, there is the danger that the Solow residual produces biased results.

The stochastic frontier approach distinguishes between technological catch-up (efficiency improvements) and technological change (shifts in the production frontier), and requires no particular assumptions on market structure and the nature of technological change. It allows to decompose growth into changes in input use, changes in total factor productivity and changes in efficiency, and is therefore a possibility to overcome the problems of the Solow residual. The chapter presents an extensive analysis of various methods and models for stochastic frontier estimation. Cross-section and panel data models are also illustrated, distinguishing the case of time invariant inefficiency from the case where the inefficiency changes over time for each producer. The model of Battese and Coelli (1995) used throughout the thesis is dicussed in detail.

Chapter 2:

This chapter uses the stochastic frontier approach to estimate different specifications of the production function, technological catch-up (efficiency improvements) and technological change (shifts in the production frontier) for 57 developing countries over the period 1960-1990. It is well known that alternative specifications of the production function lead to ambiguous empirical evidence for competing theories of economic growth (Durlauf and Quah 1999). Therefore, tests are performed to find the specification in line with the data under analysis. Then the important issue of the role of human capital in the process of economic growth is also investigated, since it is not yet unambiguously determined (Islam 1995, p.1154). Next, to better understand the importance of technology transfer for the development process of poor countries, attention turns to the analysis of four trade channels (FDI, imported capital goods, import discipline indicator and manufacturing exports) and their contribution to the explantion of deviations from the frontier.

Evidence indicates that human capital affects growth though multiple channels. The translog stochastic frontier production function with quality adjusted labour force is found to fit the data better than the one with unadjusted labour force. Moreover, human capital has a positive impact on efficiency. Therefore, as implied by growth theory, human capital influences growth through learning-by-doing (Lucas, 1988 and Romer, 1986). This result is similar to the finding obtained by Islam (1995). Non-neutral technical progress turns out to be the preferred specification. As a result, technical change shifts the frontier and changes the elasticity of substitution between the production factors. Technological progress turns out to benefit physical capital and to be labour saving. This finding confirms the hypotheses of Romer (1986, 1990) and Rebelo (1991) and contrasts with the implications of Solow's growth model. Because of the possibility to test competing hypotheses, the results clearly demonstrate that, compared with other methods, the stochastic frontier approach is superior. Finally, it is demonstrated that openness benefits efficiency through four trade channels: foreign direct investment (FDI), imports of machinery and equipment, import discipline effect and export of manufacturing goods.

Chapter 3:

The identification of the channels which can be utilized to improve productivity growth is important for the design of policies helpin LDCs in the catch-up process. To this end, this chapter analyses the results based on Model 4* (Chapter 2) in more detail to provide a consistent decomposition of output growth. The evolution of the entire distribution of the growth and productivity sources is analysed and a formal test for assessing the importance of growth factors is performed. With respect to regression analysis, this approach is likely to be more informative (Quah, 1996a,b, 1997). The base of both the test and the visual analysis is the non-parametric kernel density estimator.

The analysis in this chapter is similar to the study of Kumar and Russell (2002). But, instead of DEA, a stochastic frontier model is employed for reason discussed in Chapter 1. In addition, output growth, and not labour productivity growth is decomposed into its components. The results contradict the finding in Kumar and Russell (2002) that factor accumulation ins the most important growth determinant. In particular, evidence shows that TFP is equally important. Moreover, technical change and scale effects are significant components of TFP, whereas efficiency does not play an important role. This last result mirrors the earlier finding of Kumar and Russell (2002). Finally, a time-series convergence test supports the impression of visual analysis, and confirms the divergent evolution of per capita output among countries.

Chapter 4:

The findings in the previous chapters motivate this part of the thesis, which further explores the relative importance of FDI, imports of capital goods and human capital accumulation in the development process.

The estimation of a stochastic production frontier model which is slightly different from the one in Chapter 2 confirms that FDI and imported capital goods are important channels for improving efficiency, as well as human capital accumulation. Analysis reveals, however, an important difference between the two channels. Knowledge diffused through FDI is more general (disembodied) than that from imported capital goods (embodied). In the interaction model, it turns out that human capital has not direct significant effect on efficiency. Human capital accumulation leads to an increase in the effects of FDI and imports of machinery and equipments on efficiency. Over the observation period, all countries become more efficient. Efficiency gains are especially evident for the group of Asian countries in the panel.

Chapter 1

Methodology

1.1 Introduction

The aim of this chapter is to provide a critical and detailed review of stochastic frontier methods. Although there exist other methodological surveys on the measurement of economic efficiency (Fried *et al.*, 1993; Coelli *et al.*, 1998; Kumbhakar and Lovell, 2000), most of the literature debates the choice of estimation method, i.e the comparison between the parametric and the non-parametric approach. Moreover, the literature has a focus on microeconomic data, while this chapter goes more deeply into the analysis of stochastic frontier models and their statistical properties from a macro-data perspective. The translog production function, its properties and estimation is also discussed in detail. The flexible form of this function, which is a second order Taylor approximation to a twice differentiable but otherwise arbitrary function, addresses the critique that the usual Cobb-Douglas specification is too restrictive.

Stochastic frontier models allow to analyse technical inefficiency on the aggegate level in the framework of production functions. Countries are assumed to produce according to a common regional technology, and reach the frontier when they produce the maximum possible output for a given set of inputs. Inefficiencies can be due to structural problems or market imperfections,[1] but also factors which cannot be changed by policy, like geography and climate. They cause countries to produce below their maximum attainable output.

Over time, countries can become less inefficient and catch up to the frontier, e.g. by structural changes or an increase in infrastructure investment,[2] which makes inputs more efficient. It is also possible that the frontier shifts, indicating technical progress. In addition, countries can move along the frontier by changing input quantities. Finally, there can be some combinations of these three effects. The stochastic frontier method allows to decompose aggregate growth into changes in input use, changes in technology and changes in efficiency, thus extending the widely used growth accounting method.

When dealing with productivity, two main problems arise: its definition and its measurement. Traditionally, empirical research on productivity has suffered from a number of shortcomings. Most empirical studies have employed the so called Solow residual (Solow, 1956). The use of this measure is problematic, as discussed in the introduction: Abramovitz (1956) refers to the difference between the growth rates of output and the weighted sum of input growth rates as a "measure of our ignorance about the causes of economic growth". There are studies which associate productivity change measured by the resiudal with technical change (Solow, 1956; Kendrick, 1961, 1976; Maddison, 1987). Other studies decompose productivity change into a term due to technical change and a term due to scale economies (Denison, 1962,

[1]The current economic situation in Italy and Germany can be thought of in these terms.
[2]For the importance of infrastructure investment for efficiency in the case of regional production functions in Italy, see Mastromarco and Woitek (forthcoming).

1979, 1985). To distinguish the sources of productivity change, it is desirable to incorporate the possibility of changes in efficiency. The stochastic frontier method allows this important step.

Section 1.2 discusses other productivity measures proposed in the literature and discusses their advantages and drawbacks in the light of the data set analysed in this study. In Section 1.3, both the deterministic and stochastic frontier approaches are introduced. Section 1.4 discusses in detail stochastic frontier analysis for cross-section models. Section 1.5 extends the discussion to panel data models, distinguishing the case of time invariant inefficiency from the case where inefficiency changes over time. Section 1.6 describes Battese and Coelli's (1995) model and motivates the choice of this model in this study. Section 1.7 introduces the translog specification of the production function used in Chapters 2, 3, and 4. The chapter also includes a survey of panel unit root tests (Section 1.8) which are used to analyse both the characterstics of the data in Chapter 2 and for a convergence test for the countries under analysis in Chapter 3. Section 1.9 concludes.

1.2 Growth Accounting and the Solow Residual

In empirical research, technological change has been measured as change in total factor productivity (TFP) in the analytical framework of a production function. The usual measure for technological progress is a residual of the Abramovitz/Solow type where output growth is decomposed into a weighted sum of input growth rates. The residual representing the change in output which cannot be explained by input growth is identified as technological progress. The following example of the Solow residual illustrates the procedure to clarify the drawbacks of this productivity measure, and potential solutions.

Consider an aggregate production function (homogenous of degree λ)[3]

$$Y = ZF(\tilde{K}, \tilde{L}), \tag{1.1}$$

where Z is the level of technology, $\tilde{K} = UK$ is actual capital input with U representing utilisation, and $\tilde{L} = EHL$ is actual labour input with effort E and hours worked H. Rewriting equation (1.1) in growth rates gives

$$\begin{aligned} dy &= \gamma\left(s_K d\tilde{k} + s_L d\tilde{l}\right) + dz = \\ &= \gamma\left(s_K(dk + du) + s_L(de + dh + dl)\right) + dz = \\ &= \gamma\underbrace{\left(s_K dk + s_L(dh + dl)\right)}_{\text{observable}} + \gamma\underbrace{\left(s_K du + s_L de\right)}_{\text{not observable}} + dz, \end{aligned} \tag{1.2}$$

where γ is the markup. Output growth (dy) can be decomposed in a weighted average of input growth rates (dk,dl), if γ and the profit shares s_K, s_L were known or could be estimated, and all input components could be observed. In the case of the Solow residual, the assumptions are that the production function is linear homogenous,[4] that input factors are fully utilised ($\tilde{L} = HL, \tilde{K} = K$), and that there is perfect competition. In this case, the growth decomposition becomes

$$dy = s_K dk + s_L(dh + dl) + dz. \tag{1.3}$$

This measure is, however, subject to criticism. The Solow residual ignores monopolistic markets, non-constant returns to scale and variable factor util-

[3] For the following, see Basu and Kimball (1997) and Basu and Fernald (2001a).
[4] $\lambda = 0$ implies that $\gamma = 1$.

isation over the cycle (Saint-Paul, 1997). In the case of monopoly profits, the residual underestimates the elasticity of output with respect to all inputs. To overcome this problem, Hall (1990) uses cost based shares in the derivation of his alternative TFP measure. Basu (1996) provides a measure of TFP which is net of cyclical factor utilisation. Material inputs do not have a utilisation dimension, unlike employment and capital. Basu therefore uses relative changes in the input of raw materials and other measured factor inputs to deduce the extent to which factor utilisation changes over the cycle. Another approach is the one proposed by Basu and Kimball (1997) and Basu and Fernald (2001a). They link unobservable factor utilisation (U, E) to observable inputs (H) and arrive at the decomposition

$$dy = \gamma\left(s_K dk + s_L(dh + dl)\right) + \gamma\left(s_K \frac{\eta}{\nu} + s_L \zeta\right) dh + dz, \qquad (1.4)$$

where ζ is the steady-state elasticity of hourly effort with respect to hours, η is the rate of change of the elasticity of labor costs with respect to hours, and ν is the rate of change of the elasticity of labor costs with respect to capital utilisation.[5] This decomposition can be estimated, provided that data is available.[6] In the context of developing countries, the availability issue makes it necessary to apply other, less data intensive methods.

Empirical studies based on the (uncorrected) Solow residual described above regard productivity growth and technical progress as synonymous (Jorgenson, 1996; Crafts, 2004). However, technical progress is the change in the best practice frontier, i.e. a shift of the production function. Other productivity changes, as learning by doing, improved managerial practice, diffusion

[5]The assumption is that unobservable labour effort and capital utilization depend on observable worked hours.

[6]See Malley *et al.* (2005) for an application to the US manufacturing sector.

of new technological knowledge, and short run adjustment to external shocks are technical efficiency changes (movements towards or away from the frontier). Productivity growth is the net change in output due to changes in efficiency and technical change. Therefore, efficiency is a component of productivity.[7] To fix ideas, consider the example in Figure 1.1. 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 (I). Second, technology acquisition may differ between countries or regions, with the consequence that for the same level of inputs different outputs result (panel (II)). 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 (III)). 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.

As pointed out above, corrections to the Solow residual like the one proposed by Basu (1996) require data which are not always available. An additional drawback of the growth accounting approach is that the mechanical decomposition of output growth rates does not provide a direct, model based explanation of growth differences across countries.[8] Cross-country growth regressions of the Barro-type (Barro, 1999) try to overcome this problem by assuming a linear relationship between several conditioning variables and growth. However, this approach is not immune against criticism: the choice of explanatory variables might be arbitrary, and the error term has no struc-

[7]Nishimizu and Page (1982), Grosskopf (1993).

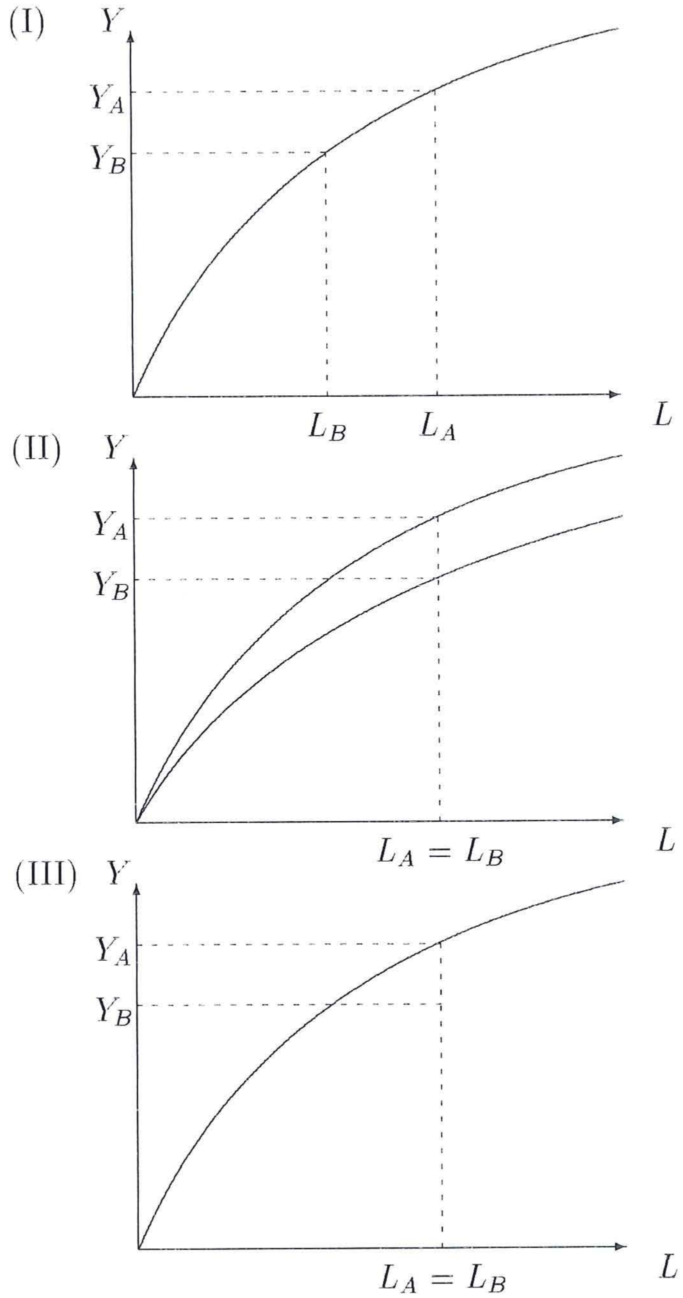
[8]Of course, after the decomposition, one could regress e.g. the residual on explanatory variables, which is a problematic approach (Wang and Schmidt, 2002).

ture.[9] Thus, as in the case of the Solow residual, it is not possible to identify efficiency changes.

Another less data intensive approach is the estimation of a frontier production function. The stochastic frontier methodology, pioneered by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), allows the important distinction between efficiency gains or losses and technical progress. In addition, it allows to include explanatory variables in both the production function and the efficiency term. "If efficiency considerations are important in cross-country growth analysis, then our manner of including them is preferable" (Koop *et al.*, 2000b, p.287).

[9]See Temple (1999) and the introduction for a more detailed discussion.

Figure 1.1: Aggregate Production Functions



1.3 The Production Frontier

The standard definition of a production function is that it gives the maximum possible output for a given set of inputs, the production function therefore defines a boundary or a frontier. All the production units on the frontier will be fully efficient. Efficiency can be of two kinds: technical and allocative. Technical efficiency is defined either as producing the maximum level of output given inputs or as using the minimum level of inputs given output. Allocative efficiency occurs when the marginal rate of substitution between any of the inputs equals the corresponding input price ratio. If this equality is not satisfied, it means that the country is not using its inputs in the optimal proportions. An initial justification for computing efficiency can be found in that its measure facilitates comparisons across economic units. Secondly, and perhaps more importantly, when divergence in efficiency is found some further research needs to be undertaken to understand which factors led to it. Finally, differences in efficiency show that there is scope for implementing policies addressed to reduce them and to improve efficiency.

Technical efficiency can be modelled using either the deterministic or the stochastic production frontier. In the case of the deterministic frontier model the entire shortfall of observed output from maximum feasible output is attributed to technical inefficiency, whereas the stochastic frontier model includes the effect of random shocks to the production frontier. There are two alternative approaches to estimate frontier models: one is a non-parametric approach which uses linear programming techniques, the other is a parametric approach and utilises econometric estimation. The characterising feature and main advantage of the non-parametric approach, (also called "Data Envelopment Analysis", or DEA), is that no explicit functional form needs to be imposed on the data. However, one problem with this approach is that it is extremely sensitive to outlying observations (Aigner and Chu, 1968; Timmer, 1971). Therefore, measures of production frontiers can produce misleading information. Moreover, standard DEA produces efficiency "measures" which are point estimates: there is no scope for statistical inference and therefore it is not possible to construct standard errors and confidence intervals.

The parametric or statistical approach imposes a specification on the production function which of course can be overly restrictive. This approach does, however, have the advantage of allowing for statistical inference. Hence, we can test the specification as well as different hypotheses on the efficiency term and on all the other estimated parameters of the production frontier. The choice of technique employed to obtain estimates of the parameters describing the structure of the production frontier and technical efficiency depends, in part, on data availability. The main difference between cross-sectional and panel-data estimation techniques is that with cross-sectional data it is only possible to estimate the performance of each producer at a specific period in time, whereas with panel data, we are able to estimate the time pattern of performance for each producer.[10] A production frontier model can be written as:

$$y_i = f(\mathbf{x}_i; \boldsymbol{\beta}) TE_i \tag{1.5}$$

where y_i is the output of producer i ($i = 1, \ldots, N$); $\mathbf{x}_i$ is a vector of M inputs used by producer i; $f(\mathbf{x}_i; \boldsymbol{\beta})$ is the production frontier and $\boldsymbol{\beta}$ is a vector of technology parameters to be estimated. Let TE_i be the technical efficiency

[10] It is assumed that producers produce only a single output. In the case of multiple outputs, these are aggregated it into a single-output index. Kumbhakar and Lovell (2000, pp. 93-95) discuss the analysis of stochastic distance functions which accommodate for multiple outputs.

of producer i,

$$TE_i = \frac{y_i}{f(\mathbf{x}_i; \boldsymbol{\beta})}, \tag{1.6}$$

which defines technical efficiency as the ratio of observed output y_i to maximum feasible output $f(\mathbf{x}_i; \boldsymbol{\beta})$. In the case $TE_i = 1$, y_i achieves its maximum feasible output of $f(\mathbf{x}_i; \boldsymbol{\beta})$. If $TE_i < 1$, it measures technical inefficiency in the sense that observed output is below the maximum feasible output. The production frontier $f(\mathbf{x}_i; \boldsymbol{\beta})$ is deterministic. That means that the entire shortfall of observed output y_i from maximum feasible output $f(\mathbf{x}_i; \boldsymbol{\beta})$ is attributed to technical inefficiency. Such a specification ignores the producer-specific random shocks that are not under the control of the producer. To incorporate the fact that output can be affected by random shocks into the analysis, we have to specify the stochastic production frontier

$$y_i = f(\mathbf{x}_i; \boldsymbol{\beta}) \exp(v_i)\, TE_i, \tag{1.5$'$}$$

where $f(\mathbf{x}_i; \boldsymbol{\beta}) \exp(v_i)$ is the stochastic frontier, which consists of a deterministic part $f(\mathbf{x}_i; \boldsymbol{\beta})$ common to all producers and a producer-specific part $\exp(v_i)$ which captures the effect of the random shocks to each producer. If we specify that the production frontier is stochastic, equation (1.6) becomes

$$TE_i = \frac{y_i}{f(\mathbf{x}_i; \boldsymbol{\beta}) \exp(v_i)}. \tag{1.6$'$}$$

If $TE_i = 1$, producer i achieves its maximum feasible value of $f(\mathbf{x}_i; \boldsymbol{\beta}) \exp(v_i)$. If $TE_i < 1$, it measures technical efficiency with random shocks $\exp(v_i)$ incorporated. These shocks are allowed to vary across producers.

Technical efficiency can be estimated using either the deterministic production frontier model given by equations (1.5) and (1.6), or the stochastic frontier model given by equations (1.5′) and (1.6′). Since the stochastic frontier model includes the effect of random shocks on the production process, this model is preferred to the deterministic frontier.

1.4 Cross-Section Stochastic Frontier Models

1.4.1 Introduction

The econometric approach to estimate frontier models uses a parametric representation of technology along with a two-part composed error term. Under the assumption that $f(\mathbf{x}_i; \boldsymbol{\beta})$ is of Cobb-Douglas type, the stochastic frontier model in equation (1.5′) can be written in logs as

$$y_i = \alpha + \mathbf{x}_i\boldsymbol{\beta} + \varepsilon_i \qquad i = 1, \dots, N, \tag{1.5''}$$

where ε_i is an error term with

$$\varepsilon_i = v_i - u_i. \tag{1.7}$$

The economic logic behind this specification is that the production process is subject to two economically distinguishable random disturbances: statistical noise represented by v_i and technical inefficiency represented by u_i. There are some assumptions necessary on the characteristics of these components. The errors v_i are assumed to have a symmetric distribution, in particular, they are independently and identically distributed as $N(0, \sigma_v^2)$. The component u_i is assumed to be distributed independently of v_i and to satisfy $u_i \geq 0$ (e.g. it follows a one-sided normal distribution $N^{+}(0, \sigma_u^2)$. The non-negativity of the technical inefficiency term reflects the fact that if $u_i > 0$ the country will not produce at the maximum attainable level. Any deviation below the frontier is the result of factors partly under the countries's control, but the frontier itself can randomly vary across countries, or over time for the same economy. This last consideration allows the assertion that the frontier is stochastic, with a random disturbance v_i being positive or negative depending on favourable or unfavourable external events.

It is important to note that given the non-negativity assumption on the efficiency term, its distribution is non-normal and therefore the total error term is asymmetric and non-normal. This implies that the least squares estimator is inefficient. Assuming that v_i and u_i are distributed independently of $\mathbf{x}_i$, estimation of (1.5$''$) by OLS provides consistent estimators of all parameters but the intercept, since $E(\varepsilon_i) = -E(u_i) \leq 0$.[11] Moreover, OLS does not provide an estimate of producer-specific technical efficiency. However, it can be used to perform a simple test based on the skewness of empirical distribution of the estimated residuals. Schmidt and Lin (1984) propose the test statistic

$$(b_1)^{1/2} = \frac{m_3}{{m_2}^{3/2}} \tag{1.8}$$

where m_2 and m_3 are the second and the third moments of the empirical distribution of the residuals. Since v_i is symmetrically distributed, m_3 is simply the third moment of the distribution of u_i.

The case $m_3 < 0$ implies that OLS residuals are negatively skewed, and that there is evidence of technical inefficiency. In fact, if $u_i > 0$ then $\varepsilon_i =$

[11]The estimator for the intercept is biased even in the absence of inefficiency (Goldberger, 1968).

$v_i - u_i$ is negatively skewed. The positive skewness in the OLS residuals, i.e. $m_3 > 0$, suggests that the model is misspecified. Coelli (1995) proposed an alternative test statistic

$$(b_1)^{1/2} = \frac{m_3}{\left(6m_2^3/N\right)^{1/2}}, \tag{1.9}$$

where N is equal to the number of observations. Under the null hypothesis of zero skewness in the OLS residuals, $m_3 = 0$, the test statistic (1.9) is asymptotically distributed as $N(0,1)$. These two tests have the advantage that they can easily be computed given that they are based on the OLS residuals. They have the disadvantage that they rely on asymptotic theory and therefore are not suitable for small samples.[12]

The asymmetry of the distribution of the error term is a central feature of the model. The degree of asymmetry can be represented by the following parameter:

$$\lambda = \frac{\sigma_u}{\sigma_v} \quad . \tag{1.10}$$

The larger λ is, the more pronounced the asymmetry will be. On the other hand, if λ is equal to zero, then the symmetric error component dominates the one-side error component in the determination of ε_i. Therefore, the complete error term is explained by the random disturbance v_i, which follows a normal distribution. ε_i therefore has a normal distribution. To test the hypothesis

[12] Coelli (1995) postulates that negative skewness in the OLS residuals occurs when the third moment is negative, therefore, a test of whether the third moment is greater than or equal to zero is appropriate. Under the null hypothesis the third moment of OLS residuals is asymptotically distributed as a normal random variable with mean zero and variance $\frac{6m_2^3}{N}$. This implies that the test statistic $(b_1)^{1/2} = m_3/\left(6m_2^3/N\right)^{1/2}$ is asymptotically distributed as a standard normal random variable. Coelli (1995) presents Monte Carlo experiments where these tests have the correct size and good power.

that $\lambda = 0$, we can compute a Wald statistic or likelihood ratio test both based on the maximum likelihood estimator of λ.[13] Coelli (1995) tests as equivalent hypothesis $\gamma = 0$ against the alternative $\gamma > 0$, where

$$\gamma = \frac{\sigma_u}{\sigma_v + \sigma_u}. \tag{1.11}$$

A value of zero for the parameter γ indicates that the deviations from the frontier are entirely due to noise, while a value of one would indicate that all deviations are due to technical inefficiency.[14]

The Wald statistic is calculated as

$$W = \frac{\widehat{\gamma}}{\widehat{\sigma}_{\widehat{\gamma}}}, \tag{1.12}$$

where $\widehat{\gamma}$ is maximum likelihood estimate of γ and $\widehat{\sigma}_{\widehat{\gamma}}$ is its estimated standard error. Under $H_0 : \gamma = 0$ is true, the test statistic is asymptotically distributed as a standard normal random variable. However, given that γ cannot be negative, the test is performed as a one-sided test. The likelihood test statistic is

$$LR = -2\left[\log\left(L_0\right) - \log\left(L_1\right)\right], \tag{1.13}$$

where $\log(L_0)$ is the log-likelihood valued under the null hypothesis and $\log(L_1)$ is the log-likelihood value under the alternative. This test statistic is asymptotically distributed as chi-square random variable with degrees of

[13] Coelli (1995) shows that the likelihood ratio test is asymptotically distributed as a mixture of Chi squared distributions.

[14] Coelli (1995) stresses that the parameter does not reflect the contribution of the inefficiency effect to the total variance, since the variance of inefficiency is not equal to σ_u^2 but to $[(\pi - 2)/\pi]\,\sigma_u^2$. Therefore, the contribution of the inefficiency effect to the total variance is equal to $\gamma/[\gamma + (1-\gamma)\,\pi/(\pi - 2)]$.

freedom equal to the number of restrictions.[15] Coelli (1995) notes that under the null hypothesis $\gamma = 0$, the statistic lies on the limit of the parameter space since γ cannot be less than zero.[16] He therefore concludes that the likelihood ratio statistic will have an asymptotic distribution equal to a mixture of chi square distributions $\left(1/2\right)\chi_0^2 + \left(1/2\right)\chi_1^2$. Kodde and Palm (1986) present critical values for this test statistic. Coelli (1995), performing a Monte Carlo study, shows that the Wald test has very poor size. With a confidence interval of 5%, the Wald test rejects the null hypothesis 20% times instead of 5% as expected (Type I error). The likelihood ratio test instead has the correct size and superior power with respect to the Wald test and the test based on the third moment of the OLS residuals. Coelli concludes that this test should be performed with maximum likelihood estimation.

Conventionally, the efficiency term can take the form of a truncated normal distribution, of a half-normal distribution, of an exponential distribution, or of a gamma distribution. The density function in the truncated normal case is defined by

$$f(u_i) = \frac{\exp\left[-\frac{1}{2}(u_i - \mu)^2/\sigma_u^2\right]}{(2\pi)^{1/2}\sigma_u\left[\Phi(-\mu/\sigma_u)\right]}, \qquad u_i > 0, \tag{1.14}$$

where $\Phi(.)$ is the cumulative distribution function (cdf) of the standard normal random variable. If a half-normal distribution for the inefficiency component is assumed, equation (1.14) can be modified simply by imposing a zero mean, i.e. $\mu = 0$. Therefore, the density function of the term u becomes

$$f(u_i) = 2\frac{\exp\left[-\frac{1}{2}(u_i)^2/\sigma_u^2\right]}{(2\pi)^{1/2}\sigma_u}, \qquad u_i > 0. \tag{1.15}$$

[15] In this case, the number of restrictions is equal to one.

[16] Because this would mean a negative variance of the inefficiency term σ_u^2.

This can be explained by the fact that the normal distribution function evaluated at zero is one half.[17]

In the exponential case, the distribution function of the inefficiency term will take the form

$$f(u_i) = \rho^{-1} \exp(-\rho^{-1} u_i), \qquad u_i > 0, \tag{1.16}$$

where ρ is the parameter of the exponential distribution to be estimated. The inverse of ρ is equal to the mean of the distribution itself, that is $E(u_i) = \frac{1}{\rho}$ and the variance $\sigma_u^2 = \frac{1}{\rho^2}$.[18] Finally, in the case where efficiency follows a gamma distribution, the density function will be equal to

$$f(u_i) = \frac{u_i^m}{\Gamma(m+1)\,\sigma_u^{m+1}} \exp\left(-\frac{u_i}{\sigma_u}\right), \qquad u_i > 0. \tag{1.17}$$

The gamma distribution is a two-parameter distribution, depending on m and σ_u. If $m = 0$, the gamma density function becomes the density function of the exponential distribution.

1.4.2 Problems related to the Estimation of the Model

It has been demonstrated here that to estimate a stochastic frontier model, several strong assumptions need to be imposed, in particular about the distribution of statistical noise (normal) and of technical inefficiency (e.g. one-sided normal). In addition, the assumption that inefficiency is independent of the regressor may be incorrect, because, as argued by Schmidt and Sickles (1984), "if a firm knows its level of technical inefficiency, this should affect its

[17]When $\mu = 0$, $\Phi(-\mu/\sigma) = \Phi(0) = \frac{1}{2}$.

[18]Thus, given that $\sigma_u^2 = \frac{1}{\rho^2}$ and $E(u_i) = \frac{1}{\rho}$, the final expression when the efficiency follows an exponential distribution is: $f(u_i) = \sigma_u^{-1} \exp(-\sigma_u^{-1} u_i)$.

input choices".[19] These problems can be solved by the use of panel data (Section 1.5). Early panel data studies hypothesised that the intercept and the inefficiency component of the error term are time-invariant, so that the country effect $\alpha_i = \alpha - u_i$ could be estimated without distributional assumptions and then be converted into measures of inefficiency. This time-invariance assumption therefore makes it possible to substitute for many of the strong assumptions necessary in the case of a single cross-section. Recent panel data literature has tried to relax the assumption of a time-invariant inefficiency component (Cornwell and Schmidt, 1996).

1.4.3 Estimation Methods

There are two main methods to estimate the stochastic frontier models: one is the Modified Ordinary Least Squares (MOLS) methodology, the other consists of maximising the likelihood function directly. The following two sections present an overview of each methodology.

1.4.4 Modified Ordinary Least Squares (MOLS)

For the system in equations (1.5$''$) and (1.7) all the assumptions of the classical regression model apply, with the exception of the zero mean of the disturbances ε_i. The OLS estimator will be a best linear unbiased and consistent estimate of the vector β. Problems arise for the intercept term α: its OLS estimate is not consistent. To illustrate this, a simple model where there is only the intercept, i.e. $y_i = \alpha + \varepsilon_i$ can be considered. The OLS estimator of the parameter α would be the mean of y, $\bar{y}$, which has plim $\bar{y} = \alpha + \mu_\varepsilon \neq \alpha$. The bias of the constant term is given by the mean of the error term μ_ε.

[19] Since this study analyses an aggregate production function for LDCs, this might be less of a problem because of statistical or policy lags.

Afriat (1972) and Richmond (1974) propose the MOLS procedure.[20] The MOLS technique consists of correcting the intercept with the expected value of the error term[21] and adopting OLS to get a consistent estimate. In the case of the half normal distribution, the mean of ε_i given by

$$\mu_{\varepsilon} = \sigma_u \sqrt{2/\pi}, \tag{1.18}$$

where σ_u is the standard deviation of the inefficiency term. The OLS intercept estimator is consistent for $\alpha + \mu_{\varepsilon}$, where σ_u has been substituted by its estimate $\hat{\sigma}_u$:

$$\hat{\sigma}_u^2 = \left[\sqrt{\pi/2}\left(\frac{\pi}{\pi-4}\right)\hat{m}_3\right]^{2/3} \quad \text{and} \quad \hat{\sigma}_v^2 = \hat{m}_2 - \left(1 - \frac{2}{\pi}\right)\hat{\sigma}_u^2. \tag{1.19}$$

The parameters $\hat{m}_3$ and $\hat{m}_2$ are the third and second moments of the OLS residuals.[22] To summarise, the estimate of σ_u is used to convert the OLS

[20]This procedure is very similar to the two-step COLS procedure. Winsten (1957) proposes corrected ordinary least squares (COLS) to estimate the production frontier. In the first step Ordinary Least Squares (OLS) is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimate of the intercept. In the second step, the estimated intercept is shifted up by the maximum value of the OLS residuals. The COLS intercept is estimated consistently by $\alpha + \max_i \hat{u}_i$, where $\hat{u}_i$ is the OLS residual at observation i. The OLS residuals are corrected in the opposite direction: $-\hat{u}_i = \hat{u}_i - \max_i \hat{u}_i$.

[21]Afriat (1972) and Richmond (1974) explicitly assume that the disturbances follow a one-sided distribution, such as exponential or half normal.

[22]The error term is $\epsilon_i = v_i - u_i$. In the case $v_i \sim N\left(0, \sigma_v^2\right)$ and u_i follows a half normal distribution, the first, second and third moments of the efficiency term are: $E\left(u_i\right) = \sqrt{2/\pi}$, $E\left(u_i^2\right) = \left[\left((\pi-2)/\pi\right)\right]\sigma_u^2$ and $E\left(u_i^3\right) = \left[-\sqrt{2/\pi}\left(1 - 4/\pi\right)\right]\sigma_u^3$. This implies that the second and the third central moments of ε_i are: $E\left(\varepsilon_i^2\right) = \sigma_v^2 + \left[(\pi-2)/\pi\right]\sigma_u^2$ and $E\left(\varepsilon_i^3\right) = \left[\sqrt{2/\pi}\left(1 - 4/\pi\right)\right]\sigma_u^3$. Then the second ($m_2$) and third moments ($m_3$) of the OLS residuals are used to estimate σ_u^2 and σ_v^2 (equation 1.19).

estimate of the constant term into the MOLS estimate. The model to be estimated is

$$y_i = (\alpha + \mu_\varepsilon) + \boldsymbol{\beta}\mathbf{x}_i + \varepsilon_i. \tag{1.20}$$

The estimation by OLS will lead to consistent but inefficient estimates of all the parameters. A problem with the MOLS technique is that the estimates can take values which have no statistical meaning. Suppose the third moment of the OLS residuals is positive, then the term in brackets in equation (1.19) becomes negative and this leads to a negative value of $\hat{\sigma}_u$. Olson *et al.* (1980) label this failure as a Type I Error. A Type II Error occurs when $\widehat{\sigma}_\varepsilon^2 < \left[\left(\pi - 2/\pi\right)\widehat{\sigma}_u^2\right]$ and implies that $\widehat{\sigma}_v^2 < 0$.

Moreover, the estimated production frontier is parallel to the OLS regression, since only the OLS intercept is corrected.[23] This implies that the structure of the "best practice" production technology is the same as the structure of the "central tendency" production technology. This is an undesirably restrictive property of the MOLS procedure, since the structure of "best practice" technology ought to differ from the production technology of the producers down in the middle of the data who are less efficient than the "best practice" producer.

1.4.5 Maximum Likelihood Estimation

As demonstrated in the previous section, consistent estimates of all the parameters of the frontier function can be obtained simply using a modification of the OLS estimator. However the distribution of the composed error term is asymmetric (because of the asymmetric distribution of the inefficiency term).

[23] This problem also affects the COLS methodology.

A maximum likelihood estimator that takes into consideration this information should therefore give more efficient estimates, at least asymptotically.[24] This has been investigated by Greene (1980a,b) who argues that the Gamma distribution is one of the distributions which provides a maximum likelihood estimator with all of the usual desirable properties and which is characterised by a high degree of flexibility. This distribution should therefore be used to model the inefficiency error term. However, it has been noticed that the flexibility of the Gamma distribution can make the shapes of statistical noise and inefficiency hardly distinguishable.[25] The log-likelihood function for the model defined by equations (1.5″) and (1.7) is derived by Aigner *et al.* (1977).[26]

When considering the half normal distribution $u_i \sim N^+(0, \sigma_u)$, the max-

[24] As discussed in the introduction, Koop *et al.* (1999, 2000a,b), and Koop (2001) adopt a Bayesian approach to estimate stochastic production frontiers. While there are certainly advantages of the Bayesian estimation method, the choice of Maximum Likelihood estimation in this thesis is justified. Kim and Schmidt (2000) examine a large number of classical and Bayesian procedures to estimate the level of technical efficiency using different panel data sets. They find that Maximum Likelihood estimation based on the exponential distribution gives similar results to the Bayesian model in which the prior distribution for efficiency is exponential and there is an uninformative prior for the exponential parameter. The problem in the classical framework is that asymptotically valid inference may be not valid in small samples. However, sample size is not a problem in the data set analysed in this study (about 1500 observations).

[25] See van den Broeck *et al.* (1994).

[26] The log-likelihood function is expressed in terms of the two parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u}{\sigma_v}$. Given that the parameter λ can assume any non-negative value, Battese and Corra (1977) suggest to use the parameter $\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$ that can vary between zero and one. Coelli (1995) observes that $\lambda = \sqrt{\gamma/(1-\gamma)}$.

imum log-likelihood function takes the form

$$\ln L\left(y\left|\alpha,\boldsymbol{\beta},\lambda,\sigma^{2}\right.\right)=N\ln\frac{\sqrt{2}}{\sqrt{\pi}}+N\ln\sigma^{-1}+\sum_{i=1}^{N}\ln\left[1-\Phi(\varepsilon_{i}\lambda\sigma^{-1})\right]-\frac{1}{2\sigma^{2}}\sum_{i=1}^{N}\varepsilon_{i}^{2}, \tag{1.21}$$

where λ is the ratio defined in equation (1.10), $\sigma=\sigma_{u}^{2}+\sigma_{v}^{2}$ and $\Phi(.)$ is the standard normal cumulative distribution function.[27]

If we assume an a truncated normal distribution $u_i \sim N^{+}(\mu,\sigma_u)$, the log-likelihood function is

$$\begin{aligned}\ln L\left(y\left|\alpha,\boldsymbol{\beta},\lambda,\sigma^{2}\right.\right) &= -\frac{N}{2}\ln\left(\frac{\pi}{2}\right)-N\ln\sigma-N\Phi\left(\frac{-\mu}{\lambda\sigma}\right)+\\ &\sum_{j=1}^{N}\ln\Phi\left(\frac{-\mu\lambda^{-1}-\varepsilon_{j}\lambda}{\sigma}\right)-\frac{1}{2\sigma^{2}}\sum_{j=1}^{N}\varepsilon_{j}^{2}.\end{aligned} \tag{1.22}$$

In the case where the efficiency follows an exponential distribution $u_i \sim \mathrm{Ex}(\theta)$, $\theta=\sigma_u^{-1}$, the log-likelihood function is

$$\ln L\left(y\left|\alpha,\boldsymbol{\beta},\lambda,\sigma^{2}\right.\right)=-N\left(\ln\sigma_{u}+\frac{\sigma_{v}^{2}}{2\sigma_{u}^{2}}\right)+\sum_{j=1}^{N}\ln\Phi\left(\frac{-\varepsilon_{j}}{\sigma_{v}}-\lambda^{-1}\right)+\sum_{j=1}^{N}\frac{\varepsilon_{j}}{\sigma_{u}}. \tag{1.23}$$

[27]The detailed derivation of the likelihood function in the half-normal case is given in Appendix 1.A.

1.4.6 Measurement of Efficiency

Battese and Coelli (1988) define technical efficiency of a firm as the ratio of its mean production (in original units), given the level of inefficiency, to the corresponding mean production if the inefficiency level were zero. Using this definition, technical efficiency for country i, TE_i is

$$TE_i = \frac{E(y_i^* \,|u_i, \mathbf{x}_i)}{E(y_i^* \,|u_i = 0, \mathbf{x}_i)}, \tag{1.24}$$

where y_i^* is the value of production (in original units) for the ith country. This measure will necessarily be bound between zero and one, because the level of production under inefficiency (the economy is producing below the production frontier) will always be smaller than the level of efficient production. If it is assumed that the production function (1.5″) is expressed in logarithmic form, then the inefficiency term will be

$$TE_i = \exp(-u_i). \tag{1.25}$$

When the data are in logarithms it is notable that the measure of efficiency is equivalent to the ratio of the level of production (when inefficiency occurs), $\exp(y_i) = \exp(a + \boldsymbol{\beta}\mathbf{x}_i + v_i - u_i)$, to the corresponding value of production without inefficiency, $\exp(y_i) = \exp(a + \boldsymbol{\beta}\mathbf{x}_i + v_i)$. Because of the way technical efficiency is measured, the latter measure (1.25) compared to (1.24) is independent of the level of the inputs. The problem that now arises is how to compute this measure of efficiency. A method has been proposed by Jondrow *et al.* (1982), and it is based on the distribution of the inefficiency term conditional to the composite error term, $u_i|\varepsilon_i$. This distribution contains all the information that ε_i yields about u_i, therefore we can use the expected value of the distribution as a point estimate of u_i. Jondrow *et al.* (1982) demonstrate under the assumptions that (i) v_i are iid $N(0,\sigma_v^2)$, (ii) $\mathbf{x}_i$ and v_j are independent, (iii) u_i are independent of $\mathbf{x}_i$ and v_i, and (iv) u_i follow a one-sided normal distribution (e.g. truncated or half-normal), the distribution of $u_i|\varepsilon_i$ is a normal random variable $N(\mu_i^*,\sigma_*^2)$ where $\mu_i^* = \sigma_u^2\varepsilon_i(\sigma_u^2+\sigma_v^2)^{-1}$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2(\sigma_u^2+\sigma_v^2)^{-1}$. A point estimate for TE_i is therefore given by

$$TE_i = E\left[\exp(-u_i)\,|\varepsilon_i\right] = \frac{[1-\Phi(\sigma_* - \mu_i^*/\sigma_*)]}{[1-\Phi(-\mu_i^*/\sigma_*)]}\exp\left[-\mu_i^* + \frac{1}{2}\sigma_*^2\right], \qquad (1.26)$$

where $\Phi(.)$ is the standard normal cumulative density function. In order to implement this procedure estimates of μ_i^* and σ_*^2 are required, and therefore estimates of the variances of the inefficiency and random components and of the residuals $\hat{\varepsilon}_i = y_i - \hat{\alpha} - \mathbf{x}_i\hat{\boldsymbol{\beta}}$. Equation (1.26) holds when the distribution of the inefficiency component is a truncated distribution; whereas, when it follows a half-normal distribution (for which $\mu_i^* = 0$), the point estimate of technical efficiency will take the simpler form

$$TE_i = E\left[\exp(-u_i)\,|\varepsilon_i\right] = 2\left[1-\Phi(\sigma_*)\right]\exp\left[\frac{1}{2}\sigma_*^2\right], \qquad (1.27)$$

where the usual notation holds.

A Monte Carlo study conducted by Kumbhakar and Löthgren (1998) shows negative bias in the estimated inefficiencies and confidence intervals to be significantly below the corresponding theoretical confidence levels.[28] The evidence is that this bias decreases as the sample size increases. Moreover, they find that the point estimator outperforms the interval estimators of technical inefficiency. Thus, the uncertainty associated with unknown parameters

[28] Kumbhakar and Löthgren (1998) assume in their Monte Carlo study that the true values of the underlying parameters are unknown and must be replaced by their ML estimates. They found that the result is true for all value of inefficiency and for sample sizes less than 200.

is reduced when the number of observations increases.[29] This result supports the empirical estimations in this thesis, where the sample size is fairly large (about 1500 observations). There are many empirical studies that show the sensitivity of the estimated efficiencies to the distribution assumption on the one-sided error component. However, Greene (1990) finds that the ranking of producers by their individual efficiency scores and the composition of the top and bottom score deciles is not sensitive to distribution assigned to the efficiency terms. Since the assumption that efficiency terms follow an half normal distribution is both plausible and tractable, it is typically employed in empirical work.[30]

1.5 Panel Data Stochastic Frontier Models

1.5.1 Introduction

In the previous sections some of the problems related to a cross-sectional analysis have been pointed out, namely the assumption that technical inefficiency is independent of the inputs and the assumptions on the distributional forms of statistical noise and technical inefficiency. Both these problems can be solved by the use of panel data. In particular, panel data allows relaxation of the assumption of independence and avoidance of distribution assumptions or testing them when they are imposed. Furthermore, with panel data it is possible to construct estimates of the efficiency levels of each country that are consistent as the number of observations per country increases. This means that inefficiency can be estimated more precisely. The general model which

[29] The Monte Carlo study is performed for sample size N=25, 50, 100, 200, 400 and 800.
[30] On this argument see Kumbhakar and Lovell (2000) pp.74-90.

will be analysed is of the form

$$y_{it} = \alpha_i + \boldsymbol{\beta}\mathbf{x}_{it} + v_{it} - u_{it} \qquad i = 1, \ldots, N; \quad t = 1, \ldots, T. \tag{1.28}$$

Before proceeding with the estimation of the model a distinction concerning the time dimension of the inefficiency term has to be made. In the first case the term defining inefficiency u will be kept constant over time for each country, whereas in the second case it will be allowed to change over time.

1.5.2 Time-Invariant Inefficiency

In this section a model with time-invariant inefficiency will be presented. Equation (1.28) can be rewritten as follows:

$$y_{it} = \alpha + \boldsymbol{\beta}\mathbf{x}_{it} + v_{it} - u_i \qquad i = 1, \ldots, N; \quad t = 1, \ldots, T. \tag{1.29}$$

By defining $\alpha_i = \alpha - u_i$ we have the standard panel data model

$$y_{it} = \alpha_i + \boldsymbol{\beta}\mathbf{x}_{it} + v_{it} \tag{1.30}$$

It is assumed that the v are i.i.d. $(0, \sigma_v^2)$ and uncorrelated with the inputs $\mathbf{x}$. This last assumption is needed for the consistency of the within and generalised estimators of the parameter vector $\boldsymbol{\beta}$, which are derived from the OLS estimation of equation (1.30) under a fixed effect model and a random effect model respectively.

1.5.3 Fixed Effects Model

The fixed effect model consists of treating the inefficiency levels u_i (and therefore the intercepts α_i) as fixed, as simple parameters to be estimated.

It should be noted that in this specific case, no assumptions are made on the distribution of the inefficiency term or on the correlation between the inefficiency term with the regressors and the statistical noise v_i. By applying ordinary least squares estimation to the model (1.30) combined for all T observations for each country, the within estimator is derived. It can be shown to be consistent as either N or T go to infinity. Once the within estimator is available, an estimate of the intercept terms α_i is possible, and therefore the country-specific technical inefficiencies can be estimated as:

$$\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i \quad \text{where} \quad \hat{\alpha} = \max_i \hat{\alpha}_i. \tag{1.31}$$

Specification (1.31) means that the production frontier is normalised in terms of the best country in the sample. A necessary condition for $\hat{\alpha}_i$ to be consistent is that the time period T is very large, whereas to have an accurate normalisation and a consistent separation of α from the one-sided inefficiency terms u_i a large number of countries N is required. This means that if N is small it is only possible to compare efficiencies across countries, but not to an absolute standard (100%). In their empirical analysis on three different sets of panel data, Horrace and Schmidt (1996) find wide confidence intervals for the efficiency estimates based on the fixed-effects model. The estimation error and the uncertainty in the identification of the most efficient observation are among the explanations adopted to justify this result. A problem related to the within estimation is that if important time-invariant regressors are included in the frontier model, these will show up as inefficiency in equation (1.31) (Cornwell and Schmidt, 1996). In other words, the fixed effects (u_i) capture both variation across producers in time-invariant technical efficiency and all phenomena that vary across producers but are time invariant for each producer. Unfortunately, this occurs whether or not the other effects are included as regressors in the model.[31] This problem can be solved by estimating model (1.28) in a random effect context.

1.5.4 Random Effects Model

In the random effects model the inefficiency terms u_i are treated as one-sided i.i.d. random variables, uncorrelated with the regressors x_{it} and the statistical noise v_{it} for all t. So far no distributional assumptions for the effects are made. Before proceeding to the estimation, the model (1.29) is rewritten in a slightly different way, defining $\alpha^* = \alpha - \mu$ and $u_i^* = u_i - \mu$, where $\mu = E(u_i)$. The estimator for the random effects model is the Generalised Least Square (GLS) estimator $\left(\hat{\alpha}^* \ \ \hat{\beta}'\right)'_{GLS}$, which is consistent as N approaches infinity. The covariance matrix appearing in the estimator depends on the variances of the two components of the error term, that is σ_v^2 and σ_u^2. In the unrealistic case that these two variances are known, the GLS estimator is consistent as N goes to infinity. In the more realistic case that they are unknown, the feasible GLS (FGLS) estimator is still consistent as $N \to \infty$, if it is based on consistent estimates of σ_v^2 and σ_u^2. The advantages offered by the FGLS estimator are that it allows the inclusion of time-invariant variables and gives more efficient estimates than the within estimator of the fixed effect. Nevertheless, the efficiency advantage depends on the orthogonality of the regressors and the inefficiency term, a condition which is often rejected by the data; in addition the gain in terms of efficiency vanishes as T approaches infinity. For this reason, Schmidt and Sickles (1984) point out that the random effects model is more suitable for short panels in which correlation is empirically rejected. Hausman and Taylor (1981) developed a test, based on Hausman (1978), for the hypothesis that the error terms are uncorrelated with the regressors. If

[31] On this argument see Kumbhakar and Lovell (2000) pp.97-100.

the null hypothesis of non-correlation is accepted, a random-effects model is chosen, otherwise a fixed-effects model is appropriate. The Hausman test is a test of the orthogonality assumption that characterises the random effects estimator, which is defined as the weighted average of the between and the within estimator.[32] The test statistic is

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE}) \left(\hat{\Sigma}_{\hat{\beta}_{RE}} - \hat{\Sigma}_{\hat{\beta}_{FE}} \right)^{-1} (\hat{\beta}_{RE} - \hat{\beta}_{FE})', \tag{1.32}$$

where $\hat{\beta}_{RE}$ and $\hat{\beta}_{FE}$ are the estimated parameter vectors from the random and the fixed effect models, and Σ_{RE} and Σ_{FE} the respective covaraince matrices. Under the null hypothesis that the random effects estimator is appropriate, the test-statistic is distributed asymptotically as a χ^2 with degrees of freedom equal to the number of the regressors. Henceforth, large values of the H test-statistic have to be interpreted as supporting the fixed effects model. Hausman and Taylor (1981) developed a similar test of the hypothesis that the inefficiency terms are not correlated with the regressors.

Technical inefficiency is estimated from equation (1.31), with the difference that the FGLS estimator is used to estimate the parameters. The inefficicency estimates are consistent if both N and T are large enough, as in the fixed effect case.

1.5.5 Maximum Likelihood Estimation

The main advantage in using panel data is that it allows relaxation of the strong assumptions required in the estimation of a cross-section, namely assumptions on the independence of the components of the error term and the regressors, and distributional assumptions on the inefficiency and statistical

[32] See Hsiao (1986).

noise. Clearly, it is still possible to make these assumptions and therefore a maximum likelihood estimator of the parameters of the model can be obtained. The advantage of panel data in this context is that, as noted by Cornwell and Schmidt (1996), "repeated observation of the same firm makes it possible to estimate its level of efficiency more precisely." The Battese-Coelli estimator presented in equations (1.24) to (1.26) can therefore be generalised to the case of panel data under the same assumptions presented for the cross-section case. It is necessary to slightly modify two of the variables involved, namely μ_i^* and σ_*^2. They are the mean and the variance of the normally distributed inefficiency term conditional on the composed error term, $u_i|\varepsilon$, which appears in (1.26). It can now be observed that the mean and the variance of the conditional distribution are given respectively by

$$\begin{aligned} \mu_i^* &= \sigma_u^2 \bar{\varepsilon}_i (\sigma_u^2 + \sigma_v^2/T)^{-1} \\ \sigma_*^2 &= \sigma_u^2 \sigma_v^2 (\sigma_u^2 + T\sigma_v^2)^{-1}, \end{aligned} \tag{1.33}$$

where $\bar{\varepsilon}_i = (1/T)\sum_i \varepsilon_{it}$.

One of the advantages of using the Battese-Coelli method is that it allows for unbalanced panels, i.e. different numbers of observations per country: with T_i observations for country i, T has to be replaced by T_i in system (1.33). Note that the variance will depend on i. Another advantage is that the intercept can be estimated directly, without the maximisation used in equation (1.31). Therefore, the best country in the sample is no longer normalised to be 100 percent efficient.

1.5.6 Time-Varying Inefficiency

If the assumption of a time invariant inefficiency term is relaxed, the model to be examined is the following:

$$y_{it} = \alpha_{it} + \boldsymbol{\beta}\mathbf{x}_{it} + v_{it}, \tag{1.34}$$

where $\alpha_{it} = \alpha_t - u_{it}$ and $u_{it} \geq 0$. Given that it is possible to estimate α_{it}, the following estimates of the inefficiency term can be obtained:

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it} \qquad \text{where} \quad \hat{\alpha}_t = \max_i(\hat{\alpha}_{it}). \tag{1.35}$$

The problem arising here is that some restrictions are needed to estimate the intercepts α_{it}, and the aim is to find weak enough restrictions which allow for some degree of flexibility. Cornwell *et al.* (1990) introduced a model where the intercepts depend on a vector of observables $\mathbf{w}_t$ in the following way:

$$\alpha_{it} = \boldsymbol{\delta}_i \mathbf{w}_t = \begin{pmatrix} \delta_{i1} & \delta_{i2} & \delta_{i3} \end{pmatrix} \begin{pmatrix} 1 \\ t \\ t^2 \end{pmatrix}, \tag{1.36}$$

and where the effects $\boldsymbol{\delta}_i$ are fixed. As Cornwell and Schmidt (1996) point out, this specification can also "be interpreted as a model of productivity growth, with rates that differ for each firm". Country-specific productivity growth rates can be constructed as the time derivatives of equation (1.36). In this framework , the general model to be estimated becomes

$$y_{it} = \boldsymbol{\beta}\mathbf{x}_{it} + \boldsymbol{\delta}_i \mathbf{w}_{it} + v_{it}. \tag{1.37}$$

The estimation procedure starts by finding the within estimator $\hat{\boldsymbol{\beta}}_w$, then continues by applying OLS to a regression of the residuals $(y_{it} - \hat{\boldsymbol{\beta}}_w \mathbf{x}_{it})$ to find estimates of the elements of $\boldsymbol{\delta}_i$ and then computing $\hat{\alpha}_{it}$ as $\hat{\boldsymbol{\delta}}_i \mathbf{w}_{it}$ (this last estimate will be consistent for $T \rightarrow \infty$). Finally, estimates of inefficiency as in (1.35) will be obtained. Cornwell *et al.* (1990) consider the fixed-effect and the random-effects approach. Since time-invariant regressors cannot be included in the fixed-effects model, they develop a GLS random-effects estimator for time-varying technical efficiency model. However, the GLS estimator is inconsistent when the technical inefficiencies are correlated with the regressors, therefore the authors compute an efficient instrumental variables (EIV) estimator that is consistent in the case of correlation of the efficiency terms with the regressors, and that also allows for the inclusion of time-invariant regressors. Lee and Schmidt (1993) specify the term u_{it} as

$$u_{it} = \left(\sum_{t=1}^{T} \beta_t d_t \right) u_i, \tag{1.38}$$

where d_t is a time dummy variable and one of the coefficients is set equal to one. This formulation of technical change, differently from that of Cornwell *et al.* (1990), does not restrict the temporal pattern of the u_{it} apart for the β_t to be the same for all producers. This time-varying technical efficiency can be estimated with both fixed- and random-effects models, where the coefficients β_t are treated as the coefficients of u_i. Since this model requires estimation of *T-1* additional parameters, it is appropriate for short panels.[33] Once β_t

[33] Ahn *et al.* (1994) developed a generalized method of moments approach to the estimation of Lee and Schmidt model specified by the equations (1.34 and 1.38).

and u_i are estimated, the following expression can be obtained:

$$u_{it} = \max_i \left(\hat{\beta}_t \hat{u}_i\right) - \left(\hat{\beta}_t \hat{u}_i\right), \tag{1.39}$$

from which the technical efficiency can be calculated as

$$TE_{it} = \exp\left(-\hat{u}_{it}\right). \tag{1.40}$$

If the inefficiency terms are independently distributed, maximum likelihood techniques can be used to estimate the time varying technical efficiency model. The technical efficiency adding time dummies can be specified as

$$u_{it} = \beta_t u_i. \tag{1.41}$$

Kumbhakar (1990) proposed the following parametric function of time for $\beta(t)$:

$$\beta\left(t\right) = \left(1 + \exp\left(\delta_1 t + \delta_2 t^2\right)\right)^{-1}. \tag{1.42}$$

Battese and Coelli (1992) suggested an alternative specification for $\beta(t)$:

$$\beta\left(t\right) = \exp\left(-\delta(t - T)\right). \tag{1.43}$$

Both of these models are estimated using the maximum likelihood procedure discussed in Section 1.5.5. Kumbhakar's 1990 model contains two parameters to be estimated: δ_1 and δ_2. The sign and the magnitude of these two parameters determine the characteristics of the function $\beta(t)$ that can be increasing or decreasing, concave or convex.[34] The function $\beta(t)$ varies between zero and one. The test of the null hypothesis of time-invariant technical efficiency can be performed by setting $H_0 : \delta_1 = \delta_2 = 0$. In this case, the function $\beta(t)$ has a constant value of 1/2. Battese and Coelli (1992) require only one parameter δ to be estimated. The function $\beta(t)$ can take any positive value. Given that the value of the second derivative is always positive,[35] and if $\delta > 0$, the function $\beta(t)$ decreases at an increasing rate. If $\delta < 0$, it increases at an increasing rate. The hypothesis of time-invariant technical efficiency can be tested by setting the null hypothesis $H_0 : \delta = 0$.

Kumbhakar and Hjalmarsson (1993) model the inefficiency term as

$$u_{it} = \tau_i + \xi_{it}, \tag{1.44}$$

where τ_i is a producer-specific component which captures producer heterogeneity also due to omitted time-invariant variables, and ξ_{it} is a producer time-specific component which has a half-normal distribution. The estimation of this model is in two steps. In the first step, either a fixed-effects model or a random-effects model is used to estimate all the parameters of the model $y_{it} = \beta_0 + \boldsymbol{\beta}\mathbf{x}_{it} - u_{it} + v_{it}$, except those in equation (1.44). In the second step, distribution assumptions are imposed on ξ_{it} and v_{it}. The fixed effects $(\beta_o + \tau_i)$ and the parameters ξ_{it} and v_{it} are estimated by maximum likelihood, conditioned on the first step parameter estimates.

[34]The fist and the second derivatives of the function defined by equation (1.42) depend on the two parameters δ_1 and δ_2.

[35]The first and second derivatives of the function defined by equation (1.43) are respectively equal to: $\partial\beta(t)/\partial t = \exp\{-\delta(t-T)\}(-\delta)$; $\partial^2\beta(t)/\partial t^2 = \exp\{-\delta(t-T)\}\delta^2$.

1.6 A Model for Stochastic Technical Inefficiency Effects for Panel Data: Battese and Coelli 1995

This thesis uses a panel data set of developing countries to analyze the sources and determinants of catching up with developed world. In particular attention is drawn on importance of trade channels in helping the technological diffusion and the development. The positive effect of trade channels on productivity may depend on correlated omitted variables (Alcalá and Ciccone, 2004). These omitted variables are country characteristics, including institutional quality, which have been shown to play a key role for productivity (Hall and Jones, 1999; Acemoglu *et al.*, 2001). If these unobservable variables are omitted and are correlated with trade, the coefficient which relates trade channels to productivity is biased upward. The panel data framework allows to correct the bias: the individual term "reflects not just technology but resources endowments, climate, institutions, and so on" (Islam, 1995, p. 1133).

The use of panel data techniques allows to solve many limitations of the cross-country method. Durlauf and Johnson (1995) postulate that cross-country differences are not explained entirely by differences in rates of physical and human capital accumulation and population growth. Initial conditions determine aggregate production opportunities that differ considerably across countries. Islam (1995) observes that the cross-country regression approach includes several explanatory variables to account for the differences in preferences and technology, and therefore in steady states. However, these differences are not measurable and observable. A panel data approach can overcome these problems by controlling for individual country effects like geography, political factors, or culture. McDonald and Roberts (1999) state that panel data method allows to analyse cross-section and time series variation in the data and to test the validity of the assumption regarding common technology implied by the cross section studies.

The inefficiency models exposed so far have not explicitly formulated a model for technical inefficiency effects in terms of appropriate explanatory variables. Battese and Coelli (1995) propose a model for stochastic technical inefficiency effects for panel data which includes explanatory variables. The panel framework permits to exploit the time and sectional dimensions of the data. The stochastic nature of the inefficiency terms, allows the estimation of both technical change - captured by time dummies - in the stochastic frontier and time-varying technical inefficiency.

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

$$Y_{it} = f(\mathbf{X}_{it})\tau_{it}\xi_{it} \quad i = 1, ...N; \quad t = 1, ...T \tag{1.45}$$

where Y_{it} is real output for country i at time t and $\mathbf{X}_{it}$ are production inputs and other factors associated with country i at time t. τ_{it} is the efficiency measure, with $0 < \tau_{it} < 1$,[36] and ξ_{it} captures the stochastic nature of the frontier. Writing a production function of the Cobb-Douglas type in log-linear form, we obtain

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + v_{it} - u_{it} \tag{1.46}$$

where $u_{it} = -ln\tau_{it}$ is a non-negative random variable. The composite error

[36]When $\tau_{it} = 1$ there is full efficiency, in this case the country i produces on the efficiency frontier.

is $ln\xi_{it} = \epsilon_{it} = v_{it} - u_{it}$, where v_{it} is normally distributed with mean 0 and variance σ_v^2.

In matrix form, we obtain the basic panel data stochastic frontier model:

$$y_t = \mathbf{I}_{\mathrm{N}}\alpha + \mathbf{x}_t\beta + \mathbf{v}_{\mathrm{t}} - \mathbf{u}_{\mathrm{t}} \qquad t = 1, \ldots, T, \tag{1.47}$$

with

$$\mathbf{y}_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ v_{N,t} \end{pmatrix}; \mathbf{x}_t = \begin{pmatrix} x_{1,1,t} & x_{1,2,t} & \ldots & x_{1,k,t} \\ x_{2,1,t} & x_{2,2,t} & \ldots & x_{2,k,t} \\ \vdots & \vdots & & \vdots \\ x_{N,1,t} & x_{N,2,t} & \ldots & x_{N,k,t} \end{pmatrix};$$

$$\mathbf{v}_t = \begin{pmatrix} v_{1,t} \\ v_{2,t} \\ \vdots \\ v_{N,t} \end{pmatrix}; \mathbf{u}_t = \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{N,t} \end{pmatrix}.$$

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

$$\tau_{it} = e^{-u_{it}} \tag{1.48}$$

Efficiency is ranked as $u_{N,t} \leq \ldots \leq u_{2,t} \leq u_{1,t}$: Country N produces with maximum efficiency in the sample.

Often studies estimate the stochastic frontier and calculate the efficiency term, 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.[37] It requires a first-stage assumption that

[37] On this argument, see Wang and Schmidt (2002).

the inefficiencies are independent and identically distributed. Kumbhakar *et al.* (1991a) and Reifschneider and Stevenson (1991) address this issue by proposing a single-stage Maximum Likelihood procedure. The approach is adopted in this thesis, but in the modified form suggested by Battese and Coelli (1995). They propose an extended version of the model of Kumbhakar *et al.* (1991a) to allow the use of panel data.[38] Battese and Coelli (1995) specify inefficiency as

$$u_{it} = \boldsymbol{\delta}\mathbf{z}_{it} + \omega_{it}, \tag{1.49}$$

where u_{it} are technical inefficiency effects in the stochastic frontier model that are assumed to be independently but not identically distributed, $\mathbf{z}_{it}$ is vector of variables which influence efficiencies,[39] and $\boldsymbol{\delta}$ is the vector of coefficients to be estimated. ω_{it} is a random variable distributed as a truncated nomal distribution with zero mean and variance σ_u^2. The requirement that $u_{it} \geq 0$ is ensured by truncating ω_{it} from below such that $\omega_{it} \geq -\boldsymbol{\delta}\mathbf{z}_{it}$. Battese and Coelli (1995) underline that the assumptions on the error component ω_{it} are consistent with the assumption of the inefficiency terms being distributed as truncated normal distribution $N^{+}(\boldsymbol{\delta}\mathbf{z}_{it}, \sigma_u^2)$.

Maximum likelihood estimation is used to take into consideration the asymmetric distribution of the inefficiency term. Greene (1980a, 1990) 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.

[38] See also Koop *et al.* (2000b).

[39] In the case of this study, $\mathbf{z}_{it}$ represents the five trade channels - foreign direct (FDI) investment, imports of machinery and equipment (ME), import discipline indicator (IMPD) and exports of manufacturing goods (EXPM).

Technical efficiency of country i at time t is

$$TE_{it} = exp\left(-u_{it}\right) = \exp\left(-\boldsymbol{\delta}\mathbf{z}_{it} - \omega_{it}\right) \tag{1.50}$$

Jondrow *et al.* (1982) suggest a measure of efficiency based on the distribution of inefficiency conditional to the composite error term, $u_{it} \mid \varepsilon_{it}$ (where $\varepsilon_{it} = v_{it} - u_{it}$). The distribution contains all the information that ε_{it} yields about u_{it}. The expected value of the distribution can therefore be used as a point estimate of u_{it}. When the distribution of the inefficiency component is a truncated distribution, a point estimate for technical efficiency TE_{it} is given by[40]

$$\begin{aligned} E\left(TE_{it}\right) &= E\left[\exp(-u_{it})\left|\varepsilon_{it}\right.\right] = \\ &= \frac{\left[\Phi(-\sigma_* + \mu_{it}^*/\sigma_*)\right]}{\left[\Phi(\mu_{it}^*/\sigma_*)\right]} \exp\left[-\mu_{it}^* + \frac{1}{2}\sigma_*^2\right] \end{aligned} \tag{1.51}$$

$\mu_{it}^* = \left(\sigma_v^2\boldsymbol{\delta}\mathbf{z}_{it} - \sigma_u^2\varepsilon_{it}\right)\left(\sigma_u^2 + \sigma_v^2\right)^{-1}$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2(\sigma_u^2 + \sigma_v^2)^{-1}$.[41] $\Phi(.)$ is the standard normal cumulative density function. Implementing this procedure requires estimates of μ_{it}^* and σ_*^2. In other words, we need estimates of the variances of the inefficiency and random components and of the residuals $\hat{\varepsilon}_{it} = y_{it} - \hat{\alpha} - \mathbf{x}_{it}\hat{\boldsymbol{\beta}}$.

By replacing the unknown parameters in equation (1.51) with the maximum likelihood estimates an operational predictor for the technical efficiency of the country i in the time period t is obtained. As opposed to the models in the previous section, these technical efficiency measures include the influence

[40]See Kumbhakar and Lovell (2000, p.271) and Battese and Coelli (1995). Equation (1.51) is similar to the cross-section version of equation (1.26).

[41]The following assumptions must hold : (i) the v_{it} are iid $N(0, \sigma_v^2)$, (ii) $\mathbf{x}_{it}$ and v_{it} are independent, (iii) u_{it} is independent of x and v, and (iv) u_{it} follows a one-sided normal distribution (e.g. truncated or half-normal).

of explanatory factors.[42] The inefficiency model in equation (1.49) include a shift parameter δ_0 which is constant across countries. The model treats multiple observations of the same country as being obtained from independent samples. Therefore the model is a pooled estimator.[43]

To better exploit the data's panel nature, Kumbhakar and Hjalmarsson (1995) and Wang (2003) suggest to incorporate individual specific effects in the inefficiency model (equation 1.49). This extension would permit to obtain a within estimator. The truncated distribution of the inefficiency does not allow to take first differences or subtract means from the data to eliminate these specific effects, given that differenced truncated normal distributions do not result in a known distribution (Wang, 2003). In this study, the suggestion of Kumbhakar (1991) is adopted by introducing regional dummies to take into account regional characteristics.

1.7 Translog Production Functions

The production functions in Chapter 2, 3, and 4 are specified as translog. The translog (transcendental logarithmic) functional form as an approximation to an unknown production function was introduced by Christensen *et al.* (1973).[44] Consider a twice differentiable, otherwise arbitrary production function $f(\mathbf{Z})$ with n input factors Z_j. A second-order approximation to this function is given by the quadratic Taylor expansion around a point

[42]Coelli *et al.* (1999) use two different approaches to account for environmental influences: one assumes that these factors influence the shape of technology and therefore are included in the production function; the other approach assumes that they directly influence the technical inefficiency. Comparing the results they conclude that the two approaches provide similar ranking of technical inefficiency.

[43]Battese and Coelli (1995) underline that the inclusion of the intercept parameter δ_0 is essential to have parameter estimates associated with explanatory variables $\mathbf{z}$ unbiased.

[44]For the following, see also Denny and Fuss (1977).

$\mathbf{Z}^{\star}$

$$\begin{aligned}\tilde{f}(\mathbf{Z}) \approx & f(\mathbf{Z}^{\star}) + \sum_{j=1}^{n} f_{Z_j}(\mathbf{Z}^{\star})(Z_j - Z_j^{\star}) + \\ & + 0.5 \sum_{j=1}^{n} \sum_{k=1}^{n} f_{Z_j Z_k}(\mathbf{Z}^{\star})(Z_j - Z_j^{\star})(Z_k - Z_k^{\star}),\end{aligned} \tag{1.52}$$

where f_{Z_j} and $f_{Z_j Z_k}$ are the first and second derivatives of $f(\mathbf{Z})$. With $f(\mathbf{Z}) = \ln(Y)$, $Z_j = \ln(X_j)$, $\beta_0 = f(\mathbf{Z}^{\star})$, $\beta_j = f_{Z_j}(\mathbf{Z}^{\star})$, $\beta_{jk} = f_{Z_j Z_k}(\mathbf{Z}^{\star}) = f_{Z_k Z_j}(\mathbf{Z}^{\star}) = \beta_{kj}$, and $Z_j^{\star} = 0$ (i.e. $X_j^{\star} = 1$) one obtains the translog production function

$$\tilde{f}(\mathbf{Z}) = \ln(\tilde{Y}) = \beta_0 + \sum_{j=1}^{n} \beta_j \ln(X_j) + 0.5 \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} \ln(X_j) \ln(X_k). \tag{1.53}$$

This transformation does not mean a loss of generality. As illustration, consider a production function for Y with two inputs, K and L, $Y = g(K, L)$, which can be written as $\ln(Y) = \ln(g(K, L))$. With $\ln(g(K, L)) = \ln(g(\exp(\ln(K)), \exp(\ln(L)))) = f(\ln(K), \ln(L))$, one arrives at the above specification.

The symmetry constraint $\beta_{jk} = \beta_{kj}$ is imposed to ensure that the parameters are identifiable. Linear homogeneity of the true production function requires that the elasticities of output with respect to all inputs sum up to one, which is an implication of Euler's Theorem:

$$\begin{aligned}& \sum_{j=1}^{n} \frac{\partial Y}{\partial X_j} X_j = Y; \sum_{j=1}^{n} \frac{\partial Y}{\partial X_j} \frac{X_j}{Y} = 1; \\ & \sum_{j=1}^{n} \frac{\partial \ln(Y)}{\partial \ln(X_j)} = \sum_{j=1}^{n} f_{Z_j} = 1.\end{aligned} \tag{1.54}$$

This implies

$$\sum_{k=1}^{n} \frac{\partial^2 \ln(Y)}{\partial \ln(X_j) \partial \ln(X_k)} = \sum_{k=1}^{n} f_{Z_j Z_k} = 0; j = 1, \ldots, n. \tag{1.55}$$

Evaluating the sum of first and second derivations of the approximation in (1.53) at the expansion point $\mathbf{X}^*$ gives

$$\sum_{j=1}^{n} \left. \frac{\partial \ln(\tilde{Y})}{\partial \ln(X_j)} \right|_{\mathbf{X}^*} = \sum_{j=1}^{n} \beta_j + \sum_{j=1}^{n} \sum_{j=k}^{n} \beta_{jk} \ln(X_j^*) = \sum_{j=1}^{n} \beta_j \tag{1.56}$$

and

$$\sum_{k=1}^{n} \left. \frac{\partial^2 \ln(\tilde{Y})}{\partial \ln(X_j) \partial \ln(X_k)} \right|_{\mathbf{X}^*} = \sum_{k=1}^{n} \beta_{jk}, j = 1, \ldots, n. \tag{1.57}$$

If $\sum_j \beta_j = 1$ and $\sum_k \beta_{jk} = 0$, these expressions are equivalent to the homogeneity conditions for the true production function.

The basic model in the following chapters is a production function for output Y with capital K and labour L as inputs. Technology is represented by an index A:

$$Y = f(A, K, L).$$

The translog approximation is given by

$$\begin{aligned} \ln(Y) =& \beta_0 + \beta_A \ln(A) + \beta_K \ln(K) + \beta_L \ln(L) + \\ & + 0.5 \left(\beta_{AA} \ln(A)^2 + \beta_{KK} \ln(K)^2 + \beta_{LL} \ln(L)^2 \right) + \\ & + \beta_{AK} \ln(A) \ln(K) + \beta_{AL} \ln(A) \ln(L) + \\ & + \beta_{KL} \ln(K) \ln(L). \end{aligned} \tag{1.58}$$

Before interpreting the estimation results it is necessary to test whether the translog specification is justified. The model under the null hypothesis is of the Cobb-Douglas type with Hicks-neutral technical change (see below), i.e. a first-order approximation to the unknown relationship between output and inputs:

$$H_0 : \beta_{AA} = \beta_{KK} = \beta_{LL} = \beta_{AK} = \beta_{AL} = \beta_{KL} = 0. \tag{1.59}$$

The second step after establishing the specification is the interpretation of the outcome. Because of the very flexible functional from, the parameter estimates of a translog production function are not directly interpretable, as it would be the case for Cobb-Douglas.[45] The output elasticities are not constant, but depend on the value of the inputs. Usually, they are calcuated at the variable means, given the estimates of the parameters of the production function. In general,

$$\hat{e}_j = \frac{\partial \ln(\hat{Y})}{\partial \ln(X_j)} = \hat{\beta}_j + \sum_{X=A,K,L} \hat{\beta}_{jk} \ln(X); j = A, K, L. \tag{1.60}$$

Using matrix notation, $\hat{e}_j$ can be expressed as

$$\hat{e}_j = \mathbf{z}_j \hat{\boldsymbol{\beta}}; j = A, K, L, \tag{1.61}$$

where $\hat{\boldsymbol{\beta}}$ is a column vector with the parameter estimates, and $\mathbf{z}_j$ is a row zero vector with variable means at the entries corresponding to the relevant elements in $\hat{\boldsymbol{\beta}}$. Let $\hat{\boldsymbol{\Sigma}}_{\hat{\boldsymbol{\beta}}}$ be the estimated variance-covariance matrix of the

[45] For a special case where a direct interpretation is possible see below.

parameters. The estimated variance of $\hat{e}_j$ is[46]

$$\hat{\sigma}_{\hat{e}_j} = \mathbf{z}_j \hat{\Sigma}_{\hat{\beta}} \mathbf{z}_j'; j = A, K, L. \tag{1.62}$$

To test the hypothesis of linear homogeneity,[47] the variance of the sum of the estimated output elasticities is needed:

$$\begin{aligned} \hat{e} &= \sum_{j=A,K,L} \hat{e}_j = \left(\sum_{j=A,K,L} \mathbf{z}_j \right) \hat{\beta} = \mathbf{z}\hat{\beta}; \\ \hat{\sigma}_{\hat{e}} &= \mathbf{z} \hat{\Sigma}_{\hat{\beta}} \mathbf{z}'. \end{aligned} \tag{1.63}$$

Note that the testing procedure and the interpretation can be simplified if one estimates the translog production function at the mean-differenced data. In this case, the output elasticities (calculated at the variable means, which are equal to zero), are given by the parameters of the first order terms, β_j (Coelli *et al.*, 2003b).

To derive the formula for the elasticity of substitution, assume Hicks-neutral technical progress as in Chapter 4.[48] The translog production function in this case is

$$\begin{aligned} \ln(Y) = &\beta_0 + \beta_K \ln(K) + \beta_L \ln(L) + \\ &+ 0.5 \left(\beta_{KK} \ln(K)^2 + \beta_{LL} \ln(L)^2 \right) + \\ &+ \beta_{KL} \ln(K) \ln(L), \end{aligned} \tag{1.64}$$

where β_0 represents the level of technology. Since there are only two inputs, it is straightforward to calculate the elasticity of substitution for a given

[46] See, e.g., Judge *et al.* (1988, Section 2.4.6).

[47] The homogeneity restriction can also simply be imposed by dividing output Y and inputs X_j through one of the inputs, e.g. X_k.

[48] For the following, see e.g. Chung (1994) and Heathfield and Wibe (1987).

output level in terms of the partial derivatives of the production function. In the general two-inputs case $Y = f(K, L)$, the elasticity of substitution describing the shape of the isoquant is given by[49]

$$s = -\frac{\mathrm{d}(K/L)}{K/L}\frac{f_K/f_L}{\mathrm{d}\,(f_K/f_L)}, \text{ with } \bar{Y} = f(K, L). \tag{1.65}$$

The elasticity of substitution represents the percentage change in the input ratio induced by a one per cent change in the marginal rate of substitution. In the two-variables translog case with Hicks-neutral technical progress one obtains[50]

$$\begin{aligned} s &= -\frac{f_K f_L (f_K K + f_L L)}{KL(f_{LL}f_K^2 - 2f_K f_L f_{KL} + f_{KK}f_L^2)} = \\ &= -\frac{f_K f_L e Y}{KL(f_{LL}f_K^2 - 2f_K f_L f_{KL} + f_{KK}f_L^2)} = \\ &= -\frac{e}{\left(\beta_{LL}\frac{e_K}{e_L} - e_K - 2\beta_{KL} + \beta_{KK}\frac{e_L}{e_K} - e_L\right)}, \end{aligned} \tag{1.65'}$$

with $e_K = \beta_K + \beta_{KK}\ln(K) + \beta_{KL}\ln(L)$, $e_L = \beta_L + \beta_{LL}\ln(L) + \beta_{KL}\ln(K)$, and $e = e_K + e_L = \frac{1}{Y}(f_K K + f_L L)$.

Since the elasticity of substitution is a non-linear function of the parameter vector $\boldsymbol{\beta}$, the delta method requires to linearise the relationship $s = g(\boldsymbol{\beta})$ to obtain the variance (Greene, 2003, p. 75). Let $\mathbf{j}$ be a row vector with the first derivatives of $g(.)$ with respect to the elements of $\boldsymbol{\beta}$. The variance of s is then given by

$$\hat{\sigma}_{\hat{s}} = \mathbf{j}\hat{\boldsymbol{\Sigma}}_{\hat{\boldsymbol{\beta}}}\mathbf{j}'. \tag{1.66}$$

[49]In this definition, the elasticity of substitution has a positive sign. The detailed derivation can be found in Silberberg (1990, p. 287-288).

[50]See Appendix 2.A for a derivation of the elasticity of substitution and its variance in the case of non-neutral technological change.

To simplify notation, define

$$
\begin{aligned}
s = g(\boldsymbol{\beta}) &= -\frac{k(\boldsymbol{\beta})}{h(\boldsymbol{\beta})}; \\
k(\boldsymbol{\beta}) &= f_K f_L (f_K K + f_L L); \\
g(\boldsymbol{\beta}) &= KL\big(f_{LL} f_K^2 - 2 f_K f_L f_{KL} + f_{KK} f_L^2\big),
\end{aligned}
\tag{1.67}
$$

with

$$
\begin{aligned}
\frac{\partial k}{\partial \beta_K} =& 1; \frac{\partial k}{\partial \beta_L} = 1; \\
\frac{\partial k}{\partial \beta_{KK}} =& \ln(K); \frac{\partial k}{\partial \beta_{LL}} = \ln(L); \\
\frac{\partial k}{\partial \beta_{KL}} =& \ln(K) + \ln(L); \\
\frac{\partial h}{\partial \beta_K} =& \beta_{LL}\frac{1}{e_L} - \beta_{KK}\frac{e_L}{e_K^2} - 1; \frac{\partial h}{\partial \beta_L} = \beta_{KK}\frac{1}{e_K} - \beta_{LL}\frac{e_K}{e_L^2} - 1; \\
\frac{\partial h}{\partial \beta_{KK}} =& \beta_{LL}\frac{\ln(K)}{e_L} + \frac{e_L}{e_K}\left(1 - \beta_{KK}\frac{\ln(K)}{e_K}\right) - \ln(K); \\
\frac{\partial h}{\partial \beta_{LL}} =& \frac{e_K}{e_L}\left(1 - \beta_{LL}\frac{\ln(L)}{e_L}\right) + \beta_{KK}\frac{\ln(L)}{e_K} - \ln(L); \\
\frac{\partial h}{\partial \beta_{KL}} =& \beta_{LL}\frac{\ln(L)e_L - \ln(K)e_K}{e_L^2} + \beta_{KK}\frac{\ln(K)e_K - \ln(L)e_L}{e_K^2} - \\
& - \ln(L) - \ln(K) - 2.
\end{aligned}
\tag{1.68}
$$

Combining the expressions in equation (1.68) according to

$$
\frac{\partial \sigma}{\partial \beta_j} = -\frac{\frac{\partial k}{\partial \beta_j} h - k \frac{\partial h}{\partial \beta_j}}{h^2}
\tag{1.69}
$$

gives the elements of the vector $\mathbf{j}$.

1.8 Convergence Analysis

1.8.1 Testing for Convergence

In the empirical literature, two definitions of convergence have emerged: absolute convergence and conditional convergence. The former occurs when there is a tendency of countries with relatively low initial levels of per capital income to grow faster than high-income countries. The latter implies that each country is converging to its own steady state and that in the long-run all growth rates will be equalized.

Different approaches for analysing convergence have been proposed. The classical approach to convergence is β-convergence introduced by Barro and Sala-i Martin (1991). Cross-country regressions relate the average growth rate of per capita income over some time period to initial per capital income and country characteristics. Convergence exists if negative correlation is found between the average growth rate and initial income. σ-convergence indicates that the income differences between countries are decreasing.[51] Sala-I-Martin (1996) highlights that β- convergence does not assure a reduction in distribution dispersion, since it is a necessary but not sufficient condition for σ-convergence.

Quah (1993) and Bernard and Durlauf (1996) criticize the cross-country growth regression approach and demonstrate that it cannot discriminate between the hypotheses of global or local convergence.[52] Durlauf and Johnson (1995), Evans (1996) and Evans and Karras (1996) show that the classical approach to convergence is valid under conditions which are never satisfied

[51] See Bernard and Durlauf (1996) for extensive discussion on this argument.

[52] The reason is Galton's fallacy. The dispersion of real per capita income across a group of economies does not imply that overall income dispersion tends to decline; this is true even if absolute convergence holds. For more details see Quah (1993, 1996c).

with available data.[53] Quah (1996a,c), Durlauf and Johnson (1995), Bernard and Jones (1996a), Evans (1996) and Evans and Karras (1996) recommend a panel unit root test of convergence which exploits both time series and cross section information included in the data.

According to the definition of Evans and Karras (1996), a sample of economies $1, 2, \ldots, N$, which have access to the same technical knowledge, converge if a common trend a_t and finite parameters $\mu_1, \mu_2, \ldots, \mu_N$ exist such that:

$$\lim_{i \to \infty} E_t(y_{n,t+i} - a_{t+i}) = \mu_n \tag{1.70}$$

where $y_{n,t}$ is the log of per capita income of country n during period t, a_t is the common trend, and μ_n is a constant. Convergence implies that for each economy n there exists a unique balanced growth path represented by μ_n which is parallel to the paths of the other economies.[54] Only in the case that the countries have identical economic structure, the parameter μ_n will be equal to zero and all the economies will converge to the same growth path. Convergence implies that the initial values of the state variables have no long run effects on their level, that is the deviations from the steady state are not permanent. Conversely, in case of divergence, the initial values affect the level of the variables in the long run, therefore the deviations from steady state values are permanent.

Since a_t is not observable, Evans and Karras (1996) suggest to reformulate

[53] They point out that the conventional approach to convergence is valid only in the case all economies are homogenous. Durlauf and Johnson (1995) present empirical evidence that the large samples used in the literature are too heterogenous for the conventional approach to provide valid inferences.

[54] The assumption of common technology knowledge determines that the state variables can differ only for a constant amount and hence the growth path are parallel.

equation (1.70). Taking the average of all terms in (1.70)

$$\lim_{i \to \infty} E_t(\bar{y}_{t+i} - a_{t+i}) = \frac{1}{N}\sum_{n=1}^{N}\mu_n, \tag{1.71}$$

where $\bar{y}_t = \frac{\sum_1^N y_t}{N}$ and subtracting equation (1.71) from equation (1.70) gives[55]

$$\lim_{i \to \infty} E_t(y_{n,t+i} - \bar{y}_{t+i}) = \mu_n. \tag{1.72}$$

Equation (1.72) implies that if $(y_{n,t} - \bar{y}_n)$ is stationary with mean μ_n, the deviations of per capita incomes $y_{n,t}$ from the cross-country average $\bar{y}_n$ will approach a constant μ_n as i goes to infinity. To derive the convergence condition from (1.70), assume that the data generating process of log per capita income is given by

$$y_{n,t} = \phi_n + \rho y_{n,t-1} + \varepsilon_{n,t}, \tag{1.73}$$

where ϕ_n is a constant, and $\varepsilon_{n,t}$ is distributed normally with mean zero and variance σ_ε^2. If per capita income $y_{n,t}$ is stationary ($|\rho| < 1$), equation (1.73) can be written as an infinite moving average process

$$y_{n,t} = \frac{\phi_n}{1-\rho} + \sum_{i=0}^{\infty}\rho^i \varepsilon_{n,t-i} \quad . \tag{1.74}$$

In equilibrium, $i \to \infty$, and $E(y_{n,t}) = \frac{\phi_n}{1-\rho}$. From equation (1.71), it follows

[55] If deviations from the steady state are not permanent, then average per capita income across economies $(\bar{y}_{t+i})$ must converge to the level of the common trend (a_{i+t}). This means that equation (1.71) is equal to zero, thus $\frac{1}{N}\sum_{n=1}^{N}\mu_n = 0$.

that

$$\lim_{i\to\infty} E_t(\bar{y}_{t+i} - a_{t+i}) \quad = \quad 0 \leftrightarrow E(a_t) = \frac{\bar{\phi}}{1-\rho}, \tag{1.75}$$

where $\bar{\phi} = \frac{1}{N}\sum_{i=1}^{N}\phi_n$. This allows to rewrite the convergence equation (1.70) as

$$\lim_{i\to\infty} E_t(y_{n,t+i} - a_{t+i}) \quad = \quad \mu_n, \tag{1.76}$$

where $\mu_n = \frac{(\phi_n - \bar{\phi})}{1-\rho}$. In the long run, the countries converge to the same equilibrium value $\phi_n = \phi = \bar{\phi}$. Absolute convergence requires $\mu = 0$ for all countries. However, if for some countries $\mu_n \neq 0$, each country will convergence to its own growth path, i.e. convergence is conditional.

To sum up: if the data generating process in equation (1.73) is stationary, the economies will converge. Income convergence can be tested for using a panel unit root test. For absolute convergence, one would test excluding individual fixed effects; with individual fixed effects, conditional convergence is tested for.

1.8.2 Panel Unit Root Tests

In the literature, different panel unit root tests have been proposed. Quah (1994) considers a panel version of the Dickey-Fuller equation (Dickey and Fuller, 1979)

$$x_{i,t} = \rho x_{i,t-1} + e_{i,t} \quad , \tag{1.77}$$

where x_t is a random variable observed over time and cross-section units and $e_{i,t}$ are errors which are independently and identically distributed both across units and time, with finite and constant variance (σ^2). This model does not allow for group specific effects and serially correlated or heterogenous errors, and is only useful for testing absolute convergence (Evans, 1996). Based on a panel version of the augmented Dickey-Fuller (ADF) equation, Levin and Lin (1992) provide a more general model by allowing individual fixed effects as well as different dynamics in the stochastic error of different groups:

$$x_{i,t} = \mu_i + \rho x_{i,t-1} + e_{i,t} \quad . \tag{1.78}$$

Bernard and Jones (1996a) extend this model to include a drift term:

$$x_{i,t} = \mu_i + \delta t + \rho x_{i,t-1} + e_{i,t} \quad . \tag{1.79}$$

The limitation of this modified test is the underlining assumption which forces all countries to converge at the same rate. The null and alternative hypothesis are:

$$\begin{aligned} H_0 :& \rho_1 = \rho_2 = \ldots = \rho_N = \rho = 1; \\ H_1 :& \rho_1 = \rho_2 = \ldots = \rho_N = \rho < 1. \end{aligned} \tag{1.80}$$

Im *et al.* (1995) and Maddala and Wu (1999) relax this assumption by using separate unit root tests for each of the cross-section units. Based on the probability test proposed by Fisher (1932), Maddala and Wu (1999) average the p-values for the individual tests. Under the null hypothesis of non-stationarity, each p_i is uniformly distributed: $p_i \sim U(0,1)$. Define a random variable

$$z_i = -2\ln(p_i); p_i = \exp(-0.5z_i). \tag{1.81}$$

Since this is a one-to-one change of variable, $h(z_i)$, the density function of z_i, can be calculated from the density function of the uniform distribution $f(p_i)$ (e.g Judge *et al.*, 1988, p. 30-36):

$$\begin{aligned} & p_i \sim U(0,1); \text{ i.e. } f(p_i) = 1; \\ & z_i \sim h(z_i) = f\left(\exp\left(-0.5z_i\right)\right) \left|\frac{\partial \exp\left(-0.5z_i\right)}{\partial z_i}\right| = \frac{1}{2}\exp\left(-0.5z_i\right), \end{aligned} \tag{1.82}$$

which is a χ^2 distribution with 2 degrees of freedom, i.e.

$$-2\ln p_i \quad \sim \quad \chi^2(2). \tag{1.83}$$

Under the assumption that the tests are independent, the test statistic is given by

$$MW \quad = \quad -2\sum_{i=1}^{N} \ln\left(p_i\right) \sim \chi^2(2) \tag{1.84}$$

The test requires cross-sectional independence among the series. One way to address the problem of cross-sectional correlations is to bootstrap empirical distributions of the test statistics under the null to calculate critical values for the test.

The first step of the simulation is to perform an ADF test for the original series $y_i, i = 1, \ldots, N$, where $N = 57$ is the number of countries under analysis. This gives a test statistic τ_i. In the next step, the distribution of the ADF-statistic under the null hypothesis is derived from fitting an AR(p) model to the difference filtered series y_i,[56] and using the estimated parameters $\hat{a}_0, \hat{a}_1, \ldots, \hat{a}_p, \hat{\sigma}$ for generating 2000 replications of an

[56]The order is determined using the AIC criterion.

ARIMA(p,1,0). The 2000 generated series are tested for the existence of a unit root using the model from the first step, which gives 2000 test statistics $\tau_s, s = 1, \ldots, S$; $S = 2000$. After sorting the τ_s in ascending order, the number of τ_s is calculated for which $\tau_s \leq \tau_i$. Dividing this number by the number of simulations $S = 2000$ gives the significance level π_i.

1.9 Conclusion

This chapter describes different approaches to estimate stochastic frontier and efficiency models for macroeconomic data. The assumptions and limitations of different specifications are discussed to find the appropriate model to analyse the determinants of efficiency in a panel of developing countries.

The main conclusions are as follows:

1. The stochastic frontier method is preferred to other productivity measures for two main reasons. First, it is less data intensive than others, for example the measure proposed by Basu and Kimball (1997) and Basu and Fernald (2001b). Second, it allows the important distinction between efficiency changes and technical progress.

2. For the estimation of the frontier, a parametric approach is the more suitable option, since it has the advantage of allowing for statistical inference. Hence specification of production function as well as different hypothesis on the efficiency terms and on all other estimated parameters can be tested. Moreover the stochastic nature of frontier enables to consider the effect of random shocks on the production process.

3. It has been illustrated that to estimate stochastic frontier models, several assumptions about the distribution of statistical noise and technical

efficiency need to be imposed. Panel data techniques permit to relax them. Because of the larger sample size, it is possible to obtain more precise estimates of efficiency.

4. A maximum likelihood estimator is preferred to within and random effect estimators. The maximum likelihood procedure is chosen because it does not restrict the frontier to be parallel to the "central tendency" production function. Another advantage is that the intercept can be estimated directly without having to normalize with respect to the "best" country.

   However, it is neccessary to make assumptions about the inefficiency distribution. Greene (1990) argues that this is not strong assumption. He demonstrates that the ranking of producers by their efficiency scores and the composition of the top and bottom score deciles are not sensitive to the choice of distribution.

5. Different specifications of inefficiency effects may restrict the temporal pattern of the inefficiency. Alternatively, the inefficiency can vary over time but the temporal path is constrained to be the same for all the producers. Battese and Coelli (1995) propose a model which includes explanatory variables. The panel framework permits to exploit time and sectional dimensions of the data. The stochastic nature of the inefficiency terms allows the estimation of both technical change - captured by time dummies - and time-varying technical inefficiency.

6. The translog production function is explained in detail to show the flexibility of the approach. To allow for statistical inference about the shape fo the function in the following chapters, formulas for the variance of output elasticities and elasticity of substitution are derived.

1.A The Likelihood Function for the Half-Normal Distribution

Consider the following frontier production function for a cross section of N countries

$$Y_i = f(\mathbf{X}_i)\exp(v_i)TE_i,\ i = 1, \ldots, N, \tag{1.85}$$

where $\mathbf{X}$ is a vector of inputs, TE is the efficiency measure, and v_i is an error term incorporating country-specific random shocks into the analysis. Efficiency is determined by

$$TE_i = \frac{Y_i}{f(\mathbf{X}_i)\exp(v_i)};0 \leq TE_i \leq 1. \tag{1.86}$$

Taking logs and assuming that $f(.)$ is a Cobb-Douglas type function, and allowing for a single input, equation (1.85) becomes

$$y_i = \alpha + \beta x_i + \epsilon_i; \epsilon_i = v_i - u_i. \tag{1.85'}$$

The problem is to find a way to decompose the composite error ϵ into the two unobservable components v and u. The error term v_i is iid and symmetric, whereas $u_i \geq 0$. Thus, the composit error term ϵ_i is asymmetric. To be more precise, assume that $v_i \sim N(0, \sigma_v^2)$ and $u_i \sim N^+(0, \sigma_u^2)$, i.e. u_i follows a half-normal distribution. Because of the independence assumption, the joint density function of u and v is[57]

$$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right), \tag{1.87}$$

and because of $\epsilon = v - u$, the joint density function of ϵ and u is

$$f(u,\epsilon) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{(\epsilon+u)^2}{2\sigma_v^2}\right). \tag{1.88}$$

The marginal density function of ϵ can be obtained from

$$\begin{aligned} f(\epsilon) &= \int_0^\infty f(u,\epsilon)du = \\ &= \frac{2}{2\pi\sigma_u\sigma_v}\int_0^\infty \exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{(\epsilon+u)^2}{2\sigma_v^2}\right)du. \end{aligned} \tag{1.89}$$

Define

$$\sigma_\star^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma_u^2+\sigma_v^2},$$

which gives

$$\begin{aligned} f(\epsilon) &= \frac{2}{2\pi\sigma_u\sigma_v}\int_0^\infty \exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{u^2+\epsilon^2+2\epsilon u}{2\sigma_v^2}\right)du = \\ &= \frac{2}{2\pi\sigma_u\sigma_v}\int_0^\infty \exp\left(-\frac{u^2\left(\sigma_u^2+\sigma_v^2\right)}{2\sigma_u^2\sigma_v^2} - \frac{2\epsilon u}{2\sigma_v^2} - \frac{\epsilon^2}{2\sigma_v^2}\right)du = \\ &= \frac{2}{2\pi\sigma_u\sigma_v}\int_0^\infty \exp\left(-\frac{u^2}{2\sigma_\star^2} - \frac{2\epsilon u}{2\sigma_v^2}\right)\exp\left(-\frac{\epsilon^2}{2\sigma_v^2}\right)du. \end{aligned} \tag{1.90}$$

[57] To simplify notation, the indices are skipped in the following.

Completing the square, the first term in equation (1.90) can be rewritten as

$$\begin{aligned}
&\exp\left(-\frac{u^2}{2\sigma_\star^2}-\frac{2\epsilon u}{2\sigma_v^2}\right)=\exp\left(-\frac{1}{2\sigma_\star^2}\left(u^2+2\sigma_\star^2 u\frac{\epsilon}{\sigma_v^2}\right)\right)=\\
&=\exp\left(-\frac{1}{2\sigma_\star^2}\left(u^2+2\sigma_\star^2 u\frac{\epsilon}{\sigma_v^2}+\sigma_\star^4\left(\frac{\epsilon}{\sigma_v^2}\right)^2-\sigma_\star^4\left(\frac{\epsilon}{\sigma_v^2}\right)^2\right)\right)= \\
&=\exp\left(-\frac{1}{2\sigma_\star^2}\left(u+\sigma_\star^2\frac{\epsilon}{\sigma_v^2}\right)^2\right)\exp\left(\frac{\sigma_\star^2}{2}\left(\frac{\epsilon}{\sigma_v^2}\right)^2\right).
\end{aligned} \tag{1.91}$$

Inserting into equation (1.89) gives

$$\begin{aligned}
f(\epsilon)=&\frac{2}{2\pi\sigma_u\sigma_v}\exp\left(\frac{\sigma_\star^2}{2}\left(\frac{\epsilon}{\sigma_v^2}\right)^2-\frac{\epsilon^2}{2\sigma_v^2}\right)\times \\
&\int_0^\infty \exp\left(-\frac{1}{2}\left(\frac{u+\sigma_\star^2\frac{\epsilon}{\sigma_v^2}}{\sigma_\star}\right)^2\right)du.
\end{aligned} \tag{1.92}$$

Define

$$\sigma^2=\sigma_u^2+\sigma_v^2, \lambda=\frac{\sigma_u}{\sigma_v}.$$

Since

$$\begin{aligned}
\sigma_\star\frac{\epsilon}{\sigma_v^2}&=\frac{\sigma_v\sigma_u}{\sqrt{\sigma_u^2+\sigma_v^2}}\frac{\epsilon}{\sigma_v^2}=\\
&=\frac{\sigma_u}{\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}}\epsilon=\frac{\lambda\epsilon}{\sigma},
\end{aligned}$$

the integral in equation (1.92) can be written as

$$\begin{aligned}
&\frac{2\sigma_\star}{\sqrt{2\pi}\sigma_u\sigma_v}\int_0^\infty\frac{1}{\sqrt{2\pi}\sigma_\star}\exp\left(-\frac{1}{2}\left(\frac{u+\frac{\lambda\epsilon}{\sigma}}{\sigma_\star}\right)^2\right)du=\\
&\qquad=\frac{2\sigma_\star}{\sqrt{2\pi}\sigma_u\sigma_v}\left(1-\Phi\left(\frac{\lambda\epsilon}{\sigma}\right)\right),
\end{aligned} \tag{1.93}$$

where $\Phi(.)$ is the standard normal cumulative distribution. The term in front of the integral simplifies to

$$\frac{2\sigma_\star}{\sqrt{2\pi}\sigma_u\sigma_v} = \frac{2\sigma_u\sigma_v}{\sqrt{2\pi}\sqrt{\sigma_u^2+\sigma_v^2}\sigma_u\sigma_v} = \frac{2}{\sqrt{2\pi}\sigma},$$

and

$$\frac{1}{2}\left(\sigma_\star^2\left(\frac{\epsilon}{\sigma_v^2}\right)^2 - \left(\frac{\epsilon}{\sigma_v}\right)^2\right) = \frac{1}{2}\left(\frac{\sigma_u^2}{\sigma_v^2\left(\sigma_u^2+\sigma_v^2\right)} - \frac{1}{\sigma_v^2}\right)\epsilon^2$$
$$= \frac{1}{2}\left(\frac{\sigma_u^2-\left(\sigma_u^2+\sigma_v^2\right)}{\sigma_v^2\left(\sigma_u^2+\sigma_v^2\right)}\right)\epsilon^2 = -\frac{1}{2}\left(\frac{\sigma_u^2-\left(\sigma_u^2+\sigma_v^2\right)}{\sigma_v^2\left(\sigma_u^2+\sigma_v^2\right)}\right)\epsilon^2 = -\frac{1}{2}\frac{\epsilon^2}{\sigma^2}.$$

Thus,

$$\begin{aligned}
\phi(\epsilon) &= \frac{2}{\sigma}\left(1-\Phi\left(\frac{\lambda\epsilon}{\sigma}\right)\right)\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\frac{\epsilon^2}{\sigma^2}\right) = \\
&= \frac{2}{\sigma}\left(1-\Phi\left(\frac{\lambda\epsilon}{\sigma}\right)\right)f\left(\frac{\epsilon}{\sigma}\right) = \\
&= \frac{2}{\sigma}\Phi\left(-\frac{\lambda\epsilon}{\sigma}\right)f\left(\frac{\epsilon}{\sigma}\right),
\end{aligned} \tag{1.94}$$

where $\phi(.)$ is the standard normal distribution. The log-likelihood in this case is

$$\ln L = \text{const} - N\ln\sigma + \sum_{j=1}^{N}\ln\left(1-\Phi\left(\frac{\epsilon_i\lambda}{\sigma}\right)\right) - \frac{1}{2\sigma^2}\sum_{j=1}^{N}\epsilon_i^2. \tag{1.95}$$

Chapter 2

Efficiency and Technology Diffusion: The Basic Model

The purpose of this chapter is to establish the basic model of efficiency and technology diffusion based on a panel of 57 developing countries in the period 1960-1990.[1] The analysis starts with the specification of the production function, focussing on the role of human capital (Section 2.1.1) and of technology (Section 2.1.2). Section 2.2 discusses the channels through which technology can be transmitted.

The production frontier at each point in time is estimated using the stochastic frontier method. Each country is compared to that frontier. Estimation of efficiency, i.e. the distance to the frontier, follows the method of Battese and Coelli (1995), which has been described in detail in Section 1.6. How much closer a country gets to the world frontier is what can be called "catching up"; how much the frontier shifts at given observed inputs is "technical change" or "innovation".

In contrast to the study of Kumar and Russell (2002), the parametric

[1] See Section 2.3 for a detailed description of the data set.

method explained in Chapter 1 is preferred to a non-parametric approach. On the one hand, this method requires the specification of a particular functional form for the technology. On the other hand, it allows for measurement errors, which is an advantage with the data analysed in this study. The functional form is the translog production function introduced in Section 1.7, which is based on a second order approximation to a twice differentiable but otherwise arbitrary production function. This choice is preferable to the more restrictive assumption of constant returns to scale in e.g. Koop *et al.* (2000b), because market imperfections, as well as technical inefficiencies, are possible reasons for countries falling below the production frontier.

2.1 Specification of the Production Function

2.1.1 The Role of Human Capital

Although many studies have established that human capital plays an important role in the growth process, the question on the way human capital affects growth remains still unresolved.[2] Human capital can be considered as a factor of production, it can be used for quality-adjustment of labour input, or as a factor influencing productivity. Mankiw *et al.* (1992) show the empirical validity of the neo-classical model by including human capital as input in the production function. They find that this inclusion generates a better fit in their cross-section regression. In contrast to their study, Islam (1995), using human capital as input, finds an insignificant coefficient in his panel regression. Instead, there is a positive relationship between human capital and individual country effects, indicating that the channel trough which human

[2]See Islam (1995, pp.25-29).

capital affects growth is total factor productivity measured by the individual effects (see also Nelson and Phelps, 1966; Benhabib and Spiegel, 1994).

An alternative approach of incorporating human capital in the production function is to include an interaction term of human capital with the labour force. Lucas (1988) and Romer (1986, 1990) argue that endogenously accumulated human capital has a direct impact on the productivity of labour (see also Tallman and Wang, 1994). Empirically, this assumption requires augmenting labour input by characterising the degree of labour skill in the economy. Taking together, it would be desireable to disentangle the direct effect of human capital on output as a factor of production, and the indirect effect through improving total factor productivity because of efficiency improvements. In the following, this issue is addressed by including human capital as a determinant of efficiency and as quality adjusted labour force into the production frontier.

2.1.2 The Role of Technology

While the neo-classical growth literature following Solow (1956), Ramsey (1928), and Samuelson (1958) considers technological change as an exogenous and neutral process, the endogenous growth literature emphasises that technical progress is an endogenous process that might be non-neutral. Technology is neutral or unbiased if it does not save relatively more of either input. In the models of Romer (1986, 1990) and Rebelo (1991) technical change affects physical capital, whereas in Lucas' (1988) model, by increasing human capital through the learning-by-doing effect, technical change affects labour.

Exogenous technological progress can be modelled in different forms, it can be labour-saving or capital-saving, depending on inventions which allow to produce the same amount of output with relatively less labour or relatively less capital. Based on the capital and labour saving concept, three different definitions of neutral technological progress can be derived. Hicks (1932) calls technology neutral if the ratio of marginal products remains unchanged for a given capital-labour ratio. An example for a production function with Hicks-neutral technological progress is[3]

$$Y = T(t)\,F(K, L)\,, \tag{2.1}$$

where Y represents output, K capital, L labour and $T(t)$ is technology which varies over time. Neutral technological progress according to Harrod (1942) leaves relative input shares unchanged for a given capital-output ratio (labour-augmenting technology), e.g.

$$Y = F(K, LT(t))\,. \tag{2.2}$$

Finally, Solow (1957)-neutral progress leaves relative input shares unchanged for a given labour-output ratio (capital-augmenting technology):

$$Y = F(KT(t), L)\,. \tag{2.3}$$

The empirical part in Section 2.4 tests for these possibilities.

2.2 Modelling Efficiency

Quah (1997), Mankiw *et al.* (1992), and Barro and Sala-i-Martin (1995) argue that slow convergence in the level of output per worker is caused by slow technological catch-up. There are a variety of channels through which new

[3]For the following, see Barro and Sala-i-Martin (1995, Section 1.2.10).

ideas and new technologies can be transmitted. Imports of high-technology products, adoption of foreign technology and acquisition of human capital are certainly the most important channels for technology diffusion.

In the standard Hecksher-Ohlin trade model of international trade, openness to foreign goods is supposed to bring benefits primarily through its effects on the market price of imported goods. Opening to imports yields a net gain in welfare due to the increase in consumer surplus that offsets the fall in profits of manufacturers. Moreover, trade liberalisation shifts the resources into the industry in which countries have a comparative advantage, and therefore improves productivity. In this model, trade causes economies to shift intersectorally, moving along their production frontier.

However, as Stiglitz (1998) underlines, the main gains from trade come from movement of the production frontier with little intersectoral shift. Trade allows the economy not only to consume a given basket of goods at lower prices, but also to produce a given set of goods at lower cost. The evidence suggests that trade liberalisation leads to an improvement in the production technology. Stiglitz states that trade reduces efficiency differentials. Moreover, dynamic sectors (import-substitution sectors) of the economy benefit from technological diffusion by trade liberalisation.

2.3 Data

The starting point of data construction is the data set by Kumar and Russell (2002). The aim of the thesis is to analyze the sources and determinants of catching up of low income countries with developed world. In particular, attention is drawn on importance of trade channels in helping the technological diffusion and the development. Hence, I need to construct my own panel data set of developing countries.

The observation period 1960-1990 is dictated by the availability of high quality data and actually extends the 1965-1990 data set analyzed by Kumar and Russell (2002). Kumar and Russell (2002)'s study is based on data from 57 countries represented by OECD countries, newly industrialized countries and some developing countries.

The panel data analyzed in this thesis consists of 57 developing countries: 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, and Zimbabwe.

The output and input data series required for the estimation are obtained from different sources (see list below on page 86). All the variables are annual. In order to exploit the time as well as the cross section dimension, the current values must be made comparable by deflating to give constant price series. Data on gross domestic product (GDP), foreign direct investments, and export of manufacturing goods are from World Bank's World Development Indicators (WDI) CD ROM 1999. GDP data is measured in 1995 US dollars which is transformed in constant 1987 US dollars using US CPI from IMF CD 2001. Physical capital stock is obtained from Nehru and Dhareshwar (1993) and is expressed in local currency. It is converted into units of constant 1987 US dollars using the 1987 real exchange rate between the local currency and US dollars (the exchange rate series, from IMF CD 2001, have been converted to real exchange rate 1987 US dollars, using CPI from the same source). The transformation to obtain capital stock in real values is

$$K_{US\$1987} = \underbrace{(XR_{Nominal})\,(NC/US\$))\left(\frac{CPI(US\$)}{CPI(NC)}\right)}_{\text{(real exchange rate)}} K_{NC1987},$$

where NC = national currency, US\$ = US dollars, and $XR_{Nominal}$ = nominal exchange rate.

Although it is possible to extend the capital stock data applying the procedure discussed below, the data on imports of machinery and equipment are the limiting factor. The World Bank's World Development Indicators (WDI) CD ROM 1999 has very few observations on imports of machinery and equipment; this source is supplemented with data from the Handbook of International Trade and Development Statistics (Table 4.1, different years). Gaps in the data were evident for many countries and above all for Mozambique, Myannar and Pakistan. These countries are not excluded from the sample. Instead, missing observations were interpolated by a moving average of length four.[4] Due to missing years it was impossible to extend the time period to a more recent date. A possibility to look at a longer observation period, one could exclude imports of capital goods. However, since this varaible is central to the topic of the thesis, it is preferable to leave it in the data set. A potential problem could be that imports of machinery and equipment (ME) and foreign direct investment (FDI) measure the same effect. The very low correlation coefficient of -0.001 shows that these two variables do not cause a multicollinearity problem.

In this and the following chapters, production frontiers are fitted for a

[4]Excluding missing observations has not effect on the results.

single output Y and two input factors, L and K:

- Y: Real Gross Domestic Product (GDP). This data is from World Bank's World Development Indicators (WDI) CD-ROM (1999) and is in constant 1995 US Dollars.

- L: Labour. This data is measured as number of workers and is calculated from the GDP per worker series in the Penn World Table, 5.6, together with the GDP data from the same source (web site: http://datacentre2.chass.utoronto.ca/pwt56/).

- K: Capital Stock. Physical capital stock is obtained from Nehru and Dhareshwar (1993). Nehru and Dhareshwar (1993) use the World Bank data on gross domestic fixed investment at constant local prices and adopt the "perpetual inventory method" to calculate capital stocks.[5] The method is based on the evolution equation for the capital stock K_t:

$$\begin{aligned} K_t &= (1-\rho)K_{t-1} + I_{t-1}; \\ K_t &= (1-\rho)^t K_0 + \sum_{j=0}^{t-1}(1-\rho)^j I_{t-j-1}, \end{aligned} \tag{2.4}$$

where I_t is gross investment and ρ is the depreciation rate. The data on gross investment are from the World Bank, which leaves the initial capital stock and the depreciation rate to be determined. The depreciation rate is assumed to be 4 per cent for all countries. To obtain the initial capital stock in 1960, they use the approach by Harberger

[5]For the following, see also OECD (2001).

(1978). According to equation (2.4), capital in 1960 is given by

$$K_{1960} = (1-\rho)^T K_{1960-T} + \sum_{j=0}^{T-1} (1-\rho)^j I_{1960-j-1}. \tag{2.5}$$

For $T \rightarrow \infty$ the first term on the right hand side of (2.5) vanishes:

$$\begin{aligned} K_{1960} &= \sum_{j=0}^{\infty} (1-\rho)^j I_{1960-j-1} = I_{1959} + (1-\rho) I_{1958} + \\ &+ (1-\rho)^2 I_{1957} + \ldots \end{aligned} \tag{2.6}$$

Under the assumption that gross investment grows at a constant rate g (g is set equal to the output growth rate), one obtains

$$I_t = (1+g) I_{t-1} = (1+g)^t I_0,$$

which gives

$$\begin{aligned} K_{1960} &= \frac{1}{(1+g)} I_{1960} + \frac{1-\rho}{(1+g)^2} I_{1960} + \frac{(1-\rho)^2}{(1+g)^3} I_{1960} + \ldots = \\ &= \sum_{j=0}^{\infty} \left(\frac{1-\rho}{1+g} \right)^j \frac{I_{1960}}{1+g} = \sum_{j=0}^{\infty} q^j \frac{I_{1960}}{1+g}; \\ \sum_{j=0}^{\infty} q^j &= \frac{1}{1-q} = \frac{1}{1-\frac{1-\rho}{1+g}} = \frac{1+g}{g+\rho}; \\ K_{1960} &= \frac{I_{1960}}{g+\rho}. \end{aligned}$$

To obtain gross investment in 1960 net of cyclical effects, Nehru and Dhareshwar (1993) fit a linear time trend to the log of investment (allowing for a structural break in 1973) and use predicted investment in 1960 to arrive at K_{1960}.

To give an impression of the validity of their method, they fit Cobb-Douglas production functions to the the data for different measures of the capital stock, and find that their approach is preferable. The Nehru and Dhareshwar (1993) data set is chosen since to date, it is considered to be the best available (Duffy and Papageorgiou 2000).

The variables which explain efficiency are:

- HC: Human Capital. This data is obtained from Collins and Bosworth (1996). They define $HC = \sum W_j P_j$ where P_j is the percentage of a country's population with level j of schooling (j ranges from 1: no schooling to 7: beyond secondary schooling). W_j are their estimates of the return to level j of schooling. These estimates are based on the observed relative earnings of different education groups and on the assumption that relative returns to schooling are constant across levels of schooling and countries. In the empirical analysis, an index is used (1960=100), based on the assumption that there is a 7 per cent return to schooling (Collins and Bosworth, 1996, Table 4).

- FDI: Foreign Direct Investments. This data is from the World Bank's World Development Indicators (WDI) CD-ROM (1999) and is measured as percentage of GDP.

- ME: Imports of Machinery and Equipment. This data is from UNCTAD (Handbook of International Trade and Development Statistics, Table 4.1, different years) and is measured as percentage of merchandise imports. Unfortunately, the 90s have to be excluded from the analysis, because for this period, the data for a large number of countries are not available.

- *IMPD*: Import Discipline Indicator. This indicator is constructed as a ratio of GDP deflator (World Bank's World Development Indicators (WDI) CD-ROM 1999) to unit import prices. Unit import prices are calculated dividing the Imports of Goods and Services measured in local currency units (World Bank CD-ROM 1999) by Imports of Goods and Services measured in constant currency units (World Bank CD-ROM 1999).

- *EXPM*: Exports of Manufacturing Goods. This data is from the World Bank's World Development Indicators (WDI) CD-ROM (1999) and is measured as percentage of merchandise exports.

Once the data set has been created, preliminary data analysis is performed to get a first impression of the data structure. One of the conditions to apply the stochastic frontier model is that the error term components are independent and identically distributed.[6] This condition requires that the error term is stationary. Basu *et al.* (2003) explicitly point out that the time series properties of the data is an important issue to explore when using a panel to investigate the relationship between FDI and growth. Inefficiency is tested for non-stationarity. The unit root test is performed on the explanatory variables for the inefficiency, since any linear combination of stationary variables will be stationary. The Fisher test is applied in in the version proposed by Maddala and Wu (1999): based on an augmented Dickey-Fuller test, significance levels π_j are constructed for all the individual series of interest in the data set.

The Maddala and Wu (1999) test is chosen because the data set under analysis is unbalanced. Another advantage is that the individual ADF

[6] See Chapter 1.

equations can have different orders p.[7] For all variables, non-stationarity is rejected at conventional significance levels. The null of nonstationarity is rejected at the 5% level for FDI, and at the 1% level for import of machinery and transport equipment, human capital, the import discipline indicator and for exports of manufacturing goods.[8]

Africa and Asia regional dummies are included to capture regional differences; the reference group is Latin America, being the one with the most observations. A time trend is added as a proxy for disembodied technical change.[9]

2.4 Empirical Results

The specification of the production frontier is (Section 1.5.6)

$$y_{it} = f(\mathbf{x}_{it}, t, \boldsymbol{\beta}) + \epsilon_{it}, \tag{2.7}$$

and

$$\epsilon_{it} = v_{it} - u_{it}, \tag{2.8}$$

where y_{it} is the output of the country i at time t, $\mathbf{x}_{it}$ is a vector of inputs of the country i at time t, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, t is a time trend, and $f(\mathbf{x}_{\mathrm{it}}, t, \boldsymbol{\beta})$ is the general form of the production function. The component v_{it} is assumed to be independently and identically distributed, uncorrelated with the regressors and the inefficiency terms, $v_{it} \sim N(0, \sigma_\varepsilon^2)$.

[7] See Section 1.8.2 for a detailed explanation of Maddala and Wu (1999) test.
[8] Note that all the measures are ratios of potentially cointegrated variables.
[9] See Kumbhakar and Lovell (2000, pp.285-286) and Coelli *et al.* (1998, pp.35-37) for a detailed explanation.

The random variable u_{it} is assumed to be non-negative and captures the inefficiency effects. Two different specifications for these effects proposed by Battese and Coelli (1992, 1995) are considered.

Human capital is included as a determinant of efficiency and as quality adjusted labour force. Technological change is modelled in two ways. The first model assumes neutral technical progress (Coelli *et al.*, 1998, pp.57-58). A quadratic time trend is included to obtain parametric measures of the rate of technical change. The square term accounts for the second order approximation of the translog form. The partial derivative of the production function with respect to time provides an indication of the rate of movement in the production function over time. For technical progress to occur, the sign of this derivative should be positive. This result indicates Hicks-neutral technological change: the frontier moves but the slopes are fixed.

The second specification assumes non-neutral technological change of the translog stochastic frontier (Kumbhakar and Lovell, 2000). Non-neutral technical change accounts for movements in the frontier with changing slopes. It is assumed that changes in technical progress affect either the elasticity of output with respect to physical capital, or the elasticity of output with respect to labour force. This means that technical changes are biased in favour of certain inputs.[10] Non-neutral technological change is modelled by including a quadratic time trend and also the cross-products of t and the inputs (in logs).

[10]In the preferred Model 4*, this hypothesis can be rejected at conventional significance levels.

2.4.1 Models

Model 1

The first model is based on the more general form for the efficiency by Battese and Coelli (1992). They consider a stochastic frontier production function with a simple exponential specification of time-varying effects (Section 1.5.6):

$$u_{it} = \{\exp\left[-\eta(t - T)\right]\} u_i \tag{2.9}$$

where the inefficiency terms u_{it} are assumed to be identically and independent distributed as a truncated-normal random variable with constant mean μ_u and variance σ_u^2; η is an unknown scalar parameter to be estimated; t is the period in which the country efficiency is observed and T is the last period. Given the specification of technical inefficiency effects, there is particular interest in testing the null hypothesis that inefficiency is time invariant.

The translog production function with regional dummy variables for African and Asian countries and neutral technical progress is

$$\begin{aligned} \ln(Y_{it}) = & \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + \beta_3 0.5 \ln(K_{it})^2 + \\ & + \beta_4 0.5 \ln(L_{it})^2 + \beta_5 \ln(K_{it}) \ln(L_{it}) + \beta_6 AFRICA_{it} + \\ & + \beta_7 ASIA_{it} + \beta_8 t + \beta_9 t^2 - u_{it} + v_{it}, \end{aligned} \tag{2.10}$$

where $\ln(Y_{it})$ is the log of output Y, $\ln(K_{it})$ is the log of capital K, and $\ln(L_{it})$ is the log of labour L. v_{it} is the random term that is assumed to be independent and identically normal with mean zero a constant variance σ_v^2. The random term is also assumed to be independent of the inefficiency term u_{it}.

Model 1*

This is an extension of Model 1 and uses quality adjusted labour force:

$$\begin{aligned}\ln(Y_{it}) =& \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L^*_{it}) + \beta_3 0.5 \ln(K_{it})^2 + \\ &+ \beta_4 0.5 \ln(L^*_{it})^2 + \beta_5 \ln(K_{it}) \ln(L^*_{it}) + \beta_6 AFRICA_{it} + \\ &+ \beta_7 ASIA_{it} + \beta_8 t + \beta_9 t^2 - u_{it} + v_{it},\end{aligned} \tag{2.11}$$

where L^*_{it}=$L_{it}HC_{it}$. HC is an index of labour quality as defined in Collins and Bosworth (1996).[11]

Model 2

The third model specifies technological change as non-neutral[12] with inefficiency modelled following Battese and Coelli (1992). Non-neutral technical change requires inclusion of the interaction terms of the capital and labour with time:

$$\begin{aligned}\ln(Y_{it}) =& \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + \beta_3 0.5 \ln(K_{it})^2 + \\ &+ \beta_4 0.5 \ln(L_{it})^2 + \beta_5 \ln(K_{it}) \ln(L_{it}) + \beta_6 AFRICA_{it} + \\ &+ \beta_7 ASIA_{it} + +\beta_8 t + \beta_9 0.5 t^2 + \beta_{10} \ln(K_{it}) t + \\ &+ \beta_{11} \ln(L_{it}) t - u_{it} + v_{it}\end{aligned} \tag{2.12}$$

[11]See the detailed definition on page 88.
[12]See Kumbhakar and Lovell (2000).

Model 2*

In this case, labour input is quality adjusted (Collins and Bosworth, 1996), and technological progress is non-neutral (Battese and Coelli, 1992):

$$\begin{aligned}\ln(Y_{it}) =&\beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L^*_{it}) + \beta_3 0.5 \ln(K_{it})^2 + \\ &+ 0.5\beta_4 \ln(L^*_{it})^2 + \beta_5 \ln(K_{it}) \ln(L^*_{it}) + \beta_6 AFRICA_{it} + \\ &+ \beta_7 ASIA_{it} + \beta_8 t + \beta_9 0.5t^2 + \beta_{10} \ln(K_{it})t + \\ &+ \beta_{11} \ln(L^*_{it})t - u_{it} + v_{it},\end{aligned} \tag{2.13}$$

with $L^*_{it} = L_{it} HC_{it}$.

Model 3

The specification of the efficiency component follows Battese and Coelli (1995).[13] They extend the stochastic frontier model of Aigner *et al.* (1977) to include explanatory variables for inefficiency:

$$\begin{aligned} u_{it} &\sim |N\,(m_{it}, \sigma_u^2)|\,; \\ m_{it} &= \delta_0 + \sum_{j=1}^{n} \delta_j x_{jt}, \end{aligned} \tag{2.14}$$

where u_{it} is a non-negative random variable, associated with technical inefficiency of production, which is assumed to be independently distributed. The random variable u_{it} is obtained by truncating the normal distribution at zero, with mean $m_{it} = \delta_0 + \sum_{j=1}^{n} \delta_j x_{jt}$, and variance σ_u^2.

There is no a-priori justification for a choice of any particular distribution function for the inefficiency effects. Half-normal and exponential distributions have mode at zero, implying highest probability that the inefficiency

[13]See Section 1.6 for an explanation of this model.

effects are close to zero. For the set of data analysed in this study, this assumption is probably violated. To address this issue, Stevenson (1980) proposes for the technical inefficiency a truncated-normal and Greene (1990) a gamma distribution. Given serious computational problems with this functional form (Ritter and Simar, 1997), a truncated-normal model is chosen.

The translog production function is defined by equation (2.10). The expected value of the inefficiency term u_{it} is determined by:

$$m_{it} = \delta_1 FDI_{it} + \delta_2 ME_{it} + \delta_3 IMPD_{it} + \delta_4 EXPM_{it} + \delta_5 HC_{it}, \qquad (2.15)$$

where FDI_{it} denotes foreign direct investment, ME_{it} denotes imported capital goods, $IMPD_{it}$ the import discipline indicator, $EXPM_{it}$ is the percentage of manufacturing exports and HC_{it} is human capital. FDI and ME represent trade channels which diffuses foreign technology and increase productivity via efficiency, therefore a negative sign is expected in the inefficiency model (2.15). $EXPM$ and $IMPD$ are the other channels through which trade affects efficiency. $EXPM$ measures the trade openness effect of increasing market size, hence, a negative sign is to be expected. $IMPD$ captures the effect of free trade due to a more efficient price system: open countries have less price distortions than closed economies. According to the definition of the index (page 89), one would expect a positive sign here. Finally, HC controls for improvements in efficiency due to human capital accumulation.

Model 3*

This model uses quality adjusted labour force (equation 2.11). Inefficiency effects are defined by

$$m_{it} = \delta_1 FDI_{it} + \delta_2 ME_{it} + \delta_3 IMPD_{it} + \delta_4 EXPM_{it}. \qquad (2.16)$$

Model 3**

An extended version of Model 3 is estimated with quality adjusted labour force (equation 2.11) and human capital in the efficiency term (equation 2.15).

Model 4

This model assumes non-neutral technological change (equation 2.12) and efficiency model proposed by Battese and Coelli (1995)(equation 2.15).

Model 4*

Model 4 is re-estimated with quality adjusted labour force (equation 2.13) and efficiency effects as defined by equation (2.16).

Model 4**

Finally, a version of Model 4* (equation 2.13) is estimated with human capital included in the efficiency term (equation 2.15).

2.4.2 Results

The parameters are estimated simultaneously using the computer program FRONTIER Version 4.1 by Coelli (1996). The maximum-likelihood estimates are displayed in Table 2.1. The estimated variance parameters for the time-varying inefficiency models (Model 1,1*, 2 and 2*) presented in Table 2.2 indicate that inefficiency tends to decline over time as the estimates for η are positive (Model 1: η=0.007; Model 1*: η=0.011; Model 2: η=0.008; Model 2*: η=0.012, see equation 2.9). Moreover, the size of the estimated γ (equation 1.11)[14] suggests that a stochastic frontier model is preferred to the traditional average production function.

Before commenting on the estimated parameters, the "best" model has to be selected, for each of the efficiency model specifications (Battese and Coelli, 1992, 1995). Although some models are nested (for example, model 3 can be reformulated as a special case of Model 4, 3* as 4*, 3** as 4**), not all models can be reformulated as a special case of a more general model,[15] hence non-nested procedures is required to test between models. The results from the selection procedure are displayed in Tables 2.3, 2.4, and 2.5.[16] As model selection criteria, Akaike's Information Criterion (AIC) and the Schwarz Criterion (SC) are calculated.[17] AIC is given by

$$AIC = -\frac{2}{T}\ln L + \frac{2K}{T}, \tag{2.17}$$

where T is the number of observations, $\ln L$ is log-likelihood function, K is

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[14]
$$\gamma = \frac{\sigma_u}{\sigma_v + \sigma_u}.$$

[15] In particular, the production frontier models in which the specification for the technical inefficiency effects is that suggested by Battese and Coelli (1992) (models 1, 1*,2, 2*) cannot be considered a special case of frontier models in which technical inefficiency effects model is that proposed by Battese and Coelli (1995). See Battese and Broca (1997, p.399).

[16] Note that the best model is chosen according to the specification of technological progress and the treatment of human capital, not between the two efficiency models by Battese and Coelli (1992) and Battese and Coelli (1995).

[17] For the following, see Judge *et al.* (1988).

the number of parameters. SC is defined as

$$SC = -\frac{2}{T}\ln L + \frac{K \ln T}{T}. \tag{2.18}$$

These two statistics incorporate a measure of the precision of the estimate and a measure of the parsimony in the parameters of the statistical model. The "best" model is the one which minimises the value of the two statistics AIC and SC. As can be seen in Tables 2.3 and 2.4, the translog stochastic frontier production functions with quality adjusted labour force (Model 2* and 4*) generate a better fit, with respect to the specifications with raw labour force, regardless of the assumption on the inefficiency component (Battese and Coelli 1992 and Battese and Coelli 1995). This supports the view that human capital influences growth through its effect on labour productivity. Moreover, Model 4**, which includes human capital by both adjusting the labour force for quality and incorporating it in the inefficicency term, provides evidence that both the direct and the indirect effect are important.[18] Thus, the implications of learning-by-doing theory (Lucas, 1988; Romer, 1986) and the empirical findings of Tallman and Wang (1994) are supported.

The discussion now turns to the other hypothesis tests associated with the different models. The hypothesis of efficient production can be tested using a one-sided generalised likelihood-ratio test (Coelli, 1995).[19] The null hypothesis is $H_0 : \gamma = 0$, and the alternative $H_1 : \gamma > 0$. Under the null, the likelihood-ratio test statistic has an asymptotic distribution which is a mixture of chi-square distributions (Coelli, 1995). Critical values can be found in Kodde and Palm (1986).

The results of the likelihood-ratio test are displayed in Table 2.5. The

[18] This issue is further explored in Chapter 4.

[19] See p. 35 ff. for a detailed discussion of this test.

hypothesis of efficient production ($H_0 : \gamma = 0$), is rejected for all models. The Cobb-Douglas specification ($H_0 : \beta_3 = \beta_4 = \beta_5 = 0$) is also strongly rejected. Technical change is present in the data, since the hypotheses $H_0 : \beta_8 = \beta_9 = 0$ (neutral technical progress; Model 1,1*,3,3*,3**), and $H_0 : \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$ (non-neutral techological progress, Model 2,2*,4,4*,4**) are rejected. The only exception is Model 4** (non-neutral technical progress, quality-adjusted labour force, efficiency specification: Battese and Coelli 1995, human capital in efficiency equation). Since the hypothesis $H_0 : \beta_{10} = \beta_{11} = 0$ is rejected in all cases with the exception of Model 4**, non-neutral technological progress is an adequate representation for the majority of models.

The test results indicate that the preferred frontier models are the translog frontiers with non-neutral technical progress. This does not depend on the specification of the inefficiency component. According to the information criteria, Model 2* is perferable. However, since the focus of this chapter is on the determinants of efficiency, the results of Model 4* with a more general inefficiency specification (Battese and Coelli, 1995) are analysed in the following sections.

Table 2.1: Maximum-Likelihood Estimates

Variable	Model 1	Model 1*	Model 2	Model 2*	Model 3	Model 3*	Model3**	Model 4	Model 4*	Model 4**
Const	10.503	21.757	−3.934	4.861	−5.457	−3.751	−1.082	−5.817	−4.574	−7.231
	(6.340)	(14.180)	(−3.689)	(2.892)	(−2.604)	(−2.933)	(−0.611)	(−2.845)	(−1.223)	(−7.628)
$ln(K_{it})$	0.057	0.028	0.602	0.730	0.511	0.603	0.511	0.544	0.675	0.622
	(0.645)	(0.350)	(7.276)	(8.710)	(5.501)	(8.514)	(6.158)	(6.030)	(4.479)	(9.657)
$ln(L_{it})$	0.867		2.394		2.130			2.194		
	(3.724)		(14.262)		(12.277)			(11.830)		
$ln(L^*_{it})$		−0.438		0.471		1.725	1.630		1.814	2.177
		(−2.566)		(1.953)		(12.128)	(9.495)		(6.468)	(19.030)
$ln(K_{it})^2$	0.032	0.035	0.022	0.028	0.018	0.019	0.016	0.018	0.019	0.019
	(12.444)	(16.239)	(9.990)	(10.019)	(5.589)	(7.550)	(6.173)	(5.471)	(6.347)	(8.589)
$\ln(L_{it})^2$	0.064	0.137	−0.018	0.164	−0.006	0.027	0.020	−0.003	0.030	0.002
	(2.864)	(8.282)	(−0.894)	(6.998)	(−0.483)	(1.931)	(1.393)	(−0.247)	(2.167)	(0.173)
$ln(K_{it})\ln(L_{it})$	−0.046	−0.046	−0.073	−0.087	−0.053	−0.059	−0.050	−0.058	−0.067	−0.063
	(−6.110)	(−6.660)	(−9.503)	(−11.834)	(−5.825)	(−9.315)	(−6.724)	(−6.329)	(−5.315)	(−11.002)
AFRICA	−0.762	−0.540	−0.816	−0.497	−0.683	−0.734	−0.682	−0.675	−0.734	−0.696
	(−12.392)	(−12.523)	(−14.638)	(−12.106)	(−16.506)	(−21.059)	(−17.507)	(−16.912)	(−19.074)	(−19.850)
ASIA	0.809	0.540	0.888	0.719	−0.191	−0.123	−0.146	−0.199	−0.125	−0.190
	(8.415)	(6.749)	(6.804)	(7.563)	(−4.617)	(−2.708)	(−3.253)	(−4.388)	(−2.622)	(−4.880)
t	0.029	0.022	−0.089	0.016	0.026	0.030	0.028	−0.034	−0.059	−0.046
	(10.338)	(8.062)	(−9.270)	(1.317)	(3.597)	(4.259)	(4.058)	(−1.723)	(−2.859)	(−2.416)
t^2	−0.001	−0.001	−0.002	−0.001	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002
	(−9.263)	(−9.563)	(−9.481)	(−6.555)	(−2.893)	(−3.174)	(−3.267)	(−3.310)	(−3.697)	(−4.250)

L: labour; K: capital; $AFRICA = 1$ for African countries; $ASIA = 1$ for Asian countries; t, t^2: quadratic time trend; t-statistic in parentheses.

Table 2.1 continued on next page.

Table 2.1 continued

Variable	Model 1	Model 1*	Model 2	Model 2*	Model 3	Model 3*	Model3**	Model 4	Model 4*	Model 4**
$ln(K_{it})t$			0.003	0.003				0.002	0.002	0.002
			(11.116)	(6.661)				(3.061)	(3.045)	(2.756)
$ln(L_{it})t$			0.004	−0.004				0.001	0.003	0.002
			(7.015)	(−5.455)				(0.459)	(1.908)	(1.900)
$Const$					4.169	0.652	2.020	4.319	0.659	0.709
					(4.672)	(6.177)	(7.669)	(4.453)	(3.244)	(8.702)
FDI					−0.030	−0.017	−0.017	−0.011	−0.016	−0.020
					(−1.570)	(−1.719)	(−1.878)	(−0.483)	(−1.596)	(−3.372)
ME					−0.017	−0.013	−0.012	−0.019	−0.013	−0.009
					(−4.828)	(−6.795)	(−6.642)	(−5.260)	(−6.790)	(−9.838)
HC					−0.026		0.106	−0.027		−0.002
					(−3.494)		(8.007)	(−3.361)		(−8.385)
$IMPD$					0.020	0.090	0.076	0.034	0.075	0.068
					(0.480)	(3.205)	(2.517)	(1.018)	(2.302)	(3.437)
$EXPM$					−0.008	−0.002	−0.001	−0.009	−0.002	−0.004
					(−2.362)	(−1.977)	(−1.448)	(−2.748)	(−2.005)	(−55.271)
N	1416	1416	1416	1416	1416	1416	1416	1416	1416	1416

K: capital; L: labour; t: time; $Const$: constant; FDI: foreign direct investment; ME: import of machinery and equipment; H: human capital; $IMPD$: import discipline; $EXPM$: exports of machinery and equipment; N: Number of observations; t-statistic in parentheses.

Table 2.2: Variance Parameters

Variable	Model 1	Model 1*	Model 2	Model 2*	Model 3	Model 3*	Model3**	Model 4	Model 4*	Model 4**
σ^2	0.238	0.290	0.293	0.287	0.300	0.251	−0.004	0.297	0.244	0.249
	(13.202)	(13.160)	(12.874)	(15.510)	(10.515)	(24.882)	(−3.562)	(12.824)	(23.035)	(24.728)
γ	0.912	0.934	0.926	0.931	0.323	0.002	0.246	0.322	0.002	0.000
	(154.814)	(138.138)	(194.783)	(245.427)	(4.459)	(0.621)	(26.545)	(4.811)	(0.058)	(2.783)
μ	0.931	1.041	1.042	1.034						
	(9.583)	(11.947)	(9.547)	(12.676)						
η	0.007	0.011	0.008	0.012						
	(9.985)	(12.836)	(8.326)	(11.894)						
LL	509.668	560.618	547.202	583.967	−1021.904	−1021.904		−1014.231	−1008.838	−1022.212
LR	3220.757	3228.047	3278.040	3251.803	157.612	157.612		155.171	66.192	39.444
N	1416	1416	1416	1416	1416	1416	1416	1416	1416	1416

Inefficiency Model (Stochastic Frontier Models 1,1*, 2,2*):

$u_{it} \sim \left|N\left(\mu_i, \sigma_u^2\right)\right|;\ u_{it} = \{\exp\left[-\eta(t-T)\right]\} u_i$

Inefficiency Model (Stochastic Frontier Models 3,3*,3**, 4,4*,4**):

$u_{it} \sim \left|N\left(m_{it}, \sigma_u^2\right)\right|;\ m_{it} = \delta_0 + \sum_{j=1}^{n} \delta_j x_{jt},$

LL: log-likelihood, LR: likelihood-ratio test ($H_0 : \delta_0 = \delta_1 = ... = \delta_n = 0$). LR is approximately distributed following a mixed chi-square distribution (critical value at the 5 per cent signifcance level: 10.371, see Kodde and Palm (1986)). N: number of observations, t-statistics in parentheses.

Table 2.3: Model Selection Criteria for Battese and Coelli (1992)

Model	Log Likelihood	AIC	SC
Model 1 neutral technical progress	509.668	-0.704	-0.664
Model 1* neutral technical progress and quality adjusted labour force	560.618	-0.776	-0.735
Model 2 non-neutral technical progress	547.202	-0.755	-0.706
Model 2* non-neutral technical progress and quality adjusted labour force	583.967	-0.806	-0.758

Table 2.4: Model Selection Criteria for Battese and Coelli (1995)

Model	Log Likelihood	AIC	SC
Model 3 neutral technical progress; human capital in inefficiency equation	-1021.904	1.465	1.520
Model 3* neutral technical progress and quality adjusted labour force	-1021.405	1.462	1.514
Model 3** neutral technical progress and quality adjusted labour force; human capital in inefficiency equation	-1015.646	1.456	1.511
Model 4 non-neutral technical progress; human capital in inefficiency equation)	-1014.231	1.457	1.520
Model 4* non-neutral technical progress and quality adjusted labour force	-1008.838	1.448	1.507
Model 4** non-neutral technical progress and quality adjusted labour force; human capital in inefficiency equation	-1022.212	1.468	1.531

Table 2.5: Generalised Likelihood-Test

	Null Hypothesis	LR	CV	DF	Decision
Model 1	H_0: γ=0	3220.76	7.05	3	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	146.61	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9$=0	77.28	5.99	2	H_0 rejected
Model 1*	H_0: γ=0	3228.05	7.05	3	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	392.50	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9$=0	109.22	5.99	2	H_0 rejected
Model 2	H_0: γ=0	3278.04	7.05	3	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	61.58	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9 = \beta_{10} = \beta_{11}$=0	152.35	9.49	4	H_0 rejected
	H_0: $\beta_{10} = \beta_{11}$=0	121.29	5.99	2	H_0 rejected
Model 2*	H_0: γ=0	3251.80	7.05	3	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	135.17	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9 = \beta_{10} = \beta_{11}$=0	155.92	9.49	4	H_0 rejected
	H_0: $\beta_{10} = \beta_{11}$=0	13.99	5.99	2	H_0 rejected
Model 3	H_0: γ=0	157.61	11.91	6	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	50.84	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9$=0	17.63	5.99	2	H_0 rejected
Model 3*	H_0: γ=0	64.00	10.37	5	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	83.03	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9$=0	34.75	5.99	2	H_0 rejected
Model 3**	H_0: γ=0	75.52	11.91	6	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	63.35	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9$=0	30.14	5.99	2	H_0 rejected

Model 1: neutral technical progress; efficiency model: Battese and Coelli (1992); **Model 1***: neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1992); **Model 2**: non-neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1992); **Model 2***: non-neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1992); **Model 3**: neutral technical progress; efficiency model: Battese and Coelli (1995); human capital in inefficiency equation; **Model 3***: neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1995); **Model 3****: neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1995); human capital in inefficiency equation.

LR: likelihood-ratio test statistic; CV: critical values; DF: degrees of freedom. The critical values for the LR test are obtained from Table 1 of Kodde and Palm (1986).
Table 2.5 continued on next page.

Table 2.5 continued

	Null Hypothesis	LR	CV	DF	Decision
Model 4	H_0: γ=0	155.17	11.91	6	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	60.55	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9 = \beta_{10} = \beta_{11}$=0	32.97	9.49	4	H_0 rejected
	H_0: $\beta_{10} = \beta_{11}$=0	15.35	5.99	2	H_0 rejected
Model 4*	H_0: γ=0	3251.80	10.37	5	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	135.17	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9 = \beta_{10} = \beta_{11}$=0	155.92	9.49	4	H_0 rejected
	H_0: $\beta_{10} = \beta_{11}$=0	13.99	5.99	2	H_0 rejected
Model 4**	H_0: γ=0	39.44	11.91	6	H_0 rejected
	H_0: $\beta_3 = \beta_4 = \beta_5$=0	143.27	7.82	3	H_0 rejected
	H_0: $\beta_8 = \beta_9 = \beta_{10} = \beta_{11}$=0	3.84	9.49	4	H_0 not rejected
	H_0: $\beta_{10} = \beta_{11}$=0	0.69	5.99	2	H_0 not rejected

Model 4: non-neutral technical progress; efficiency model: Battese and Coelli (1995); human capital in inefficiency equation; **Model 4***: non-neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1995); **Model 4****: non-neutral technical progress and quality adjusted labour force; efficiency model: Battese and Coelli (1995); human capital in inefficiency equation.
LR: likelihood-ratio test statistic; CV: critical values; DF: degrees of freedom. The critical values for the LR test are obtained from Table 1 of Kodde and Palm (1986).

2.4.3 Elasticities and Returns to Scale

Because the parameters of the translog production function do not have a direct intepretation (Piesse and Thirtle, 2000, p. 487), the estimates have to be transformed. From the output elasticities of capital and labour it is possible to obtain more information on the form of the production function. Output elasticities can be calculated by taking the partial derivative of output with respect to the factor under consideration (equation 1.60). Since the analysis in the previous section established that the non-neutral technological change specification of the translog stochastic frontier fits the data better (Model 4*), the labour and capital output elasticities are calculated for this model only:

$$\frac{\partial \ln Y_{it}}{\partial \ln K_{it}} = \beta_1 + \beta_3 \ln (K_{it}) + \beta_5 \ln (L_{it}) + \beta_{10} t \tag{2.19}$$

and

$$\frac{\partial \ln Y_{it}}{\partial \ln L_{it}} = \beta_2 + \beta_4 \ln (L_{it}) + \beta_5 \ln (K_{it}) + \beta_{11} t. \tag{2.20}$$

To test for the significance of the marginal effect the estimated variance for this linear combination of maximum likelihood estimates is computed:

$$VAR \{\beta_1 + \beta_3 \ln (K_{it}) + \beta_5 \ln (L_{it}) + \beta_{10} t\} = \mathbf{z}_K{}' \boldsymbol{\Sigma} \mathbf{z}_K \tag{2.21}$$

$$VAR \{\beta_2 + \beta_4 \ln (L_{it}) + \beta_5 \ln (K_{it}) + \beta_{11} t\} = \mathbf{z}_L{}' \boldsymbol{\Sigma} \mathbf{z}_L \tag{2.22}$$

where $\boldsymbol{\Sigma}$ is the (19×19) estimated covariance matrix of maximum likelihood parameters and $\mathbf{z}'$ is a vector of the same row dimension, which has zero entries everywhere except when corresponding to the relevant βs. For capital elasticity, $\mathbf{z}'$ is given by

$$\mathbf{z}'_K = \left[0\ 1\ 0\ \overline{\ln K}\ 0\ \overline{\ln L}\ 0\ 0\ 0\ 0\ \bar{t}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\right],$$

and in the case of labour elasticity, we have

$$\mathbf{z}'_L = \left[0\ 0\ 1\ 0\ \overline{\ln L}\ \overline{\ln K}\ 0\ 0\ 0\ 0\ 0\ \bar{t}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\right],$$

where $\overline{\ln L}$, $\overline{\ln K}$ and $\bar{t}$ are mean values of the log of capital, labour, and time.[20]

Table 2.6: Output Elasticities, Model 4*

		Capital	Labour
Africa	Elasticity	0.116**	0.876**
	Standard Error	0.008	0.016
Asia	Elasticity	0.091**	0.723**
	Standard Error	0.008	0.032
Latin America	Elasticity	0.168**	0.815**
	Standard Error	0.015	0.017
Panel	Elasticity	0.132**	0.816**
	Standard Error	0.009	0.016

**: significant at the 5 per cent level.

The results displayed in Table 2.6 are based on variable means for the panel and the three regional groups in the observation period 1960-1990. As expected, all elasticities are positive and significant. Output is especially elastic with respect to labour (about 0.8 in Africa and Latin America, and more than 0.7 for Asia). Capital elasticity is much lower (0.2 in Latin America, and less than 0.15 for Africa and Asia). The higher labour elasticity is not so surprising because of the predominance of labour intensive sectors in developing countries. Moreover, labour force is quality adjusted, taking into account embodied skills. Thus, the contribution to the total variance of output increases, a result which is in in line with other studies (e.g. Piesse and Thirtle, 2000; Koop *et al.*, 2000a). Given the flexibility of the translog pro-

[20] See Section 1.7 for details.

duction function, it is informative to calculate the elasticities at the regional mean: elasticities change when moving along the frontier, i.e. the value of the elasticity depends on the location of the region.

To test the hypothesis of linear homogeneity, the variance of the sum of the estimated output elasticities is needed (equation 1.63). If this sum is not statistically different from one, we have constant returns to scale, a value greater than one indicates increasing returns to scale, and less than one means decreasing returns to scale.

Table 2.7: Returns to Scale

	$\sum \beta_j$	Standard Error
Africa	0.992	0.0184
Asia	0.814***	0.0340
Latin America	0.984	0.0200
Panel	0.948***	0.0140

$H_0 : \sum \beta_j = 1$; ***: H_0 rejected at the 1 per cent level.

Table 2.7 shows that the hypothesis of constant returns to scale cannot be rejected for Africa and Latin America. In Asia there are substantial decreasing returns to scale. For the panel, the constant returns are rejected in favor of slightly decreasing returns.

The panel structure of the data which encompasses corss-section as well as time dimension, does not allow to draw any conclusion on the benefits from free trade when production technology exhibits increasing returns to scale. The argument is that the benefits of free trade do not depend on differences in technologies or in factor endowments between two countries but from the existence of increasing returns technology and the possibility to increase the size of the market - due to free trade - which would result in a larger quantity produced. Because of increasing returns to scale, per unit cost of production falls as the value of production expands reducing the price of the good and increasing the net welfare benefits. The underlined assumption of similarity in technology and factor endowment between countries cannot be retained for the data set analyzed. The presence of countries with different size and the time dimension presented in the data, do not allow to interpret the results in terms of advantage of trade through increasing returns.

2.4.4 Elasticities of Substitution

Let us now turn to the issue of measuring the degree of substitutability between capital and labour for Model 4*. The formula derived in Section 1.7 for the case of two inputs with Hicks-neutral technical progress can also be applied here (equation 1.65′), because the second order terms of the time variable disappear in the second derivatives of the translog production function with non-neutral technical progress. The elasticities e_K, e_L, and e in equation (1.65′) are substituted with the values calculated above (equations 2.19 and 2.20).[21]

[21] Details for the derivation of the elasticity of substitution and the standard error can be found in Appendix 2.A.

Table 2.8: Elasticity of Substitution, Model 4*

	Elasticity	Standard Error
Africa	1.398***	0.086
Asia	1.604***	0.214
Latin-America	1.313***	0.054
Panel	1.376***	0.076

Null hypothesis: $\sigma = 1$; ***: rejected at the 1 per cent significance level.

Table 2.8 shows that all estimates are positive and significantly greater than one:[22] if the marginal rate of substitution changes by one per cent, the induced change in the input ratio is more than one per cent. This outcome confirms that the choice of translog production function is appropriate and that imposing an elasticity of substitution equal to one, as in the Cobb-Douglas case, would bias the results. Asia exhibits the highest elasticity of substitution, followed by Africa and Latin America.

2.4.5 Trade Channels and Efficiency

In the attempt to determine the importance of international trade in explaining the deviation from the frontier, the attention is focused on technology diffusion.

Table 2.1 presents estimates for different model specifications to examine the link between trade and efficiency through four different trade channels: foreign direct investments (FDI), imports of machinery and equipment (ME),

[22]Note that following e.g. Silberberg (1990, p.285-287), the elasticity of substitution has by definition a positive sign (equation 1.65).

import discipline (IMPD)[23], and exports of manufacturing goods (EXPM). Again, Model 4* is the specification which is discussed here.

The positive effect of FDI on efficiency is explained by Stiglitz (1998): if accompanied by appropriate complementary policies and structures, FDI fosters technology diffusion and growth in the host country. Endogenous growth models (Grossman and Helpman 1991, Rivera-Batiz and Romer 1991, Barro and Sala-i-Martin 1995, Borensztein *et al.* 1998) highlight the role of introducing advanced technology in the host country as an important determinant of economic growth. In the theoretical models of technology diffusion, the rate of economic growth of a backward country depends on the extent of adoption and implementation of new technologies that are already in use in leading countries. Efficiency is driven by FDI and imports of machinery and equipment. Multinational corporations account for a substantial part of the research and development investments in the world. Being the most technologically advanced firms, they are a natural channel through which technology diffuses.[24]

The evidence in Table 2.1 shows that also the second trade channel, machinery and equipment imports, intended to capture possible spillovers resulting from the use of capital goods with embodied foreign knowledge, is inversely related to technical inefficiency in developing countries. Hence, it is an important determinant for the development process. This result supports the empirical finding of Coe *et al.* (1997) and Eaton and Kortum (2001). They show that advanced economies are major exporters of capital goods and

[23]Domestic-import prices ratio. This indicator captures the effect of "imports-as-competitive-discipline" discussed later in this section.

[24]Findlay (1978) argues that foreign direct investment increases the rate of technical progress in the host country through a "contagion" effect from the more advanced technology, management practices, etc. used by the foreign firms. Wang (1990) uses the neoclassical growth approach to show that foreign direct investment increases the "knowledge" applied to production.

these, in turn, are an important channel for the transmission of technology to emerging countries. The outcome reflects the Rivera-Batiz and Romer (1991) model, where new knowledge is embodied in specific machines or procedures, and is acquired through the purchase of these machines. It also confirms, to some extent, the finding of De Long and Summers (1991) and Temple (1998) on the importance of equipment investment in the growth process of developing countries.[25] It is also interesting to compare these results with the one obtained by Blomstrom *et al.* (1994). They find that imported machinery and equipment have no impact on growth. Unlike this, the effect of FDI is found to be positive and significant.[26] The econometric approach used by Blomstrom *et al.* (1994) is different from that adopted here and it may explain the contrasting result of the effect of machinery and equipment. This stresses the importance of identifying the channel through which this trade channel affects output, which might not be possible in a growth regression context, but is one of the strength of the stochastic frontier approach.

The discussion turns to the third trade channel, the import discipline indicator which captures competition effects. The estimated relationship is positive. This implies that a reduction in this indicator decreases inefficiency. A decline in this measure indicates a decrease in price distortion which positively affects efficiency. The theoretical argument of "imports-as-competitive-discipline" explains that trade liberalisation fosters competition by exposing domestic producers to increased import supplies, which provide improved access to technology and investment. The results here support the

[25] They examine the role of equipment investment on growth, without distinguishing between domestic and foreign capital. However, given the embodied knowledge of imported capital goods, the latter are expected to be more important than domestic capital in the growth process of LDCs.

[26] In Blomstrom *et al.* (1994) imported machinery and transport equipment are used as a proxy of embodied knowledge; whereas FDI is used as a proxy of disembodied knowledge.

hypothesis of a positive influence of competition on economic growth through increasing efficiency. According to Stiglitz (2000), "competition allows the emergence of multiple important actors, promoting pluralism and ultimately also efficiency".

The final trade channel "exports of manufacturing goods" is also found to improve efficiency. This result is consistent with earlier findings of Aitken *et al.* (1997) and Clerides *et al.* (1998). Trade, through increasing the production of manufacturing exports, helps the accumulation of specific human capital via learning-by-doing, and thus improves efficiency (Feeney, 1999). Aitken *et al.* (1997) provide evidence of external benefits generated from exporting. These can take the form of transferring knowledge acquired through trade, or of inducing improvements in international transport and export support services. The positive effect of export of manufacturing goods on efficiency is in line with studies which find a positive correlation between exports and output growth in developing countries.

2.5 Conclusion

This chapter uses the stochastic frontier model to estimate different specifications of the production function, technological catch-up (efficiency improvements) and technological change (shifts in the production frontier) for 57 developing countries over the period 1960-1990. It is well known that alternative specifications of the production function lead to ambiguous empirical evidence for competing theories of economic growth (Durlauf and Quah 1999). Therefore, tests are performed to find the specification in line with the data under analysis. Then the important issue of the role of human capital in the process of economic growth is also investigated (Islam 1995, p.1154).

Next, to better understand the importance of technology transfer for the development process of poor countries, four trade channels (FDI, imported capital goods, import discipline indicator and manufacturing exports) are examined with respect to their ability to explain deviations from the frontier. Recent empirical literature - based on theoretical models of Rivera-Batiz and Romer (1991) and Grossman and Helpman (1991) - underlines international trade as the main channel for the diffusion of technological knowledge (Coe and Helpman, 1995; Coe *et al.*, 1997; Keller, 2001a,b; Eaton and Kortum, 1999).

The principal conclusions are as follows:

- Formal tests of the stochastic frontier against the average production function show that the stochastic frontier is the preferred model. Evidence is found that the translog, rather than the Cobb-Douglas production function, provides a better fit to the underlying data.

- The hypothesis of neutral technological change is rejected as the translog production function with non-neutral technical progress turns out to be the preferred specification. As a result, technical change shifts the frontier, and changes the elasticity of substitution between the production factors.

- The translog stochastic frontier production function with quality adjusted labour force is found to fit the data better than that with unadjusted labour force. Moreover, human capital has a positive impact on efficiency. This evidence leads to modify the conclusion of Mankiw *et al.* (1992) and also Benhabib and Spiegel (1994) and Koop *et al.* (2000a) and indicates that human capital affects output though multiple channels: it has a direct effect on production and a positive effect on productivity via efficiency. This last result is similar to the finding obtained by Islam (1995). He states that the positive correlation between the individual fixed effect and human capital seems to suggest that human capital affects growth through productivity: "this does not resolve the question quoted above, but it perhaps at least indicates where to look for the answer" (Islam 1995, pp. 1161-1162).

- The estimated elasticity of output with respect to labour is much higher than with respect to capital. Elasticity of subsitutiton is also very high; it follows that the countries in the sample have the opportunity to respond to changing conditions with regard to input availability.

- Trade channels play an important role in catching-up by improving efficiency. Efficiency is driven by international competition, FDI and imports of machinery and equipment. The last result confirms Tybout's assertion that "imported capital and intermediate goods may be the most important channel through which trade diffuses technology, but clearly, further work is needed to quantify the effects" (Tybout 2000, p.35).

The chapter adds to existing knowledge on the catch-up process by providing new evidence on the he importance of trade channels in helping developing countries to close the technological gap. The results clearly demonstrate that, compared with other methods, the stochastic frontier approach is superior. In fact, Kumar and Russell (2002) underline that "studies of technical change based on total factor productivity, while taking account of capital deepening, require Hicks neutrality of technical change in order to represent the state of technology by a scalar, as in the classic study of technological change by Solow (1957)" (Kumar and Russell 2002, p.6). Moreover, the method adopted here allows solving of the problem in growth accounting methodology emphasised by Temple: the "danger of spurious correlation driven by the omission of initial efficiency" (Temple 1999, p.125).

2.A Elasticity of Substitution for Model 4*

Ignoring the regional dummies and the subscripts for time and country, and adjusting the indices to fit with the notation in equation (1.64), the production function of Model 4* is given by

$$\begin{aligned}\ln(Y) =&\beta_0 + \beta_K \ln(K) + \beta_L \ln(L^*) + \beta_{KK} 0.5 \ln(K)^2 + \\ &+ \beta_{LL} 0.5 \ln(L^*)^2 + \beta_{KL} \ln(K)\ln(L^*) + \beta_t t + \beta_{tt} 0.5 t^2 + \\ &+ \beta_{Kt} \ln(K) t + \beta_{Lt} \ln(L^*) t.\end{aligned} \tag{2.13''}$$

The definition of the substituion elasticity for a production function with two inputs is given by equation (1.65′) from Section 1.7:

$$s = -\frac{f_K f_L (f_K K + f_L L)}{KL(f_{LL} f_K^2 - 2 f_K f_L f_{KL} + f_{KK} f_L^2)}.$$

Since

$$\begin{aligned} f_K &= e_k \frac{Y}{K}; e_K = \beta_K + \beta_{KK} \ln(K) + \beta_{KL} \ln(L) + \beta_{Kt} t; \\ f_L &= e_L \frac{Y}{L}; e_L = \beta_L + \beta_{LL} \ln(L) + \beta_{KL} \ln(K) + \beta_{Lt} t; \\ f_{KL} &= \frac{Y}{K} \frac{\partial e_K}{\partial L} = \beta_{KL} \frac{Y}{KL}; \\ e &= e_K + e_L = \frac{1}{Y} (K f_K + L f_L), \end{aligned}$$

the last line of equation (1.65′) applies here as well:

$$s = -\frac{e}{\left(\beta_{LL}\frac{e_K}{e_L} - e_K - 2\beta_{KL} + \beta_{KK}\frac{e_L}{e_K} - e_L\right)}.$$

The delta method (Greene, 2003, p. 75) requires first derivatives of s with respect to all parameters β_j. Once the gradient vector $\mathbf{j}$ is constructed, the variance of s can be obtained from equation (1.66).[27] Using equation (1.67) to simplify this expression,[28] one obtains

$$\begin{aligned}
\frac{\partial k}{\partial \beta_K} =& 1; \frac{\partial k}{\partial \beta_L} = 1;\\
\frac{\partial k}{\partial \beta_{KK}} =& \ln(K); \frac{\partial k}{\partial \beta_{LL}} = \ln(L);\\
\frac{\partial k}{\partial \beta_{KL}} =& \ln(K) + \ln(L); \frac{\partial k}{\partial \beta_{Kt}} = \frac{\partial k}{\partial \beta_{Lt}} = t;\\
\frac{\partial h}{\partial \beta_K} =& \beta_{LL}\frac{1}{e_L} - \beta_{KK}\frac{e_L}{e_K^2} - 1; \frac{\partial h}{\partial \beta_L} = \beta_{KK}\frac{1}{e_K} - \beta_{LL}\frac{e_K}{e_L^2} - 1;
\end{aligned}$$

$$\begin{aligned}
\frac{\partial h}{\partial \beta_{KK}} =& \beta_{LL}\frac{\ln(K)}{e_L} + \frac{e_L}{e_K}\left(1 - \beta_{KK}\frac{\ln(K)}{e_K}\right) - \ln(K);\\
\frac{\partial h}{\partial \beta_{LL}} =& \frac{e_K}{e_L}\left(1 - \beta_{LL}\frac{\ln(L)}{e_L}\right) + \beta_{KK}\frac{\ln(L)}{e_K} - \ln(L);\\
\frac{\partial h}{\partial \beta_{Kt}} =& \beta_{LL}\frac{t}{e_L} - \beta_{KK}\frac{e_L}{e_K^2} - t; \frac{\partial h}{\partial \beta_{Lt}} = \beta_{KK}\frac{t}{e_K} - \beta_{LL}\frac{e_K}{e_L^2} - t;\\
\frac{\partial h}{\partial \beta_{KL}} =& \beta_{LL}\frac{\ln(L)e_L - \ln(K)e_K}{e_L^2} + \beta_{KK}\frac{\ln(K)e_K - \ln(L)e_L}{e_K^2} - \\
& - \ln(L) - \ln(K) - 2.
\end{aligned}$$

[27] $\mathrm{Var}[\hat{s}] = \mathbf{j}\hat{\Sigma}_{\hat{\beta}}\mathbf{j}'$.

[28] $s = -k(\boldsymbol{\beta})/h(\boldsymbol{\beta})$.

Chapter 3

Growth and Productivity Components

3.1 Introduction

The issue of how to improve economic conditions in LDCs in a globalized economy is central in the political discussion. The recent debates about the recommendations of the Copenhagen Consensus and the results of the G8 Summit in July 2005 show that there are still phenomena which are not well understood. Aid sceptics list success stories like China, India, and Vietnam as examples for the superiority of homegrown reforms over foreign intervention, while the other side points towards problems which cannot be solved on a national base. To identify the channels which can be utilized to impove productivity and growth is a crucial first step towards tackling an important part of the "growth tragedy" problem. To this end, this chapter follows the work by Bosworth and Collins (1996), Temple (1999), Easterly and Levine (2001), and Kumar and Russell (2002) and analyses the results based on Model 4* (Section 2.4.1) in more detail to provide a consistent decomposition of output growth.

Foreign aid can have an impact on factor accumulation. Improving health care[1] and human capital formation improves labour input, while foreign direct investment helps to increase the capital stock.[2] If productivity growth turns out to be the key determinant, it will be necessary to decompose it further and base policy advice on the relative importance of technological change, scale effects and efficiency changes.

The method of choice is a distribution analysis of the determinants of output growth. This apporach is justified because of Quah's 1993; 1996a; 1997 finding[3] that the growth distribution has been transformed from a unimodal to a bimodal shape with higher mean. Empirical analysis based on standard regression methods cannot adequately capture this phenomenon. The first step is a visual analysis for the empirical distributions, based on a non-parametric kernel density estimator. Results from a formal test provide further evidence on the relative importance of input and TFP growth, in addition to a comparison of the contributions of TFP components like technical change, sclae effects, and efficicency changes.

The analysis in this chapter is similar to the study by Kumar and Russell (2002). But, instead of DEA, a stochastic frontier model is employed for reasons discussed in the methodology chapter. In addition, output growth and not labor productivity is decomposed into its components. Finally, the analysis here is focused on a large number of developing countries whereas the study by Kumar and Russell (2002) includes also industrialised countries.

[1] In 2004, Africa accounted for 85 per cent of deaths from Malaria and 75 per cent of deaths from AIDS (source: The Economist, July 2nd 2005, Special Report on Africa).

[2] Given that in 2003 gross national savings were only 16 of GDP, as compared to 42 per cent in East Asia, it is hard to imagine how Africa can overcome its shortage of capital (source: The Economist, July 2nd 2005, Special Report on Africa).

[3] See also Jones (1997).

The results contradict the Kumar and Russell (2002) finding that factor accumulation accounts for most of the output growth. In particular, evidence shows that both TFP and factor accumulation are important for output growth. Moreover, technical change and scale effects are significant components of TFP, whereas efficiency does not play an important role. This last result mirrors the earlier finding of Kumar and Russell (2002). Finally, time-series convergence tests support the impression of visual analysis, and confirm the divergent evolution of output among countries.

3.2 Growth Decomposition

Several studies have tried to assess the importance of TFP and factor accumulation in explaining GDP growth, reporting non conclusive results. De Long and Summers (1993), Bosworth and Collins (1996), and Temple (1998) find that both physical and human capital accumulation are key factors in the development process. Other authors highlight the importance of TFP in accounting for the differences in economic growth and income across countries (Easterly and Levine, 2001; Temple, 1999; Barro and Sala-i-Martin, 1995). TFP is found to be a key component of the growth of output per worker. 50% of output growth of OECD countries is due to TFP growth (Christensen *et al.*, 1980). For seven Latin American countries, Elias (1992) shows that TFP growth explains around 30% of growth. Differently, Young (1995) stresses that factor accumulation is the main source of fast growth in East Asian countries. This section tries to shed some more light on this important issue.

The starting point is a visual analysis of the decomposition of output growth into the contribution of weighted input growth and TFP growth:

$$\frac{\dot{Y}}{Y} = \frac{\dot{\theta}}{\theta} + e_K \frac{\dot{K}}{K} + e_L \frac{\dot{L}}{L}. \tag{3.1}$$

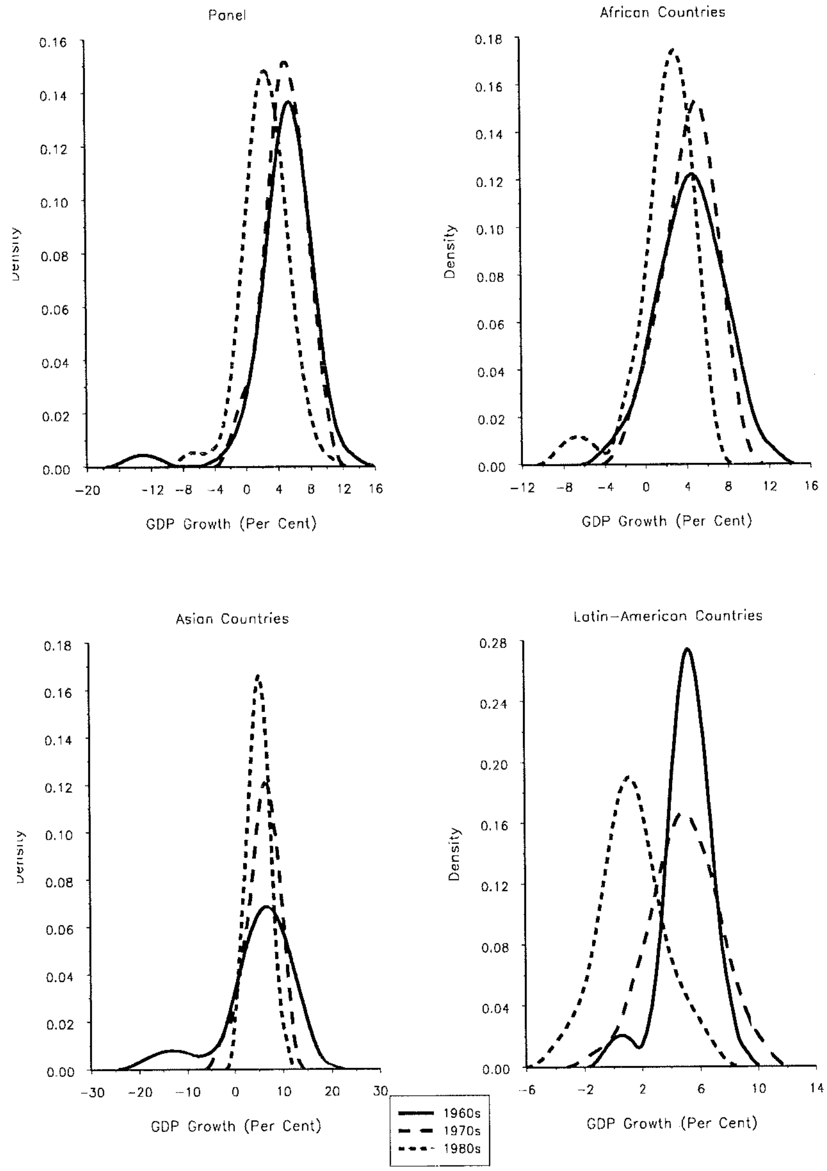
Figure 3.1 illustrates the distribution of GDP growth based on nonparametric kernel density estimates.[4] It reveals that growth has fallen from 6 per cent in the sixties to around 2 per cent in the eighties.[5] Although this decrease in the growth rate characterises all countries, there are regional differences. African countries exhibit a decrease from 5 per cent to 2 per cent and a change from unimodal to bimodal distribution, with some countries concentrated on negative values. Growth rates in Latin American countries fall from 5 per cent to 0 per cent. Asian countries, by contrast, show a stable growth rate around 7 per cent. Since the sample consists of developing countries, this evidence represents an indicator of the divergence process that is taking place between poor and developed countries: Quah (1996a,b, 1997) labels this stylised fact as "twin-club convergence".

Distributions of changes in factor accumulation for Model 4* are displayed in Figure 3.2. Overall, weighted input growth increased from 2 per cent to around 4 per cent in the seventies, and decreased again in the eighties. The distribution changed shape from unimodal to bimodal, with some countries concentrated at very high values. African countries experience an increase from 2 per cent to 3 per cent in the eighties. Asian and Latin American countries do not exhibit changes in factor accumulation; the growth rate is constant around 3 per cent for Asia and 2 per cent for Latin America, although the distribution for Latin American countries becomes bimodal.

[4]These graphs can be interpreted as smoothed histograms of changes of GDP, weighted input growth, and TFP components. For an extensive technical explanation see Appendix 3.A and Pagan and Ullah (1999).

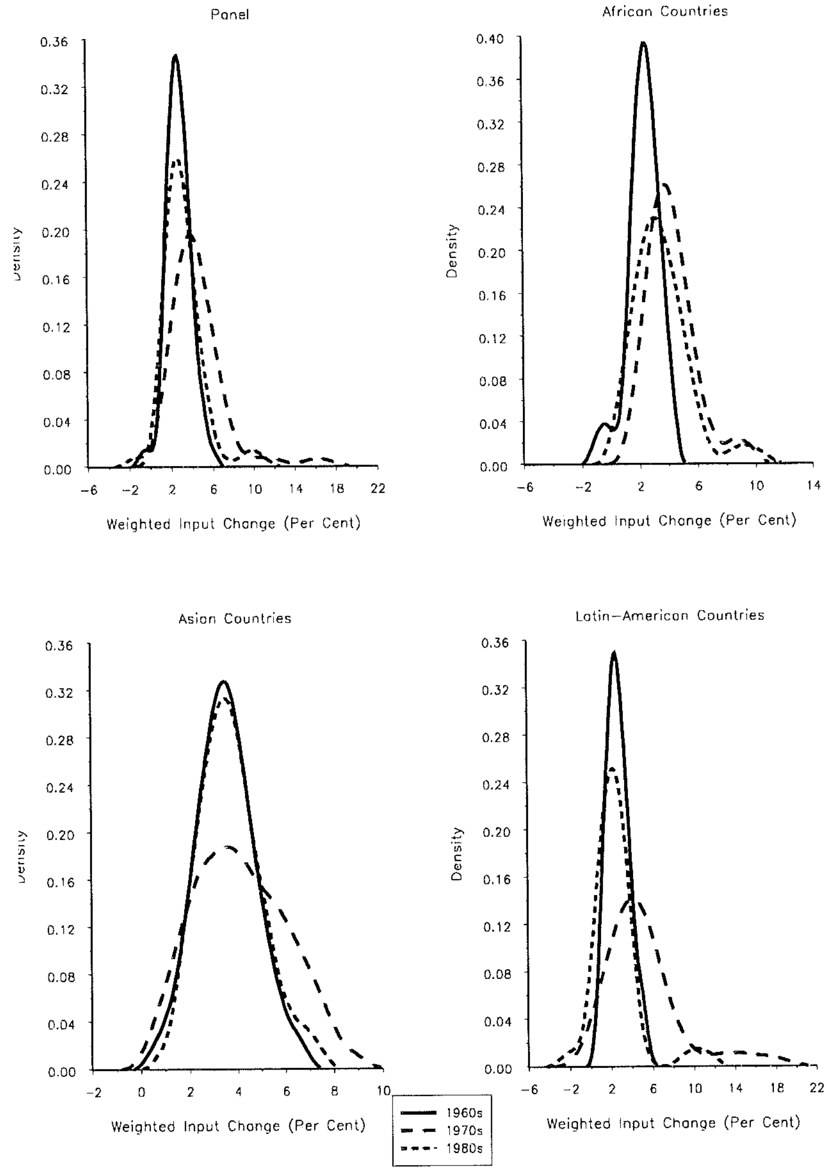
[5]Easterly (2001) and Easterly and Levine (2001) report similar evidence.

Figure 3.1: Distribution of GDP Growth



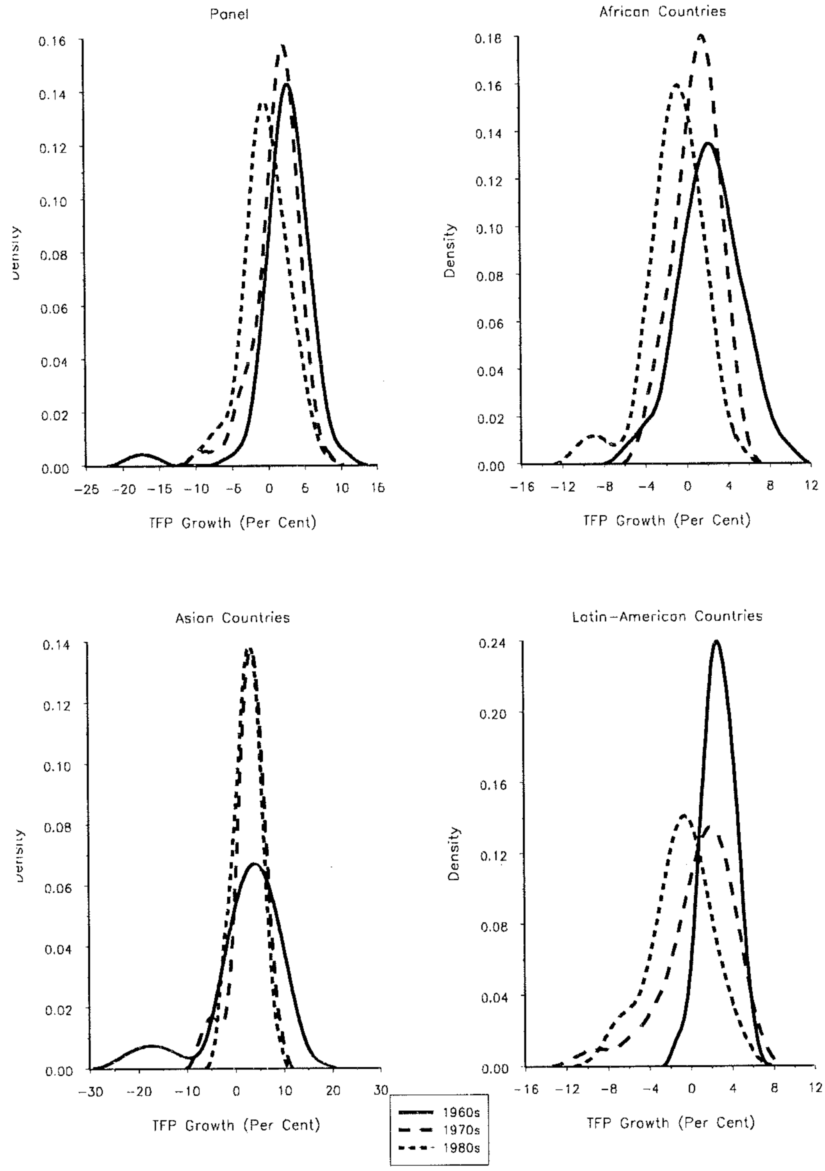
Notes:
The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek. Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

Figure 3.2: Distribution of Weighted Input Growth



Notes:
The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek.
Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

Figure 3.3: Distribution of TFP Growth



Notes:

The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek. Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

The TFP distributions are displayed in Figure 3.3. For all countries, TFP growth collapses from 4 per cent in the sixties to -2 per cent in the eighties. African and Latin American countries exhibit a decrease from 2 per cent to -2 per cent. Asian countries, by contrast, show a stable rate around 4 per cent.

The discussion in Chapter 1 indicates that TFP growth calculated as the Solow residual is not an adequate representation of technical change, because important assumptions are violated. It has to be decomposed into contributions associated with change in technical efficiency, technical change and returns to scale. The objective is to assess the degree to which each of the three components accounts for productivity change.

Consider a two-factor production frontier with Hicks-neutral technical progress:

$$Y = \theta F(L, K)\exp(-u) \tag{3.2}$$

where Y is real output; θ stands for an index of Hicks neutral technical progress; L and K are labour and capital inputs; $u \geq 0$ represents output-oriented technical inefficiency.

Taking logs on both sides of equation (3.2) and differentiating with respect to time yields:

$$\frac{\dot{Y}}{Y} = \frac{\dot{\theta}}{\theta} + \frac{\Theta F_L L}{Y}\frac{\dot{L}}{L} + \frac{\Theta F_K K}{Y}\frac{\dot{K}}{K} - \dot{u}, \quad \text{where} \quad \Theta = \theta\exp(-u), \tag{3.3}$$

where $\frac{\Theta F_L L}{Y} = e_L$ and $\frac{\Theta F_K K}{Y} = e_K$ are elasticities of output with respect to labour and capital, and $e = e_L + e_K$. The term e can be greater, less, or equal to one, and it provides a measure of returns to scale characterising the production frontier.[6]

The Solow residual ($\frac{\dot{\theta}_S}{\theta_S}$) is given as the difference in the growth of output and the contribution of the inputs weighted by their respective factor shares in value added:[7]

$$\frac{\dot{\theta}_S}{\theta_S} = \frac{\dot{Y}}{Y} - \left(s_L \frac{\dot{L}}{L} + s_K \frac{\dot{K}}{K} \right), \tag{3.4}$$

where $s_L = \frac{wL}{PY}$ and $s_K = \frac{rK}{PY}$ are the observed expenditure share of inputs.[8] Assuming "true" output growth $\frac{\dot{Y}}{Y}$ to be represented by equation (3.3), i.e. allowing for inefficiencies, and substituting this into equation (3.4) yields

$$\frac{\dot{\theta}_S}{\theta_S} = \frac{\dot{\theta}}{\theta} + e_L \frac{\dot{L}}{L} + e_K \frac{\dot{K}}{K} - \dot{u} - \left(s_L \frac{\dot{L}}{L} + s_K \frac{\dot{K}}{K} \right), \tag{3.5}$$

where $e_L = \frac{\Theta F_L L}{Y}$ and $e_K = \frac{\Theta F_K K}{Y}$. Equation (3.5) can be rewritten as

$$\frac{\dot{\theta}_S}{\theta_S} = \frac{\dot{\theta}}{\theta} + (e_L - s_L)\frac{\dot{L}}{L} + (e_K - s_K)\frac{\dot{K}}{K} - \dot{u}. \tag{3.6}$$

Substracting and adding $\frac{e_L}{e}\frac{\dot{L}}{L} + \frac{e_K}{e}\frac{\dot{K}}{K}$ gives

$$\begin{aligned} \frac{\dot{\theta}_S}{\theta_S} = & \underbrace{\frac{\dot{\theta}}{\theta}}_{\text{(I)}} + \underbrace{(e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L} + \frac{e_K}{e}\frac{\dot{K}}{K} \right)}_{\text{(II)}} + \\ & + \underbrace{\left(\frac{e_L}{e} - s_L\right)\frac{\dot{L}}{L} + \left(\frac{e_K}{e} - s_k\right)\frac{\dot{K}}{K}}_{\text{(III)}} - \underbrace{\dot{u}}_{\text{(IV)}}. \end{aligned} \tag{3.7}$$

Equation (3.7) distinguishes four components of total factor productivity

[6]See Tables 2.6 and 2.7 for estimates based on Model 4*.
[7]For the following decomposition, see Kumbhakar and Lovell (2000, pp. 282-284).
[8]Wage: w; interest rate: r.

change as measured by the Solow residual $\frac{\dot{\theta}_S}{\theta_S}$. The first component (I) on the right-hand side is technical change, $\frac{\dot{\theta}}{\theta}$. Many empirical studies, using the growth accounting method, consider productivity growth $\frac{\dot{\theta}_S}{\theta_S}$ and technical progress $\frac{\dot{\theta}}{\theta}$ as synonymous, but as equation (3.7) shows this is only true if all the other components are equal to zero.

The second component (II) represents the scale economies effect, $\left[(e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L}+\frac{e_K}{e}\frac{\dot{K}}{K}\right)\right]$. It captures how changing inputs changes productivity. The contribution of scale economies depends on returns to scale. In the case of constant returns to scale $\{e = 1 \rightarrow (e-1) = 0\}$, input changes $\left(\frac{\dot{L}}{L}, \frac{\dot{K}}{K}\right)$ do not affect productivity change. Either increasing returns to scale $\{e > 1 \rightarrow (e-1) > 0\}$ and input expansion $\left(\frac{\dot{L}}{L} > 0, \frac{\dot{K}}{K} > 0\right)$ or decreasing returns to scale $\{e < 1 \rightarrow (e-1) < 0\}$ and input contraction $\left(\frac{\dot{L}}{L} < 0, \frac{\dot{K}}{K}\right) < 0$ have a positive contribution to productivity change. In this case, the value of expression $\left[(e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L}+\frac{e_K}{e}\frac{\dot{K}}{K}\right)\right]$ will be positive.[9]

The third component (III) captures allocative inefficiency, $\left\{\left(\frac{e_L}{e} - s_L\right)\frac{\dot{L}}{L} + \left(\frac{e_K}{e} - s_k\right)\frac{\dot{K}}{K}\right\}$. The allocative inefficiency component represents the deviations of output elasticities of inputs ($e_L = \frac{\Theta F_L L}{Y}$, $e_K = \frac{\Theta F_K K}{Y}$) from their expenditure shares ($s_L = \frac{wL}{PY}$, $s_K = \frac{rK}{PY}$). It quantifies how much the input prices ratio diverts from the marginal products ratio.[10]

The fourth component is technical inefficiency change, $\dot{u}$. Equation (3.7) demonstrates that only in the case of time invariant technical efficiency, constant returns to scale, and allocative efficiency, the Solow residual measures technical change correctly. In this study, all the components except allocative

[9] By definition, the values of e, e_L, e_L are always positive.

[10] Allocative efficiency occurs when the marginal rate of substitution between any of the inputs equals the corresponding input price ratio. If this equality is not satisfied, it means that the producer is not using its inputs in the optimal proportions.

efficiency are estimated.[11] The expression evaluated is

$$\frac{\dot{\theta}_S}{\theta_S} = \frac{\dot{\theta}}{\theta} + (e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L} + \frac{e_K}{e}\frac{\dot{K}}{K}\right) - \dot{u}. \tag{3.8}$$

The estimates of the three sources of productivity change are derived from the parameter estimates of the translog stochastic frontier production function assuming non-neutral technological change with quality-adjusted labour force (Model 4*). The decomposition approach in this chapter is equivalent to various nonparametric productivity indices (Fried *et al.*, 1993, p.173).[12]

3.3 Productivity Components

Table 3.1 lists the median and interquartile range for the entire panel and the three regions (Africa, Asia and Latin America), from 1961 to 1970, from 1971 to 1980 and 1981 to 1990, of GDP growth and each of two components: weighted input growth and TFP growth. In addition, the three components of TFP growth - technological change, scale effect and efficiency - are shown. The median for the panel provides evidence that GDP growth is decreasing over time. Substantial regional differences are evident. Asia shows the lowest decline (from 6.2 per cent to 5.2 per cent), whereas Africa and Latin America register a fall in GDP growth rate from 5 per cent to 2 per cent.

For the panel, Africa, and Latin America, input growth is more important

[11] This decision is based on data restrictions. For the countries under analysis, input price data for a sufficiently long time period could not be found.

[12] The use of Malmquist productivity index introduced by Caves *et al.* (1982a,b) has become common in the literature. This index does not provide, however, an accurate measure of productivity change, because it ignores the contribution of scale economies. The results of Chapter 2 show that this is a significant feature of the estimated production function (Model 4*). Therefore, the Malmquist index is not suitable in the present context, as demonstrated by Grifell-Tatjé and Lovell (1995).

than TFP growth in explaining the growth rate of GDP, except in the period 1961-1970. For Asian countries, most of the GDP growth over the period is attributable to TFP growth. The finding that total factor productivity change has been a major contributor to growth in Asia is consistent with Young (1995) and Chang and Luh (1999).[13] Easterly and Levine (2001) argue that it is productivity gains and not factor accumulation, that is the fundamental cause of growth.

In terms of the tripartite decomposition, the derminants of TFP have regionally specific relative importance. For the panel, TFP growth is driven primarily by technological change, followed by efficiency and then the scale factor. Africa stagnation is primarily attributable to a collapse in technological change (from 2.1 per cent to 0.0 per cent) and in efficiency growth (from 0.1 per cent to 0.0 per cent). The decrease in TFP growth in Latin America (from 2.5 per cent to 0.1 per cent) is due to a decline of technological change and the scale factor. Efficiency shows a slowly increasing rate. Asian countries exhibit a persistent TFP growth over all the period, primarily driven by technological change and efficiency improvement, with a deterioration in the scale effect factor. These results confirm the view that rapid economic growth such as in East Asia can largely be explained by successfully catching up with technology.[14]

[13]This result is at odds with the studies of Bosworth *et al.* (1995), Bosworth and Collins (1996) and Kim and Lau (1994, 1995). Bosworth *et al.* (1995) and Bosworth and Collins (1996) emphasize the importance of physical and human capital accumulation in explaining the growth performance of many East Asia economies. Rodrik (2000) comments on this paper and underlines that East Asia has a high level of skilled workers relative to its capital stock in the early stage of development, and this raises the return to capital and induces capital accumulation. Kim and Lau (1994, 1995) do not take into account human capital, and, as Chang and Luh (1999) stress, part of the growth in productivity may be due to the effect of human capital.

[14]See Barro and Sala-i Martin (1992), Romer (1990, 1993), and Pack (1992).

Table 3.1: Distribution of Growth Rates

								TFP Components					
		GDP		INPUT		TFP		TC		SE		EFF	
Group	Period	M	IQR	M	IQR	M	IQR	M	IQR	M	IQR	M	IQR
Panel	1961-70	5.7%	5.0%	2.4%	1.4%	2.9%	5.0%	2.2%	1.2%	-0.1%	0.5%	0.0%	1.3%
	1971-80	5.1%	6.7%	3.2%	2.1%	2.0%	6.3%	1.3%	1.2%	-0.1%	0.7%	0.2%	3.2%
	1981-90	3.0%	5.9%	2.4%	2.1%	0.6%	6.1%	0.0%	1.5%	-0.1%	0.6%	0.2%	5.2%
Africa	1961-70	5.1%	6.0%	2.4%	1.1%	2.4%	6.5%	2.1%	1.0%	-0.2%	0.3%	0.1%	1.3%
	1971-80	4.9%	7.0%	3.1%	1.8%	1.1%	6.5%	1.3%	1.2%	-0.1%	0.4%	0.3%	2.5%
	1981-90	2.9%	5.3%	2.5%	2.5%	-0.4%	5.9%	-0.2%	1.4%	0.0%	0.4%	0.0%	5.3%
Asia	1961-70	6.2%	5.0%	2.4%	1.3%	3.6%	4.7%	3.0%	0.8%	-0.6%	0.4%	0.6%	1.4%
	1971-80	6.8%	5.2%	2.9%	2.2%	3.8%	4.5%	2.3%	1.1%	-0.8%	0.4%	0.7%	4.1%
	1981-90	5.2%	6.0%	2.3%	1.4%	3.0%	5.5%	1.0%	1.2%	-0.7%	0.5%	0.2%	3.8%
Latin-America	1961-70	5.1%	4.9%	2.4%	1.6%	2.5%	4.5%	1.9%	0.8%	0.0%	0.2%	-0.2%	1.0%
	1971-80	5.1%	5.3%	3.5%	2.3%	1.7%	5.7%	1.0%	0.8%	0.1%	0.3%	-0.1%	3.1%
	1981-90	2.1%	5.0%	2.3%	2.2%	0.1%	5.9%	-0.3%	1.2%	0.0%	0.3%	0.2%	6.2%

Notes:

GDP: GDP growth; INPUT: weighted input growth; TFP: TFP growth; TC: technological change; SE: scale effect; EFF: efficiency.
M: median; IQR: interquartile range.

Table 3.2: Median Efficiency, 1960-1990

Country	Efficiency	Country	Efficiency
Mauritius	0.60	Uruguay	0.73
Sri Lanka	0.61	Tunisia	0.74
Uganda	0.64	Pakistan	0.74
Egypt	0.65	Malta	0.74
India	0.65	Philippines	0.75
El Salvador	0.67	Argentina	0.75
Mali	0.67	Chile	0.75
Haiti	0.68	Thailand	0.76
Kenya	0.69	Zambia	0.76
Ghana	0.69	Cameroon	0.76
Panama	0.69	Dominican Republic	0.76
Sudan	0.69	Côte d'Ivoire	0.77
Senegal	0.70	Tanzania	0.78
Trinidad and Tobago	0.70	Algeria	0.79
Sierra Leone	0.70	Paraguay	0.80
Bangladesh	0.70	Indonesia	0.80
Jordan	0.71	Singapore	0.80
Rwanda	0.71	Malaysia	0.82
Madagascar	0.71	Republic of Korea	0.83
Jamaica	0.71	Ecuador	0.84
Honduras	0.71	Turkey	0.85
Guatemala	0.71	Colombia	0.85
Morocco	0.72	Bolivia	0.85
Costa Rica	0.72	Iran	0.87
Malawi	0.73	Zimbabwe	0.88
Peru	0.73	Venezuela	0.90
Cyprus	0.73	Mexico	0.95

Notes:
Ascending order; median: Ethiopia (0.73).

In Table 3.2, the median efficiency levels for all 55 countries over the sample period 1960-1990 are displayed. The overall median is Ethiopia, with an efficiency level of 0.73. The results show that 65% of the African countries in the sample are below the median, and 40% in the 25% percentile. The other regions are more efficient. Especially, Asian countries tend to have high efficiency levels, with 67% above the median, and 42% in the 75% percentile. 55% of the countries in the reference group are above the median.

Within the group of Asian countries, there is relatively little variation in median efficiency levels. Korea, Singapore, Indonesia and Malaysia stand out as being very efficient, but Sri Lanka and India are inefficient. Within the set of Latin American countries, El Salvador, Haiti and Panama are less efficiency than others, whereas Venezuela and Mexico are very close to the frontier. Most of the African countries are extremely inefficient with the exception of Zimbabwe. Zimbabwe became independent from Britain in 1980. At that period, the economy was more industrialised than most African countries, with a diversified productive base, well-developed infrastructure and a relatively advanced financial sector. Economic deterioration started in the late 1990s with inequities in land distribution, poverty, unemployment, and the HIV/AIDS epidemic.[15] Given that the observation period ends in 1990 for resasons explained in Section 2.3, these effects do not show up in the results.

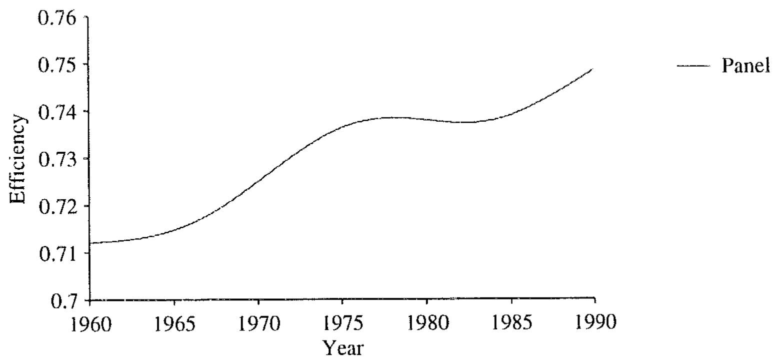
Mexico, Colombia, Bolivia, Iran and Venezuela turn out to be very efficient. One potential explanation of this peculiar finding is that they are all oil producers with economies based on capital intensive petroleum industries. They result efficient with respect to a production frontier which has been found to be characterised by capital intensive technology (see Chapter 2). These results are consistent with other studies. In particular, Kumar and Russell (2002, footnotes 4 and 8) find that Iran and Venezuela are on the production frontier in 1965, and Mexico in 1990. Mexico is also found to be efficient in the study by Suhariyanto and Thirtle (2001). Koop *et al.* (2000a,

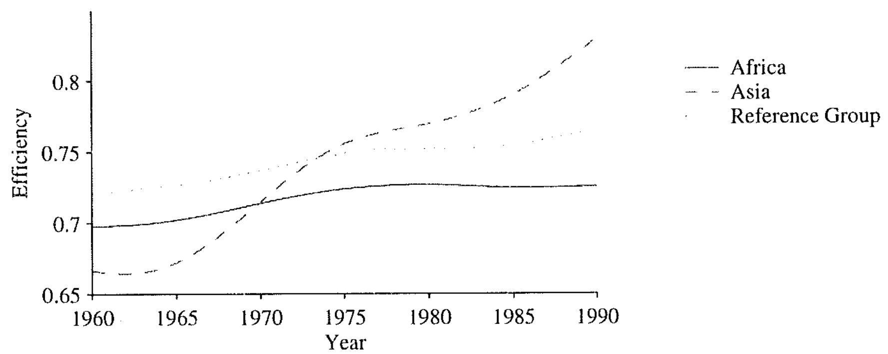
[15] "Country Brief 2003", The World Bank Group, web site http://www.worldbank.org/afr/.

p.295) conclude that Venezuela is notably efficient.

To give a visual impression of the change of efficiency over time, median efficiency for each year is displayed in Figure 3.4. Efficiency in the panel increases from 1960 to 1990 by 5%. This increase is mainly due to the Asian countries, while efficiency in Africa and the reference group remains almost constant.

Figure 3.4: Development of Efficiency over Time





The efficiency levels are smoothed using the Hodrick and Prescott (1997) filter.

Figure 3.5 shows how the frontier changes over time, by plotting efficiencies for each year for the two countries which are closest to the frontier over the observation period: Mexico and Singapore.[16] The diverse experience of these two countries is highlighted in figure 3.5. At the beginning of the observation period, production in Mexico is close to the frontier (efficiency value of 0.99), then a downward trend in efficiency is observed, with an average growth rate of -0.01. In 1990, efficiency reaches its minimum (0.86). For Singapore, the story is reverse: efficiency starts to grow from a level of 0.62 with an average rate of 0.02 and reaches a maximum of 0.98 at the end of the observation period.

How can this difference be explained? In the late 1960s, Singapore trade policy changed from protectionistic import substitution to a outward-oriented strategy based on promoting manufacturing exports (Bosworth and Collins, 1996).[17] Moreover, throughout the seventies and eighties, imports of capital goods and FDI have been substantially encouraged by government policies.[18] Finally also the investment and saving rates increased during the period. Differently, in the 1980s the Latin American countries were hit by the debt crisis. As a consequence, external macroeconomic conditions have been dramatically adverse, and the decrease in the real oil price affected Mexico's major export product. The policy responses to the 1982 debt crisis and the 1986 oil price collapse involved exchange rate and fiscal adjustments; three

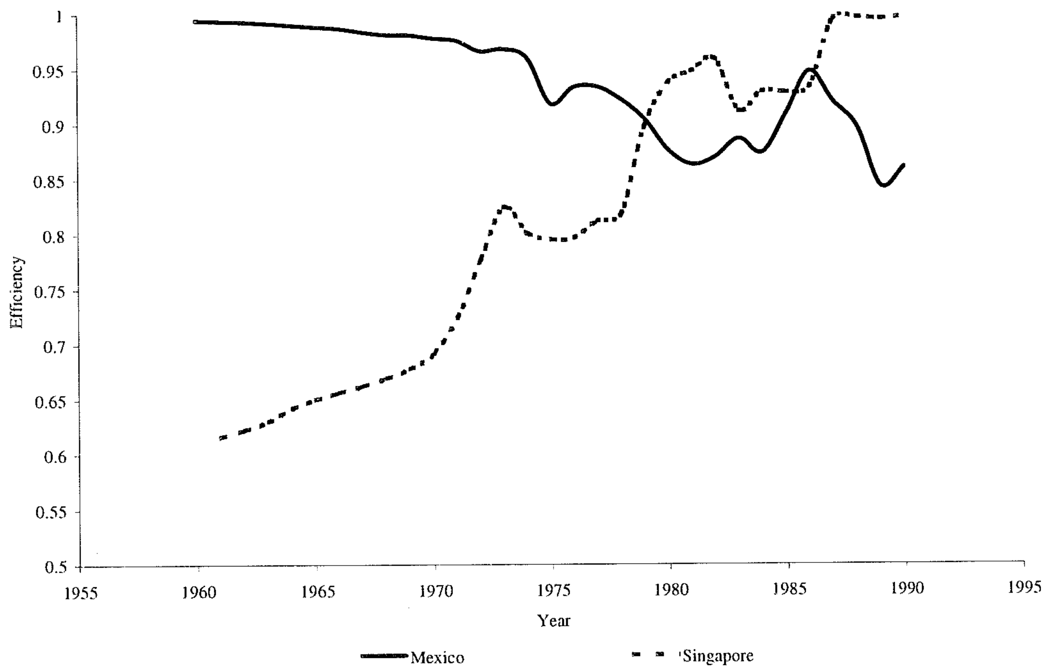
[16]From 1960 to 1979, Mexico is the most efficient country (19 years), after 1979, it is Singapore (7 years). For some years, Ecuador (1 year), Zimbabwe (2 years), and Malaysia (2 years) can be found closest to the frontier.

[17]Japan and all East Asian countries, except Hong Kong, increased openness during the late 1960s.

[18]Bosworth and Collins (1996) underline that, during the period 1960-1990, while Malaysia and Singapore encouraged FDI, Indonesia and Thailand, and especially Taiwan and Korea, restricted FDI. Taiwan is not in the data set analyzed here, but for Indonesia and Thailand, the average growth of FDI is less than 0.01.

large devaluations took place in 1982. These difficulties lead to reverse the import liberalization policies adopted during 1970s and to establish direct import controls in the mid-1980s (World Bank, 1986, 1988). Supporting empirical evidence comes from the study of Blomstrom and Wolff (1994), who find a convergence process between Mexican and US industries during the late 60s and the 70s. This is in line with the finding that Mexico is closest to the frontier in this period.

Figure 3.5: Development of the Efficiency Leaders over Time



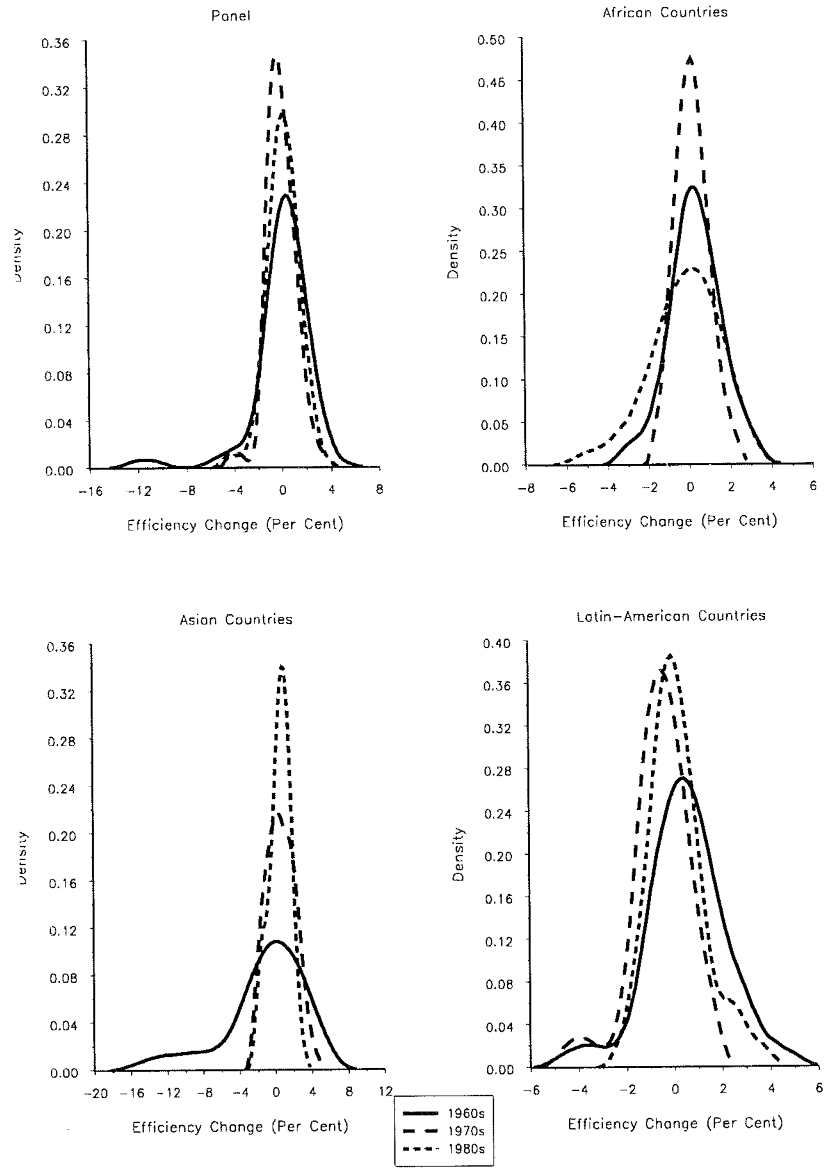
This section adds evidence to the results in the body of literature analyzing the economic success of East Asian countries. It turns out that it is technical change which determines economic growth. Moreover, the findings support the view that technological progress and increasing efficiency are the principal forces for catching up with industrial economies. Therefore, policies which promote efficiency and technological progress will help developing countries to close the technology gap.

3.4 Analysis of Productivity Distributions

The discussion turns now to the analysis of the distributions of the productivity components. The distributions are nonparametric kernel-based estimates.[19] Figure 3.5 illustrates the distribution of percentage change in efficiency when the underlining stochastic frontier model is Model 4*. Efficiency shows little variation across time. For all countries, efficiency growth is around 1-2 per cent, and there is a higher concentration of the values around the mean in the last decade. This is particularly true for Asian and Latin American countries. Over time, African countries show a higher dispersion with a left skewness. This indicates that some African countries had been experiencing a sizeable decrease in efficiency from the sixties to the eighties. Some countries appear to have lost with respect to efficiency over the entire sample period.

[19]See Appendix 3.A for details.

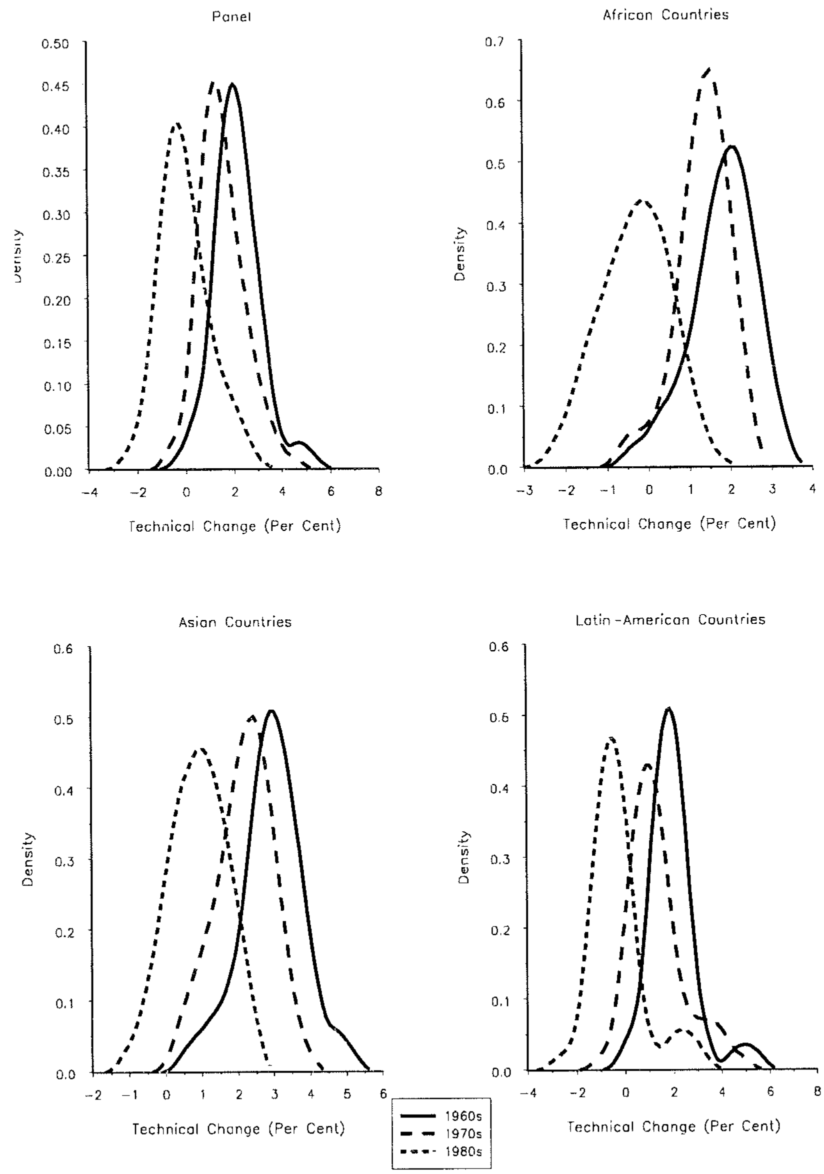
Figure 3.6: Distribution of Efficiency Change



Notes:

The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek. Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

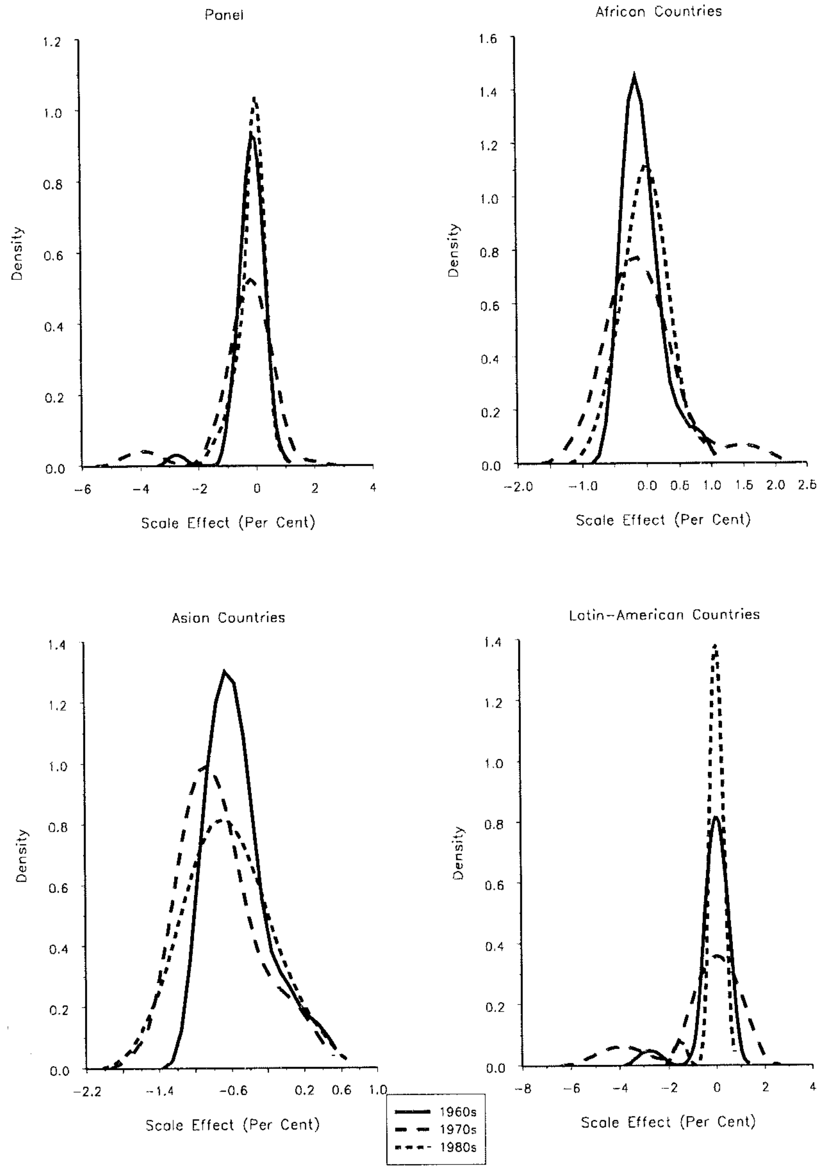
Figure 3.7: Distribution of Technical Change



Notes:

The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek. Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

Figure 3.8: Distribution of Scale Effects



Notes:
The distributions are calculated using the quartic kernel density estimator from a GAUSS procedure archive by Markus Heintel and a GAUSS graphics programm by Ulrich Woitek.
Subperiods: 1960s (1961-1970), 1970 (1971-1980), 1980s (1980-1990).

The distribution of technical change for the model in equation (2.13) is displayed in Figure 3.7. Overall, there is a decrease in the mode of technical change from 2 per cent to around zero. Africa and Latin America report a negative growth rate in technology during the eighties for most of the countries, although the Latin American distribution shows lower variance and it is bimodal at the right. This means that technological change has benefited only some Latin American countries. Latin American countries become divided, as a stylized fact, into two categories: countries with high rate of technological progress and others with technological degradation.

Turning to the distribution of scale effect changes, Figure 3.8 provides evidence for a mode of zero for the panel. In the eighties, the distribution for the entire panel of countries reveals a greater variation in the values of returns to scale. Moreover, there are regional differences. For African countries there is evidence of an increase in the scale effect from the 60s to the 90s. The scale effect for Asian countries becones less important over time, and for the Latin-American countries in the sample, the change is close to zero.

Visual analysis of empirical distributions has obvious limitations. Therefore, additional evidence is provided from a formal test. Applying the distribution test outlined in Appendix 3.A, Kumar and Russell (2002) analyze a decomposition of output growth in 37 countries for the period 1965-1990. The basic idea is to compare counterfactual growth distributions with the actual outcome. In the following section, this approach is adapted to the decomposition of the growth rate of output $\dot{Y}/Y$ into the contribution of weighted input growth $\dot{X}/X$ and TFP growth $\dot{\theta}_S/\theta_S$. The first test analyses the importance of TFP:

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X}\right).$$

If the null hypothesis can be rejected, the contribution of TFP is significant. For the assessment of the contribution of input growth, the null hypothesis is

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{\theta}_S}{\theta_S}\right).$$

Using equation (3.8), TFP growth can be further decomposed into technical change, scale effects, and the contribution of efficiency.[20] If TFP growth plays an important role, the identification of the exact source of the contribution is neccessary, because of the "grab-bag" nature of this measure. If the role of TFP turns out to be neglegible, this might be due to the fact that the TFP componments compensate each other. The following three hypotheses are tested:

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - \frac{\dot{\theta}}{\theta}\right)\right);$$
$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - (e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L} + \frac{e_k}{e}\frac{\dot{K}}{K}\right)\right)\right);$$
$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - \dot{u}\right)\right).$$

Because the number of observations is low, Kumar and Russell (2002) do not rely on the asymptotic distribution of the test statistic, but perform a bootstrap approximation of the distribution. The number of countries which are both in 1965 and 1990 in the sample is only 32,[21] therefore, the same approach is applied here.[22]

[20]In the empirical application, TFP contains also a measurement error.
[21]Starting in 1960 would mean to lose another 4 observations.
[22]See Appendix 3.B for details.

The results of the test are displayed in Table 3.3. The first two tests (first two rows of Table 3.3) reject the hypothesis that actual distribution of output growth $\left(\frac{\dot{Y}}{Y}\right)$ is identical to the counterfactual distribution constructed by using only input accumulation $\left(\frac{\dot{X}}{X}\right)$ or TFP growth $\left(\frac{\dot{\theta}_S}{\theta_S}\right)$. Since the null hypothesis can clearly be rejected, one can conclude that both input growth and TFP growth are important for output growth. The next three tests (rows 3-5) verify the significance of productivity components.

The null hypothesis of no difference between actual and counterfactual distribution, i.e. the assumption that changes in productivity $\left(\frac{\dot{\theta}_S}{\theta_S}\right)$ can be explained only by scale effects $(e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L}+\frac{e_k}{e}\frac{\dot{K}}{K}\right)$ and efficiency change $(\dot{u})$, is rejected (row 3). Similarly, the fourth row indicates that the hypothesis that only technological change and efficiency change are important is not supported by the data. It is no possible to reject the hypothesis that only technological change and scale effect account for productivity changes (row 5). The tests provide evidence that technical change and scale effect are important components, while efficiency changes have no significant influence on the distribution of TFP growth.

These last findings are consistent with the results in the previous section. Both TFP growth and factor accumulation play a relevant role in the growth performance of the countries under analysis. However, TFP appears to be the most important component for the success of Asian countries, whereas the poor growth performance of African and Latin American countries can be attributed to problems with factor accumulation.

The stochastic frontier method allows to recognise that the efficiency of a country can only be correctly measured against the available technology. Consequently, the technical frontier faced by a country may differ from the global frontier, due to time lags in the international transfer of technology.

The countries investigated are low income countries, which face a global frontier exogenously expanding by research in the developed countries. From the results the movements of the regional frontiers toward the global frontier seem to be more relevant than the catching up toward the common frontier. The conclusion is that the countries on the regional frontier absorb new foreign technology more than the countries below the frontier. This is consistent with the view that the potential to adopt foreign technology depends on the stage of development (Grossman and Helpman, 1994). According to this theory, growth in the early stages may be primarily associated with physical and human capital accumulation, and significant potential for growth through technological catching-up may only emerge once a country has crossed some development threshold. Asian countries, differently from the other developing countries, have adopted policies that have played a positive role in both factor accumulation and productivity gain. These include stable macroeconomic policies, human capital accumulation and trade openness (Krueger, 1995; Sachs and Warner, 1995; Rodrik, 1992, 1996; Easterly *et al.*, 1993). The different stages of development help to explain why efficiency changes contribute significantly to the productivity distribution of Asian countries but not of other countries under analysis.

Table 3.3: Test Results

H_0	T	%10	%5	%1
$f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X}\right)$	5.72	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{\theta}_S}{\theta_S}\right)$	8.52	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - \frac{\dot{\theta}}{\theta}\right)\right)$	14.00	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - (e-1)\left(\frac{e_L}{e}\frac{\dot{L}}{L} + \frac{e_k}{e}\frac{\dot{K}}{K}\right)\right)\right)$	11.67	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{\dot{\theta}_S}{\theta_S} - \dot{u}\right)\right)$	-0.12	0.67	1.06	2.03

Notes:
The critical values are based on the simulation results from Table 3.5, $N = 32$.

3.5 Convergence

Slow technological catch-up often causes lack of convergence in output levels (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1995). Technological catch-up is represented by movement towards the frontier, captured by increases in efficiency. However, an increase in efficiency does not necessarily imply that there is a tendency for technology transfer to reduce the gap between the rich and the poor, since it is possible that relatively rich countries benefit from efficiency improvements as much as or even more than poor countries.

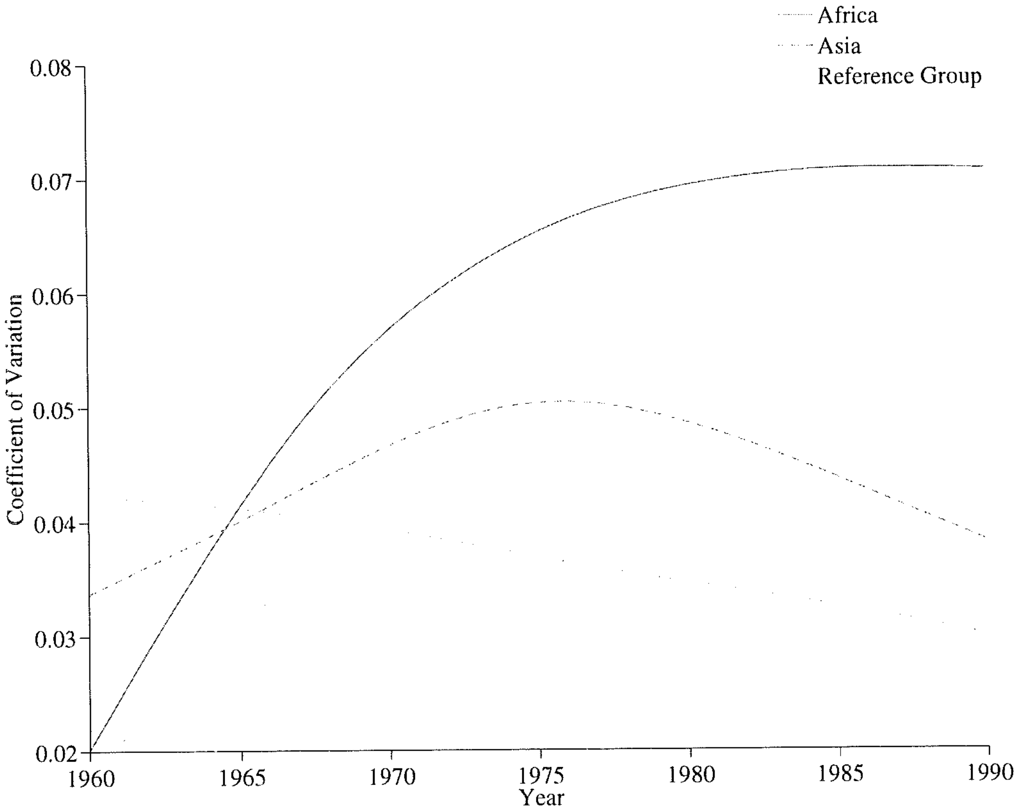
To test β-convergence,[23] a generalised least-squares regression of the change in GDP per capita over the observation period on its level in 1960 is used. The coefficient of -0.002 with a t-statistic of -6.520 indicates that backward countries converge only very slowly towards the more advanced ones. This simple test presents only weak evidence of convergence and mo-

[23] See Section 1.8 for a description of the tests.

tivates further examination.

The second test, σ- convergence, investigates the cross-sectional tendency of income disparities between countries to narrow over time. The coefficient of variation for each of the regions is displayed in Figure 3.9. There is a decrease in income disparities between Asian countries, as well as between Latin American countries, although less pronounced. African countries exhibit an increase in dispersion over time.

Figure 3.9: σ-Convergence



The time paths of the coefficient of variation are smoothed using the Hodrick and Prescott (1997) filter.

The validity of the classical approach to convergence is restricted to homogeneous countries (Durlauf and Johnson, 1995; Evans, 1996; Evans and Karras, 1996; Quah, 1996b). Since the countries in the sample under analysis are very inhomogenous, the previous analysis of β-convergence could be misleading. Following the suggestion of Quah (1996a,c) to exploit the time series and cross-sectional information in the data,[24] the panel unit root test developed by Maddala and Wu (1999) is used.[25] This test allows for an unbalanced panel, cross-sectional correlations, and heterogeneity effects across countries.

The starting point is a panel version of the ADF equation

$$y_{i,t} = \mu_i + \delta t + \rho y_{i,t-1} + \sum_{j=1}^{p} \beta_j y_{i,t-1-j} + e_{i,t}, \tag{3.9}$$

where $y_{i,t}$ is the log of income per capita at time t for country i; and $e_{i,t}$ is an error term following the usual assumptions. The null hypothesis of non-stationary ($H_0 : \rho = 1$) is tested against the alternative that the model is stationary ($H_1 : \rho < 1$). The general model in equation (3.9) allows for individual fixed effects μ_i (and hence, testing for conditional convergence) as well as different dynamics. In addition, Maddala and Wu (1999) relax the assumption that $\rho_1 = \rho_2 = \ldots = \rho_N = \rho$: for each of the countries, a separate ADF test is performed and the average over the p-values is calculated (equation 1.84 on p. 72). The p-values are derived based on the simulation exercise described in Section 1.8.[26]

[24] See also Durlauf and Johnson (1995); Bernard and Jones (1996a); Evans (1996) and Evans and Karras (1996).

[25] For full details of this test see Section 1.8.

[26] Countries with less than 10 observations are excluded from the analysis (sample size: 49).

Table 3.4: Panel Unit Root Test for Convergence

Country	τ	p-value	Country	τ	p-value
Algeria	-0.63	0.34	Madagascar	-3.29	0.07
Argentina	-0.49	0.56	Malawi	-1.41	0.75
Bolivia	-1.88	0.50	Malaysia	-2.98	0.13
Cameroon	-1.23	0.50	Malta	-1.27	0.78
Chile	-2.56	0.23	Mauritius	-4.37	0.01
Colombia	-0.39	0.78	Mexico	-0.67	0.60
Costa Rica	-1.82	0.60	Morocco	-1.10	0.84
Cote d'Ivoire	0.26	0.78	Pakistan	-2.46	0.27
Cyprus	-2.95	0.12	Panama	-0.21	0.69
Dominican Republic	-0.27	0.74	Paraguay	-2.44	0.29
Ecuador	-0.58	0.73	Philippines	-0.63	0.91
Egypt, Arab Republic of	-1.25	0.79	Rwanda	-1.17	0.78
El Salvador	-1.81	0.37	Senegal	-0.97	0.65
Ethiopia	-3.19	0.10	Sierra Leone	-1.41	0.41
Ghana	-1.72	0.27	Singapore	-2.37	0.19
Guatemala	-1.17	0.59	Sri Lanka	-1.80	0.59
Haiti	-1.23	0.81	Sudan	-1.11	0.25
Honduras	-0.23	0.74	Tanzania	-2.02	0.48
India	-2.89	0.02	Thailand	-2.58	0.25
Indonesia	-2.28	0.36	Trinidad and Tobago	-0.58	0.76
Iran	-1.46	0.75	Turkey	-2.01	0.52
Jamaica	-3.14	0.06	Uruguay	-3.61	0.30
Jordan	0.03	0.59	Venezuela	-1.65	0.31
Kenya	0.31	0.89	Zimbabwe	-1.70	0.36
Korea, Republic of	-1.50	0.69			

The test fails to reject the null hypothesis of nonstationarity at conventional significance levels:

$$-2\sum_{j=1}^{N} \ln p_i = 95.76;\ df\text{: } 98\ p\text{-value: } 0.55$$

Thus, this test reverses the above result on β-convergence, and the conclusion is that there is no evidence of long-run convergence.

The finding of divergence should be interpret in line with the previous results; they show that: (1) TFP and weighted input growth contribute significantly to GDP growth and (2) TFP growth is not determined by efficiency growth. This means that GDP growth is caused by both movements of the frontier and along the frontier, but that technological catching-up does not play an important role. The catch-up process is not the driving force behind the productivity distribution during the observation period. These results provide empirical support for theoretical and empirical studies which underline the importance of technological catch-up as a force for convergence.

3.6 Conclusion

This chapter disentangles growth and productivity components and, in the spirit of Quah (1997), analyses the distribution of output and productivity sources. The evolution of the entire distribution of factor accumulation, TFP and the three productivity components (technological change, technological catch-up and economies of scale) is analysed. Recent developments in non-parametric methods (Fan and Ullah, 1999) are exploited to test formally for the statistical significance of the relative contribution of the growth components.

The analysis yields striking results: both total factor productivity growth and input growth are important for output growth. Moreover, the driving forces of productivity change are technological change and scale effects, but not efficiency changes: movement towards the frontier is not important, and therefore, countries do not converge towards a common frontier. This outcome corresponds to the finding in Kumar and Russell (2002). Obviously, there is scope for economic policy to improve the tehcnological catch-up in developing countries. This results motivate the analysis of the determinants of efficiency in Chapter 4.

3.A Kernel Density Estimator

The base of the test in Kumar and Russell (2002) is the nonparametric kernel density estimator (Fan and Ullah, 1999). Consider a discrete random variable X,[27] with realisations $x_1, x_2, \ldots, x_n$. A consistent estimator for the density $f(x)$ is

$$\hat{f}(x) = \frac{1}{n}\sum_{j=1}^{n} I(x_j = x); \;\; I(x_j = x) = \begin{cases} 1 & \text{if } x_j = x, \\ 0 & \text{else.} \end{cases} \tag{3.10}$$

With continuous random variables, $f(x)$ can be estimated in an interval around x, e.g. $x \pm \frac{h}{2}$, where h is the interval width:

$$\begin{aligned} \hat{f}(x) &= \frac{1}{nh}\sum_{j=1}^{n} I\left(x - \frac{h}{2} \leq x_j \leq x + \frac{h}{2}\right) = \\ &= \frac{1}{nh}\sum_{j=1}^{n} I\left(-\frac{1}{2} \leq \frac{x_j - x}{h} \leq \frac{1}{2}\right) = \\ &= \frac{1}{nh}\sum_{j=1}^{n} I\left(\psi_j\right); \end{aligned} \tag{3.11}$$

$$I(\psi_j) = I\left(-\frac{1}{2} \leq \psi_j \leq \frac{1}{2}\right) = \begin{cases} 1 & \text{if } |\psi_j| \leq \frac{1}{2}; \\ 0 & \text{else.} \end{cases}$$

[27] For the following, see Pagan and Ullah (1999).

The weight function $I(\psi)$ has the property that

$$\int_{-\infty}^{\infty} I(\psi)d\psi = \int_{-\infty}^{-1/2} I(\psi)d\psi + \int_{-1/2}^{1/2} I(\psi)d\psi + \int_{1/2}^{\infty} I(\psi)d\psi =$$
$$= \int_{-1/2}^{1/2} I(\psi)d\psi = 1.$$

Using the substitution rule and $\frac{\mathrm{d}\psi_j}{\mathrm{d}x} = -\frac{1}{h}$, one obtains

$$\int_{-\infty}^{\infty} \hat{f}(x)dx = \frac{1}{n}\sum_{j=1}^{n}\int_{-\infty}^{\infty} I(\psi_j)d\psi_j = 1.$$

This histogram estimator assigns each x_j in the interval around x the same estimate $\hat{f}(x)$, which might be overly restrictive. To obtain a smoother set of weights, one can replace the indicator function $I(\psi)$ with a kernel function $K(\psi)$, with

$$\int_{-\infty}^{\infty} K(\psi)d\psi = 1.$$

The general kernel estimator is then

$$\hat{f}(x) = \frac{1}{nh}\sum_{j=1}^{n} K(\psi_j); \psi_j = \frac{x_j - x}{h}. \tag{3.12}$$

The window width h is a function of the sample size: for $n \longrightarrow \infty$, $h \longrightarrow 0$. As a starting point, consider a random variable $X \sim N(\mu, \sigma^2)$. Under this assumption, one can identify an optimal h by minimising the integrated mean squared error $\mathrm{E}\left[\int \left(\hat{f}(x) - f(x)\right)^2\right]$, which turns out to be (Pagan and Ullah, 1999, p.25)

$$\hat{h} = 1.06\hat{\sigma}n^{-\frac{1}{5}}. \tag{3.13}$$

Under the normality assumption, this is an optimal estimator for the window width. More robust estimators can be found by replacing the standard deviation $\hat{\sigma}$ by the interquartile range. Let $X \sim N(\mu, \sigma^2)$ and $Z = \frac{X-\mu}{\sigma} \sim N(0,1)$. One obtains

$$\begin{aligned} R &= x_{0.75n} - x_{0.25n} = \mu + \sigma z_{0.75n} - \mu - \sigma z_{0.25n} = \\ &= \sigma \left(z_{0.75n} - z_{0.25n} \right); \\ R &\approx \sigma \left(0.67 - (-0.67) \right) = 1.34\sigma; \\ \sigma &= \frac{R}{1.34}. \end{aligned} \tag{3.14}$$

Plugging this expression into equation (3.13) gives

$$\hat{h} = 1.06 \frac{\hat{R}}{1.34} n^{-\frac{1}{5}} = 0.79 \hat{R} n^{-\frac{1}{5}}. \tag{3.15}$$

An alternative choses the minimum from $\hat{\sigma}$ and $\hat{R}/1.34$:

$$\hat{h} = 0.9 \min\left(\hat{\sigma}, \frac{\hat{R}}{1.34} \right) n^{-\frac{1}{5}}. \tag{3.16}$$

Following Fan and Ullah (1999), Kumar and Russell (2002) a standard normal kernel

$$K(\psi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\psi^2}{2} \right) \tag{3.17}$$

is used to derive the test statistic for the comparison of two unknown densities $f(x)$ and $g(x)$. These two densities represent the distributions of technological change, technological catch-up and capital accumulation at the beginning and the end of their observation period (1965-1990). The null hypothesis $H_0 : f(x) = g(x)$ is tested against the alternative $H_1 : f(x) \neq g(x)$, using the integrated squared distance between the two density estimators

$$\hat{I}(f,g) = \int_{-\infty}^{\infty} \left(\hat{f}(x) - \hat{g}(x)\right)^2 dx. \tag{3.18}$$

This expression can be decomposed into

$$\int \left(\hat{f}(x) - \hat{g}(x)\right)^2 dx = \int_{-\infty}^{\infty} \hat{f}(x)^2 dx - 2\int_{-\infty}^{\infty} \hat{f}(x)\hat{g}(x)dx + \int_{-\infty}^{\infty} \hat{g}(x)^2 dx.$$

The expression

$$\int_{-\infty}^{\infty} \hat{f}(x)^2 dx = \int_{-\infty}^{\infty} \hat{f}(x) \underbrace{\hat{f}(x)}_{\frac{d\hat{F}(x)}{dx}} dx = \int_{-\infty}^{\infty} \hat{f}(x) d\hat{F}(x)$$

is the expected value of $\hat{f}(x)$ and can be estimated by

$$\int_{-\infty}^{\infty} \hat{f}(x) d\hat{F}(x) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(x_i).$$

Plugging in the expression for $\hat{f}(x)$ from equation (3.12) gives

$$\int_{-\infty}^{\infty} \hat{f}(x) d\hat{F}(x) = \frac{1}{n^2 h}\sum_{i=1}^{n}\sum_{j=1}^{n} K\left(\frac{x_i - x_j}{h}\right).$$

Applying the same principle to the other two terms in the decomposition of equation (3.18), one obtains[28]

$$\begin{aligned}
\hat{I} &= \frac{1}{n^2 h}\sum_{i=1}^{n}\sum_{j=1}^{n} K\left(\left(\frac{x_i - x_j}{h}\right) + \left(\frac{y_i - y_j}{h}\right) - 2\left(\frac{y_i - x_j}{h}\right)\right) = \\
&= \hat{I}_1 + \hat{I}_2; \\
\hat{I}_1 &= \frac{1}{n^2 h}\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n} K\left(\left(\frac{x_i - x_j}{h}\right) + \left(\frac{y_i - y_j}{h}\right) - \left(\frac{x_i - y_j}{h}\right) - \left(\frac{y_i - x_j}{h}\right)\right); \\
\hat{I}_2 &= \frac{2}{n^2 h}\sum_{j=1}^{n}\left(K(0) - K\left(\frac{x_j - y_j}{h}\right)\right).
\end{aligned}$$

This decomposition allows to construct a test statistic which is centered at zero (Pagan and Ullah, 1999, p.63). Li (1996) demonstrates that for $h \rightarrow 0$, $nh \rightarrow \infty$, and under $H_0 : f(x) = g(x)$, the test statistic T follows a standard normal distribrution:

$$T = \frac{n\sqrt{h}\hat{I}_1}{\hat{\sigma}} \sim N(0,1), \tag{3.19}$$

where

$$\begin{aligned}
\hat{\sigma}^2 = & \frac{2}{n^2 h}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(K\left(\frac{x_i - x_j}{h}\right) + K\left(\frac{y_i - y_j}{h}\right) + 2K\left(\frac{x_i - y_j}{h}\right)\right) \times \\
& \times \int_{-\infty}^{\infty} K(\psi)^2 d\psi.
\end{aligned}$$

[28]In the following, x_i are realisations based onf $f(x)$, and y_i are realisations based on $g(x)$.

For the standard normal kernel in equation (3.17), the last term in $\hat{\sigma}^2$ becomes[29]

$$\begin{aligned}\int_{-\infty}^{\infty} K(\psi)^2 d\psi &= \int_{-\infty}^{\infty} \left(\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-\psi^2}{2}\right)\right)^2 d\psi = \\ &= \int_{-\infty}^{\infty} \left(\frac{1}{2\pi} \exp\left(-\psi^2\right)\right) d\psi = \\ &= \frac{1}{2}\sqrt{\pi}\underbrace{\frac{1}{\sqrt{\pi}}\int_{-\infty}^{\infty} \exp\left(-\psi^2\right) d\psi}_{0.5\text{erfc}\,(-\infty)} = \frac{1}{2}\sqrt{\pi},\end{aligned}$$

which gives

$$\begin{aligned}\hat{\sigma}^2 =& \frac{1}{n^2 h\sqrt{\pi}} \times \\ &\times \sum_{i=1}^{n}\sum_{j=1}^{n}\left(K\left(\frac{x_i - x_j}{h}\right) + K\left(\frac{y_i - y_j}{h}\right) + 2K\left(\frac{x_i - y_j}{h}\right)\right).\end{aligned} \tag{3.20}$$

3.B Simulation Study

Given the small sample size of 32 countries, the asymptotic distribution of the test statistic described in Appendix 3.A is not reliable, therefore following Kumar and Russell (2002) a bootstrap approximation of the distribution is performed. 2000 realisations of the test statistic are generated under the Null hypothesis that $f(x) = g(x)$. A small simulation study helps to assess the extent of the small-sample-bias problem. 2000 replications of two standard normally distributed random variables are generated (sample sizes: 50, 100, 250, 500). Since the asymptotic distribution of the test statistic is standard normal, one expects that with increasing sample size, the difference between simulation results and standard normal distribution will become smaller.

[29] The function erfc(z) is the complementary error function: erfc(z) = $\frac{2}{\sqrt{\pi}}\int_z^{\infty} \exp\left(-t^2\right)dt$; erfc$(-\infty) = 2$ (see e.g. Press *et al.*, 1992, p. 220).

The empirical distributions are displayed in Table 3.5. The results from the bootstrap exercise used for the critical values are in the first line; the other part of the table contains the outcome of the simulation study. The Table shows that, with increasing in sample size N, the critical values from the simulated distribution and the standard normal distribution, reported in the last row, become closer. The results provide clear evidence of small sample bias, hence, the approach adopted here is justified.

Table 3.5: Empirical Distribution of T

N	0.900	0.950	0.975	0.990	μ	σ
32	0.67	1.06	1.46	2.03	-0.01	0.58
50	0.87	1.21	1.63	2.51	-0.02	0.68
100	0.90	1.37	1.79	2.37	-0.01	0.70
250	0.95	1.34	1.76	2.13	-0.02	0.71
500	1.02	1.42	1.81	2.47	-0.03	0.77
∞	1.28	1.64	1.96	2.33	0.00	1.00

Notes:

$N = \infty$ indicates the critical values from the standard normal distribution.

Chapter 4

Openness, Human Capital, and Efficiency

4.1 Introduction

To analyse the sources of productivity growth in the previous chapter, the model of choice was Model 4*, where techological progress is non-neutral, labour force is quality adjusted, and mean efficiency is explained by FDI, import of machinery and equipment, import discipline, and export of manufacturing goods. To capture technological change, Model 4* includes a time trend. The main results are that technological change and catch-up explain the growth of Asian countries, while the stagnation of Latin America and especially Africa is characterised by a lack of technological diffusion. Convergence tests show that the gap between the more productive Asian countries and the poorer African countries widened.

These are important results, however, to understand the determinants of efficiency better, it is necessary to extend the analysis. Empirical studies emphasize the role of human capital for technology diffusion. Barro (1991) interprets the significant positive effect of human capital on growth as an indication that poor countries could catch-up if their initial education level was high enough (see also Barro, 1997). Dollar (1992) provides empirical evidence that Asian countries have benefited from the interaction of the rapid transfer of technology and a highly skilled labour force able to adapt rapidly to a new technology. A similar result can be found in Collins and Bosworth (1996). Given these findings, it seems justified to incorporate human capital into the efficiency function again.

Nelson and Phelps (1966) and Benhabib and Spiegel (1994) conclude that human capital cannot be included as an independent factor of production, but rather influences growth through total factor productivity. Similarily, Islam (1995) finds an insignificant coefficient on human capital as production factor in a panel regression. Instead, he underlines the positive relationship between human capital and individual country effects, which can be interpreted as an alternative measure for TFP. More recently, Borensztein *et al.* (1998) use data on FDI flows from OECD countries to 69 developing countries and find that FDI has a positive effect on per capital income growth only if the recipient country has acumulated a threshold level of human capital. This threshold effect is also demonstrated by Xu (2000). Analysing the technology diffusion of US multinational firms in forty developed and developing countries over the period 1966-1994, he shows that a country needs to reach a a minimum level of human capital to benefit from the technology transfer. Finally, Navaretti and Tarr (2000) find that inflows of technology are more beneficial the faster importers are able to master new knowledge. Given this evidence, it is reasonable to proceed with a specification where human capital is a determinant of efficiency, thus affecting output growth through TFP.

The chapter is organised in two sections, and builds on the stylised facts identified in Chapter 2. Section 4.2 contains a short overview on the methodological background. The idea of the relative importance of FDI, imports of capital goods, and human capital accumulation is further explored, using a model which allows for direct effects (Section 4.3.1) as well as a model with interaction terms to account for interaction between human capital and the other two determinants of efficiency (Section 4.3.2).

The estimation of a stochastic production frontier for a panel of 57 countries confirms that FDI and imported capital goods are important channels for improving efficiency, as well as human capital accumulation. Analysis reveals, however, an important difference between the two channels. Knowledge diffused through FDI is more general (disembodied) than that from imported capital goods (embodied). In the interaction model, it turns out that human capital has no direct significant effect on efficiency. However, human capital accumulations leads to an increase in the positive effect the other determinants have on efficiency. Over the observation period all countries become more efficient. Efficiency gains are especially evident for the group of Asian countries in the panel. This result can be linked to the early outward orientation and the favourable climate for FDI in the 80s.

4.2 Methodology

The empirical analysis builds on the theoretical literature emphasizing the important role technological diffusion plays in the process of economic development (Nelson and Phelps, 1966; Jovanovic and Rob, 1989; Grossman and Helpman, 1991; Segerstrom, 1991; Barro and Sala-i-Martin, 1995). These growth models explain how growth rates in developing countries depend on the catch-up process in the level of technology. An important issue to address is the identification of the channels through which the adoption and implementation of technologies used in leading countries takes place. Foreign direct investment and imported capital are important candidates for the transmission of new technologies.

Consider an aggregate production function

$$Y_{it} = F(M_{it}, L_{it}, K_{it}). \tag{4.1}$$

For country i at time t production Y_{it} is determined by the levels of labor input and private capital, L_{it} and K_{it}, and technology M_{it}:

$$Y_{it} = M_{it} f(L_{it}, K_{it}). \tag{4.2}$$

Borensztein *et al.* (1998) and Findlay (1978) argue that FDI increases the rate of technical progress through the diffusion of more advanced technology and management practices used by foreign firms. They present a model in line with Romer (1990), Grossman and Helpman (1991) and Barro and Sala-i-Martin (1995), in which technological progress takes place through the introduction of new varieties of capital goods at lower costs from foreign firms. However, the efficiency with which countries use foreign technologies depends on human capital and social institutions (Edwards, 1992; Fagerberg, 1994; Harrison, 1996; Levin and Raut, 1997; Borensztein *et al.*, 1998; Xu, 2000).

In the light of this theoretical discussion, foreign capital and human capital are assumed to have a positive external effect on the productivity of production factors. Since foreign capital F_{it} and human capital HC_{it} increase productivity, they are modelled as shift factor. Technology is assumed to evolve according to

$$M_{it} = M_{i0}e^{(\delta_1 F_{it} + \delta_2 HC_{it})}. \tag{4.3}$$

From (4.3), we see that total factor productivity (TFP) is defined as

$$TFP = M_{i0}e^{(\delta_1 F_{it} + \delta_2 HC_{it})}. \tag{4.4}$$

Log linearizing equation (4.4) yields

$$tfp = m_{i0} + \delta_1 F_{it} + \delta_2 HC_{it} \tag{4.5}$$

where $tfp = \ln(TFP)$ and $m_{i0} = \ln(M_{i0})$. Equation (4.3) indicates that the level of TFP is determined by the initial values M_{i0} and the contribution of foreign capital F_{it} and human capital HC_{it}. The initial values represent country characteristics, including institutional quality and are modelled as affecting the frontier directly through regional dummies. These unobservable variables "reflects not just technology but resources endowments, climate, institutions, and so on" (Islam, 1995, p. 1133) and are captured by the technological parameter.

Assume the following common production frontier for the countries under analysis:[1]

$$Y_{it} = f(X_{it})\Theta_{i,t} \qquad i = 1, \ldots, 57; \quad t = 1960, \ldots, 1990 \tag{4.6}$$

where Θ can be decomposed into the level of technology A, an efficiency

[1]For a full explanation of the panel data production frontier model, see Section 1.6.

measure τ_{it}, with $0 < \tau_{it} \leq 1$,[2] and a measurement error w_{it}:

$$\Theta_t = A\tau_{it}w_{it}. \tag{4.7}$$

Writing equation (4.6) in logs, we obtain

$$y_{it} = \alpha + \mathbf{x}_{it}\beta - u_{it} + v_{it}; \tag{4.8}$$

where $u_{it} = -ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$. Expected inefficiency is specified as in Battese and Coelli (1995) (Section 1.6):

$$\mathrm{E}[u_{it}] = \mathbf{z}_{it}\boldsymbol{\delta}, \tag{4.9}$$

where the u_{it} are assumed to be independently but not identically distributed, $\mathbf{z}_{it}$ is a $(1 \times K)$ vector of variables which influence efficiencies, and $\boldsymbol{\delta}$ is the $(K \times 1)$ vector of coefficients.

To estimate the parameters of the production function together with the parameters in equation (4.9), a single-stage Maximum Likelihood procedure proposed by Kumbhakar *et al.* (1991b) and Reifschneider and Stevenson (1991) is applied, in the modified form suggested by Battese and Coelli (1995).[3]

In light of the results of the previous chapters, model (4.9) looks at foreign direct investment, imports of machinery and equipment and human capital as the principal channels for the diffusion of technological knowledge. These factors are specified as exogenous variables in equation (4.9) and their im-

[2]When $\tau_{it} = 1$, country i produces on the efficiency frontier, i.e. is fully efficient.
[3]See Section 1.4.5 for a discussion of the estimation method.

portance in explaining deviations from the frontier is estimated in the next section.

4.3 Results

4.3.1 Model without Interaction

The panel data set covers 57 developing countries for the period 1960-90.[4] The first version of the empirical model is a translog production function with regional dummy variables for African countries (D_1), Asian countries (D_2),[5] and five time dummies ($D_{3,\ldots,7}$)[6]:

$$y_{it}{=}b_0{+}b_1k_{it}{+}b_2l_{it}{+}\frac{1}{2}b_3k_{it}^2{+}\frac{1}{2}b_4l_{it}^2{+}b_5k_{it}l_{it}{+}\sum_{\mathrm{j}=1}^{7}\mathrm{d}_jD_j{+}\mathrm{v}_{it}-u_{it} \tag{4.10}$$

where y_{it} is the log of output (Y), k_{it} is the log of capital (K), and l_{it} is the log of labour (L). The translog production specification is more flexible than a function of the Cobb-Douglas type, because it does not impose constant substitution elasticity.[7] This seems more appropriate when analysing low-income countries, where structural rigidities may be more in evidence (Blomstrom *et al.* 1994).

The expected value of the inefficiency term u_{it} is determined by

$$E(u_{it}) = \delta_1 FDI_{it} + \delta_2 ME_{it} + \delta_3 HC_{it} \tag{4.11}$$

[4]See Section 2.3 for a detailed description of the data.

[5]The reference group contains the Latin American countries, Cyprus, Malta, and Turkey.

[6]The time periods covered by the dummies are 1966-1970, 1971-1975, 1976-1980, 1981-1985, and 1986-1990.

[7]See Section 1.7 for details.

where FDI_{it} denotes foreign direct investment, ME_{it} is imported capital goods, and HC_{it} human capital. While FDI_{it} and ME_{it} allow us to test the hypothesis in equation (4.5) concerning the importance of these factors for explaining productivity differences in developing countries; HC_{it} controls for other determinants of efficiency. The estimation results are displayed in Table 4.1.

Note that because the variable on the lhs of (4.10) is the log of real GDP, the parameters associated with the time dummies can be reformulated as growth rates to compare the average technology levels for the 5 subperiods:

$$\begin{aligned} \frac{Y_{66-70}}{Y_{60-65}} - 1 &= \frac{Y_{66-70} - Y_{60-65}}{Y_{60-65}} = \exp(d_3) - 1; \\ \frac{Y_{71-75}}{Y_{66-70}} - 1 &= \frac{Y_{71-75} - Y_{66-70}}{Y_{66-70}} = \frac{\exp(d_4)}{\exp(d_3)} - 1, \end{aligned} \tag{4.12}$$

etc. The same holds for the country dummies: $exp(d_1) - 1$ measures the percentage technical change in moving from the reference group to Africa, and $exp(d_2) - 1$ measures the percentage difference between Asia and the reference group.

The time dummies show a trend with positive slope (Table 4.2, Figure 4.1). However, the last period mirrors the results in Chapter 3 and is characterized by a slowdown of technological change. There is a significant difference between the reference group and the Asian and African countries in the data set. Converting these differences into growth rates, the technology level in the reference group is about 50 per cent higher than in the group of African countries, but only 16 per higher than for the Asian countries.

Table 4.1: Estimation Results

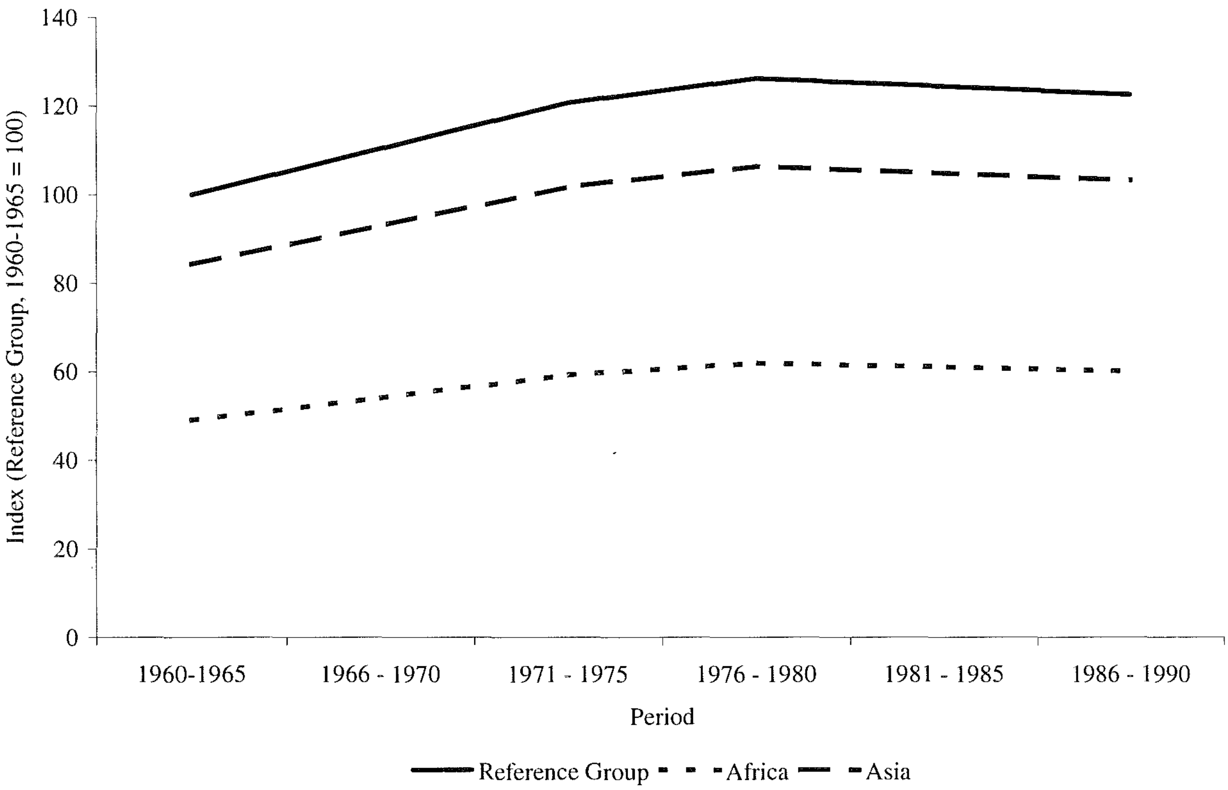
Parameter	Estimates	Std.Err.	t-Ratio
b_0	0.681	1.926	0.354
b_1	0.392	0.081	4.867
b_2	1.574	0.175	8.999
b_3	0.013	0.003	4.929
b_4	0.007	0.013	0.495
b_5	−0.038	0.007	−5.301
d_1	−0.712	0.039	−18.301
d_2	−0.171	0.044	−3.878
d_3	0.099	0.053	1.881
d_4	0.189	0.053	3.581
d_5	0.233	0.053	4.381
d_6	0.219	0.055	3.998
d_7	0.203	0.055	3.700
δ_0	2.656	0.238	11.152
δ_1	−0.028	0.013	−2.181
δ_2	−0.012	0.002	−6.653
δ_3	−0.012	0.002	−4.869
$\bar{\sigma}^2$	0.256	0.012	21.204
γ	0.260	0.137	1.898

Number of observations: 1416, log-likelihood: -1030.494. The estimates $b_{1,\ldots,5}$ are the parameters of the translog production function (equation 4.10), d_1 and d_2 are the parameters of the regional dummies for the Asian and African countries, and $d_{3,\ldots,7}$ are the parameters of the time dummies. The estimates $\delta_{0,\ldots,3}$ are the parameters of the inefficiency model (equation 4.11), $\bar{\sigma}^2$ the estimate of the composite variance, and γ is the estimate of the variance ratio. The constant b_0 can be interpreted as the technology parameter of the reference group in the period 1960-66.

Table 4.2: Percentage Difference of Technology Level to the Reference Group in 1960-1965

1966 - 1970	1971 - 1975	1976 - 1980	1981 - 1985	1986 - 1990
10%	21%	26%	24%	23%

Figure 4.1: Development of Technology over Time (Reference Group in 1960-1965 =100)



The parameters of the model defined by (4.10) and (4.11) are estimated simultaneously using the computer program FRONTIER Version 4.1 (Coelli 1996). It provides maximum-likelihood estimates of the parameters and predicts technical efficiencies. The results of the estimation are displayed in Table 4.1. The variance parameter

$$\gamma = \frac{\sigma_u^2}{\bar{\sigma}^2} \qquad \textit{and} \qquad \bar{\sigma}^2 = \sigma_u^2 + \sigma_v^2 \tag{4.13}$$

can be used to perform a diagnostic likelihood-ratio test to show of whether inefficiency is present in the model ($H_0 : \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$). The test statistic LR is approximately distributed following a mixed chi-square distribution, critical values can be found in Kodde and Palm (1986). The null hypothesis is rejected at the 5 per cent level of significance.[8] A likelihood ratio test with the Cobb-Douglas production function as null model ($H_0 : \beta_3 = \beta_4 = \beta_5 = 0$) can be used to test whether the translog production function is adequate. The test statistic follows a χ_3^2 distribution. Again, the hypothesis can be rejected at the 5 per cent level.[9]

Efficiency medians for all subperiods and regions are displayed in Table 4.3 (see also Figure 4.2 for the distribution).[10] Although there is an increase over time (25 per cent for all countries from 1960 to 1990), substantial regional differences are evident. The increase from 1960 to 1990 is about 50 per cent for the Asian countries, but only 7 per cent for Africa. Furthermore, the efficiency median for the African countries actually decreases in

[8]Test statistic LR=144.8, critical value: 10.371 (Kodde and Palm 1986).

[9]Test statistic LR=41.2, critical value of the χ_3^2 distribution (%5 significance level): 12.84. Following Coelli *et al.* (1998, p. 215), the results allow discrimination between a stochastic and a deterministic frontier: if the frontier was deterministic, we would be unable to reject the hypothesis that $\gamma = 1$. A t-ratio of $t = -5.408$ allows rejection of this hypothesis at the 1% significance level.

[10]The boxplots in Figure 4.2 give a visual impression of the efficiency distributions. The box indicates the 75, 50, and 25 per cent percentiles, and the two "whiskers" represent the minimum and maximum values.

the period 1966-1975. The result for the reference group is in between (20 per cent). For all regional groups, the spread of efficiency increases over time, i.e. the distance between efficient and inefficient countries increases. African countries in the panel exhibit the lowest efficiency spread. They are more homogeneously concentrated at a lower efficiency level than the other country groups. The relative size of the medians and the spread is comparable to the averages reported in Koop *et al.* (2000b).

The results for the determinants of technical inefficiency strongly support the implications of the theoretical models which emphasize the significant role of FDI in the growth process (Findlay, 1978; Borensztein *et al.*, 1998). All the variables reduce inefficiency significantly. Besides the more general effect of human capital accumulation, knowledge diffuses through both FDI and imported machinery and equipment. It should be stressed, however, that the coefficient of FDI (δ_1) is greater (1 per cent significance level) than those of either imported capital goods (δ_2) or human capital (δ_3): at the same efficiency level, FDI has the biggest impact on efficiency.[11] With respect to imported capital, this result is consistent with the importance of externalities in FDI: its knowledge transfer is more general than imported machinery and equipment. Knowledge embodied in imported capital is specific to the technology of the firms that use them, and therefore less neutral than knowledge associated with FDI. Accordingly, FDI has the stronger effect on efficiency. The comparison with human capital is not as straightforward, and is analysed in detail in the following section.

[11] $\frac{\partial \tau}{\partial FDI} = -\delta_1 \tau$; $\frac{\partial \tau}{\partial IMP} = -\delta_2 \tau$; $\frac{\partial \tau}{\partial HC} = -\delta_3 \tau$.

Figure 4.2: Efficiency Distribution

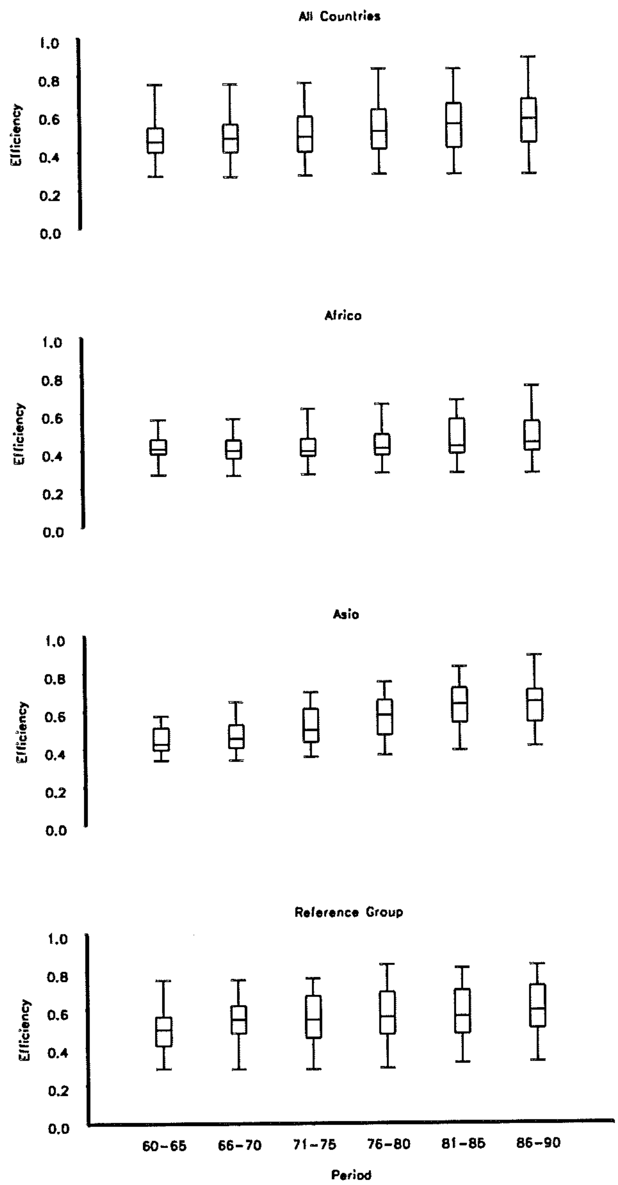


Table 4.3: Efficiency (Median)

	1960-65	1966-70	1971-75	1976-80	1981-85	1986-90
All Countries	0.452	0.469	0.476	0.503	0.540	0.566
	(0.128)	(0.147)	(0.186)	(0.209)	(0.227)	(0.229)
Africa	0.408	0.397	0.396	0.409	0.418	0.436
	(0.074)	(0.095)	(0.090)	(0.107)	(0.177)	(0.156)
Asia	0.427	0.455	0.498	0.577	0.633	0.644
	(0.117)	(0.121)	(0.176)	(0.184)	(0.180)	(0.168)
Reference Group	0.492	0.544	0.541	0.556	0.560	0.589
	(0.151)	(0.145)	(0.221)	(0.222)	(0.229)	(0.228)

Notes: interquartile ranges (distance between 75^{th} and 25^{th} percentile) in parentheses.

4.3.2 Model with Interaction

Some authors argue that openness leads to growth primarily in countries with enough human capital to effectively absorb new technolodies (Edwards, 1992; Harrison, 1996; Levin and Raut, 1997; Borensztein *et al.*, 1998; Chang and Luh, 1999; Xu, 2000). To allow for this effect, the model in equation (4.11) is extended to include two interaction terms of human capital with FDI and imported capital goods:

$$\begin{aligned} E(u_{it}) =& \delta_0 + \delta_1 FDI_{it} + \delta_2 ME_{it} + \delta_3 HC_{it} + \\ &+ \delta_4 HC_{it} FDI_{it} + \delta_5 HC_{it} ME_{it}. \end{aligned} \tag{4.14}$$

This setup allows to examine the reaction of inefficiency to one of the determinants dependent on the level of the other:

$$\begin{aligned} \frac{\partial E(u)}{\partial FDI} &= \delta_1 + \delta_4 HC; \\ \frac{\partial E(u)}{\partial ME} &= \delta_2 + \delta_5 HC; \\ \frac{\partial E(u)}{\partial HC} &= \delta_3 + \delta_4 FDI + \delta_5 ME. \end{aligned} \tag{4.15}$$

The basic results for the interaction model are displayed in Table 4.4. The parameters of the production function are very similar to the estimates for the original specification (see Appendix 4.A for a comparison of the elasticities, and Appendix 4.C for the efficiency distribution). The analysis of the efficiency equation provides additional insight in the interaction of the transmission channels.

Table 4.4: Estimation Results

Parameter	Estimates	Std.Err.	t-Ratio
b_0	-1.830	1.444	-1.267
b_1	0.457	0.076	5.980
b_2	1.764	0.137	12.908
b_3	0.015	0.003	5.652
b_4	0.007	0.013	0.539
b_5	-0.046	0.007	-6.237
d_1	-0.693	0.040	-17.271
d_2	-0.175	0.045	-3.908
d_3	0.087	0.053	1.649
d_4	0.163	0.053	3.066
d_5	0.216	0.053	4.072
d_6	0.206	0.054	3.820
d_7	0.185	0.054	3.430
δ_0	0.679	0.755	0.899
δ_1	0.456	0.119	3.836
δ_2	0.063	0.030	2.070
δ_3	0.001	0.006	0.224
δ_4	-0.004	0.001	-4.478
δ_5	-0.001	0.000	-2.442
$\bar{\sigma}^2$	0.277	0.019	14.950
γ	0.305	0.066	4.647

Number of observations: 1416, log-likelihood: -1023.122. The estimates $b_{1,\ldots,5}$ are the parameters of the translog production function (equation 4.10), d_1 and d_2 are the parameters of the regional dummies for the Asian and African countries, and $d_{3,\ldots,7}$ are the parameters of the time dummies. The estimates $\delta_{0,\ldots,5}$ are the parameters of the inefficiency model (equation 4.14), $\bar{\sigma}^2$ the estimate of the composite variance, and γ is the estimate of the variance ratio. The constant b_0 can be interpreted as the technology parameter of the reference group in the period 1960-66.

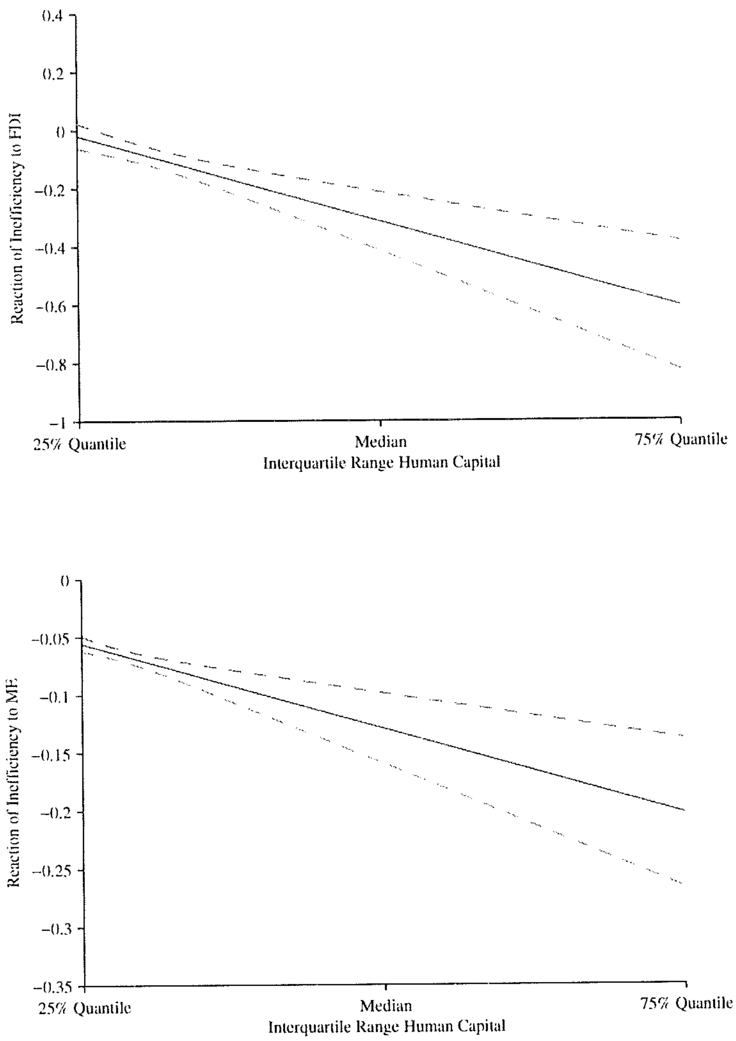
The coefficients on FDI (δ_1) and imports of machinery and equipment (δ_2) have the wrong sign and are statistically significant, suggesting that the presence of FDI and foreign machinery and equipments decreases the productivity of the country. The human capital parameter δ_3 has a positive sign, but is statistically not significant.

Since zero is not included in the observations of the explanatory variables except for FDI, the parameters δ_1, δ_2, and δ_3 measuring the direct effects of FDI, imports of capital goods, and human capital on inefficiency have no meaningful interpretation in the context of the sample analyzed here. Instead, the results are presented based on equation (4.15), for the interquartile range of the explanatory variables. Since the reagibilities of inefficiency in (4.15) are linear combinations of the three parameters $\delta_1, \ldots, \delta_3$, it is straightforward to calculate the standard errors.

The partial derivative of inefficiency with respect to human capital depends on both FDI and ME (see equation 4.15). It turns out that the confidence interval around the response surface includes the zero at every possible combination of FDI and ME over the interquartile ranges, i.e. in this specification, human capital has no direct impact on inefficiency. The results for FDI and ME are displayed in Figure 4.3.[12] The specification with interaction supports the main result from the previous section: FDI has a stronger impact on inefficiency than ME. In addition, there is another interesting outcome: both effects become stronger with the increase of human capital accumulation; in fact, at very low levels of human capital the effect of both FDI and ME is insignificant. Countries benefit from foreign technology only when they have the opportunity to exploit them. Another interpretation of the result is that there are positive spillovers from human capital only in the presence of advanced knowledge embodied in FDI and ME.

[12] Interquartile range for human capital: 25%-quantile: 118.9; 75%-quantile: 146.7; median: 131.4.

Figure 4.3: Reaction of Inefficiency



Solid lines: point estimates; dashed lines: 95 per cent confidence intervals.

4.3.3 Further Implications

Based on the empirical results, one might ask the question why Africa fails to attract foreign capital goods, and why Asia obviously did better. The results in Tables 4.1-4.11 are indicative for "Africa's Growth Tragedy" (Easterly and Levine 1997). The decrease in efficiency in 1966-1975 is in line with the implications of the model. As Devarajan *et al.* (2001, p. 7) point out, typical African countries at the beginning of the 80s were characterised by a very high level of government intervention, especially trade intervention. These policies did not lead to an improvement in the standard of living, and, in addition, "seemed to exacerbate the effects of the external shocks of the 1970s" (Devarajan *et al.*, 2001, p. 7). Political pressure generated by economic disasters forced some countries into reforms, which is reflected in the increase in efficiency after 1976.

However, the increase in efficiency with respect to the other countries is low. Besides the choice of policy, there are other factors determining the lack of growth performance in Sub-Saharan Africa. The high inefficiency is perfectly in line with Devarajan *et al.* (1999), who find public and private capital to be not productive. The lack of "social capability" (Temple and Johnson, 1998) and the geographic determinants of the "Tragedy" identified in e.g. Gallup *et al.* (1999) have certainly also a deteriorating effect on the diffusion of technology via trade, because they induce transfer cost. The group of countries is characterised by a very high proportion of land concentrated in the tropics, 81 per cent of population concentrated in the interior regions, i.e. far away from the coast, and more than a quarter of population actually living in landlocked regions. In addition, the distance to core markets in Europe is very high.[13] All in all, if FDI and imports of machin-

[13] One could also speculate on how the devastating effect of HIV/AIDS on physical and

ery and equipment increase efficiency, all these factors will push Africa away from the frontier. Although reform-oriented governments and policies were able to attract foreign investors in some African countries (Morriset, 2000), the above mentioned characteristics have had an inevitably negative effect on overall business climate.

For Asia, on the other hand, the historical and geographical circumstances were less problematic.[14] The literature stresses three elements in explaining the "Asian Miracle": outward orientation, sound macroeconomic management, and investment in human capital. Although there were early attempts to protect import substitution industries, these policies were soon abandoned,[15] reducing import control and tariffs, together with strong incentives to export. Government intervention was systematic, selective and performance based. Leipziger (1997, p.11) stresses the especially favourable domestic climate for FDI in the eighties, which, in the framework in Section 4.2, would have had an efficiency increasing effect.

human will show up in the framework of the model. The epidemic started in sub-Saharan Africa in the late 70s/early 80s. As pointed out by Bonnel (forthcoming), AIDS-related diseases are the main cause of mortality in this region. It affects the most productive age group, and reduces saving and investment incentives. With respect to human capital, (Bonnel, forthcoming, Table 1) shows that the HIV epidemic had a negative effect on formal education (measured by the change in secondary enrolment rate) - by destroying human capital, this would reduce efficiency.

[14]For the following, see Leipziger (1997) and World Bank (1993).

[15]For Latin-America, the distortions caused by import-substituting industrialisation were persistent in the seventies and eighties, although this policy has shown to have deteriorating effects on economic growth (Taylor, 1998). This explains the lower efficiency in the reference group with respect to Asia after 1975 (Table 4.3).

4.4 Conclusion

The central feature of this chapter is to discuss the forces that cause technological diffusion and productivity growth. To better understand the link between trade policy and output growth patterns in developing countries, a slightly different version of the production frontier with respect to that analysed in Chapter 2 is presented. Evidence support the conclusion in previous chapters that technological transfer are important to explain productivity differences in developing countries. It is demonstrated that the positive effect of FDI and imports of capital goods depend crucially on the level of accumulated human capital.

As noted by Tybout (2000), imported capital and intermediate goods may be the most important channel through which trade diffuses technology. Using the stochastic frontier methodology and applying the method by Battese and Coelli (1995), this chapter provides the first empirical evidence on the relative importance of these channels. Low income countries benefit from foreign technological by importing capital goods in which this technology is embedded. Because of the externalities in foreign direct investment, knowledge diffused through this channel is more general (disembodied) than that from imported capital goods (embodied). Such foreign technology transfer has important policy implications. In fact, since imported capital goods create externalities, government intervention is justified. Governments need to facilitate the process of technology transfer by encouraging the establishment of the necessary infrastructure and providing incentives to support the development of domestic innovative capabilities. For countries at the early stage of industrialisation, it will be more effective and economically more convenient to import foreign technologies rather than developing them locally. Another important policy implication that the infant-industry argument seems invalid for countries which are above the threshold level for human capital accumulation: with respect to efficiency, protectionism is harmful. Policies promoting free trade and importing foreign capital goods will help developing countries to increase productivity growth and to close the gap with the technology frontier.

4.A Elasticities and Returns to Scale

As in Chapter 2, the output elasticities of capital and labour for the two models are calculated, being more informative than the coeffcients of the translog production function.[16]

Table 4.5: Output Elasticities, Model (4.11)

		Capital	Labour
Africa	Elasticity	0.098**	0.860**
	Standard Error	0.007	0.019
Asia	Elasticity	0.091**	0.767**
	Standard Error	0.008	0.017
Latin America	Elasticity	0.136**	0.834**
	Standard Error	0.009	0.020
Panel	Elasticity	0.113**	0.828**
	Standard Error	0.007	0.017

**: significant at the 5 per cent level.

[16]See the discussion in Sections 1.7 and 2.4.3 for details.

Table 4.6: Output Elasticities, Model (4.14)

		Capital	Labour
Africa	Elasticity	0.086***	0.878***
	Standard Error	0.007	0.016
Asia	Elasticity	0.075***	0.764***
	Standard Error	0.008	0.017
Latin America	Elasticity	0.131***	0.847***
	Standard Error	0.009	0.016
Panel	Elasticity	0.103***	0.839***
	Standard Error	0.007	0.014

***: significant at the 1 per cent level.

The results displayed in Tables 4.5 and 4.6 are very similar to those obtained in Chapter 2. Output is especially elastic with respect to labour, output elasticity with respect to capital is much lower. The analysis then turns to test the hypothesis of constant returns to scale. To establish the statistical significance of the sum of the estimated output elasticities the variance is calculated using the formula explained in section 1.7. In the case of Model (4.11), constant returns are rejected in favour of slightly decreasing returns for Asia and the panel (Table 4.7), confirming the results from Chapter 2. For model (4.14), constant returns are also rejected for the Africa and Latin America (Table 4.8).

Table 4.7: Returns to Scale, Model (4.11)

	$\sum \beta_j$	Standard Error
Africa	0.959	0.019
Asia	0.859***	0.016
Latin America	0.965	0.020
Panel	0.941***	0.017

$H_0 : \sum \beta_j = 1$; ***: H_0 rejected at the 1 per cent level.

Table 4.8: Returns to Scale, Model (4.14)

	$\sum \beta_j$	Standard Error
Africa	0.964**	0.016
Asia	0.839***	0.015
Latin America	0.978*	0.016
Panel	0.942***	0.014

$H_0 : \sum \beta_j = 1$; ***/**/*: H_0 rejected at the 1,5,10 per cent level.

4.B Elasticities of Substitution

The final characteristic of the production function is the the degree of substitutability between capital and labour. The formula derived in Section 1.7 and in Appendix 2.A is used for the estimation of elasticity of substitution.

The findings in Tables 4.9 and 4.10 mirror those in Chapter 2. The results indicate that the null hypothesis of unit elasticity is rejected in all cases, i.e. the choice of a translog specification for the production function is appropriate.

Table 4.9: Elasticity of Substitution, Model (4.11)

	Elasticity	Standard Error
Africa	1.244***	0.058
Asia	1.272***	0.070
Latin-America	1.190***	0.037
Panel	1.220***	0.047

Null hypothesis: $\sigma = 1$; ***: rejected at the 1 per cent significance level.

Table 4.10: Elasticity of Substitution, Model (4.14)

	Elasticity	Standard Error
Africa	1.343***	0.083
Asia	1.411***	0.111
Latin America	1.242***	0.042
Panel	1.296***	0.060

Null hypothesis: $\sigma = 1$; ***: rejected at the 1 per cent significance level.

4.C Efficiency Distribution for the Interaction Model

Table 4.11: Efficiency (Median)

	1960-65	1966-70	1971-75	1976-80	1981-85	1986-90
All Countries	0.590	0.605	0.615	0.650	0.710	0.730
	(0.180)	(0.210)	(0.260)	(0.278)	(0.270)	(0.255)
Africa	0.510	0.500	0.500	0.520	0.520	0.550
	(0.073)	(0.140)	(0.170)	(0.175)	(0.200)	(0.220)
Asia	0.560	0.600	0.670	0.760	0.780	0.795
	(0.105)	(0.183)	(0.238)	(0.235)	(0.180)	(0.170)
Reference Group	0.630	0.680	0.720	0.760	0.750	0.790
	(0.170)	(0.165)	(0.200)	(0.250)	(0.260)	(0.215)

Notes: interquartile ranges (distance between 75^{th} and 25^{th} percentile) in parentheses.

Note that efficiency is slightly higher for the model with interaction (4.14) than for Model (4.11), but the overall pattern from Table 4.3 is preserved.

Conclusion: Summary of Findings and Avenues for Further Research

Summary of Findings

To solve the problem of underdevelopment, a key issue is the identification of the sources of growth: is it technical progress, factor accumuluation, or other determinants which explain differences in growth patterns? This study sheds light on this important issue.

The aim of Chapter 1 is to provide a critical and detailed review of stochastic frontier methods. Different approaches to estimate stochastic frontier and efficiency models are considered. Although there exist other methodological surveys on measurement of economic efficiency, most of the literature debates the choice of estimation methods, i.e. the comparison between the parametric and the non-parametric approach. Moreover, the literature is focussed on microeconomic data, while this chapter goes more deeply into the analysis of stochastic frontier models and their statistical properties from a macro-data perspective.

Theoretical models of panel unit root tests for convergence are also considered. The limitations and assumptions of different production frontier specifications are underlined to find the best model for the aim of this study. The method of choice is the stochastic frontier methodology. It allows the important decomposition of productivity into technological change (shifts in the technological frontier) and efficiency (distance to the technological frontier). Moreover, this method does not require neutral technical change and particular institutional or market structures. Indeed, market imperfections, as well as technical inefficiencies, are seen as possible reasons for countries falling below the frontier. Chosing a panel framework, heterogeneity across countries can be taken into account, and the issue of omitted variable bias can be addressed which has been shown to be particularly important in the analysis of the effects of openness on growth (Alcalá and Ciccone, 2004). Because of asymmetries in the error term, the parameters of the frontier are estimated using a maximum likelihood estimator instead of within and random effect estimators. The model of Battese and Coelli (1995) is discussed in detail, a model which allows to incorporate explanatory variables for the expected value of inefficiency. Then, the chapter turns to survey the theory of convergence. The conclusion is that the classical approach of convergence is not valid for the data set analyzed in this thesis, because it requires homogeneity between countries. Instead, a time series approach to convergence is adopted using the test suggested by Maddala and Wu (1999). This test allows for individual effects as well as different dynamics in the stochastic error of different groups. Finally, the translog production function, its properties and estimation is also discussed in detail. The flexible form of this function, which is a second order Taylor approximation to a twice differentiable but otherwise arbitrary function, address the critique that the usual Cobb-Douglas specification is too restrictive.

The analysis in Chapter 2 attempts to identify the most suitable specification of the translog production function, because it is well known that alternative specifications of the production function lead to ambiguous empirical evidence for competing theories of economic growth (Durlauf and Quah, 1999). The focus is on the role of human capital and on the neutrality of technoligcal change. Evidence indicates that human capital affects growth though multiple channels. The translog stochastic frontier production function with quality adjusted labour force is found to fit the data better than the one with unadjusted labour force. Moreover, human capital has a positive impact on efficiency. As implied by some endogenous growth models (Lucas, 1988; Romer, 1986), human capital influences growth through learning-by-doing. Technological progress is best characterised by non-neutrality, i.e. technical change shifts the frontier and changes the elasticity of substitution between the factors of production. In explaining efficiency, Chapter 2 focuses on four trade channels (foreign direct investment, imports of machinery, import discipline, and export of manufacturing goods), and provides for the first time empirical evidence of the importance of these channels as determinants of efficiency. The finding is consistent with predictions of endogenous growth models including trade (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Romer, 1990; Young, 1991; Barro and Sala-i-Martin, 1995). Efficiency shows to be mainly driven by international competition, FDI and imports of machinery and equipment, which is in line with Tybout (2000).

The main contribution of Chapter 3 is to shed light on the contribution of different growth sources - including efficiency - to the development process of a large number of LDCs. The results from Chapter 2 (Model 4*) are utilized to provide a consistent decomposition of output growth into its sources. The analysis is similar to Kumar and Russell (2002), but the approach and the data set are different. The investigation of the distributions of growth and its components allows us to examine their relative importance in the development process in a way consistent with Quah's(1993; 1996a; 1997) suggestion.

To provide additional evidence to the visual analysis of empirical distributions, a formal test is included. The base of both the test and the visual analysis is the non-parametric kernel density estimator. The first test assesses the importance of TFP and input growth. TFP growth is then further decomposed into technical change, scale effects and efficiency, and the contribution of these components is tested. Both TFP and input growth are found to be important for output growth. This result contradicts the finding in Kumar and Russell (2002) that factor accumulation accounts for most of the output growth. Moreover, it is demonstrated that technical change and scale effects are important components of TFP growth, but gains in efficiency do not play a prominent role. There is a movement towards the frontier of 5 per cent over the observation period, which is entirely driven by the Asian countries in the sample.

Finally, a time-series convergence test supports the impression of visual analysis, and confirms the divergent evolution of output among countries. Taking into account that with the exception of Asian countries, catch-up towards a common frontier does not play a role in explaining productivity growth over the sample period, the chapter has an important policy implication: policy measures which help to improve efficiency will support LDCs in the catching-up process. Therefore, the next chapter turns to a more detailed analysis of the determinants of efficiency.

Chapter 4 is motivated by the evidence provided in the previous chapters: technological change and technological catch-up explain the growth of

Asian countries, while the stagnation of Latin America and especially African countries is characterized by a lack of technological diffusion. Moreover, the gap between the more productive Asian countries and the poorer African countries widened. To understand the determinants of efficiency better, it is necessary to extent the analysis. The aim of the chapter is to further explore the relative importance of FDI, imports of capital goods and human capital accumulation in the development process.

Countries benefit from foreign technology only when they have the capability to exploit it. The estimation of a stochastic production frontier which is slightly different from the one in Chapter 2 confirms that FDI and imported capital goods are important channels for improving efficiency, as well as human capital accumulation. Analysis reveals, however, an important difference between the channels. Knowledge diffused through FDI is more general (disembodied) than that from imported capital goods (embodied). In the model allowing for interaction between trade and human capital interaction, it turns out that human capital does not have a direct significant effect on efficiency. Instead, human capital accumulation leads to an increase in the effects of FDI and imports of machinery and equipment on efficiency. Over the observation period, all countries become more efficient. Efficiency gains are especially evident for the group of Asian countries in the panel. This result can be linked to the early outward orientation and the favorable climate for FDI in the 80s.

Foreign technology transfer has important policy implications. For countries at the early stage of industrialisation, it will be more effective and economically more convenient to import foreign technologies rather than to develop them locally. To adopt a new technology, the country must bear the adoption cost, an important component of which is the cost of creating the human capital specific to the new technology, that is the cost of training workers to use the technology. Governments need to facilitate the process of technology transfer by encouraging the establishment of the necessary infrastructure and by providing incentives to support the development of domestic innovative capabilities. Another policy implication is the observation that the infant-industry argument seems invalid for countries above the threshold level of human capital accumulation: with respect to efficiency, protectionism is harmful. Policies promoting free trade and the importing of foreign capital goods will help developing countries to increase productivity growth and to close the gap with the technology frontier.

Avenues for Further Research

The long-term analysis in this thesis has not taken into account short-run economic fluctuations, which Lovell (2001) mentions as one of the most fruitful directions of future research. The stochastic frontier model estimates a long-term equilibrium relationship between output and production factors, without considering the dynamic adjustments which take place in an attempt by agents to achieve equilibrium. Due to time delays, delivery lags and installation costs, the adjustment from current input use to desired future input use is imperfect. The failure to incorporate such partial adjustment into the model can lead to an inappropriate classification of an intertemporally efficient producer as being inefficient during the adjustment period. There are two distinctive ways to take this effect into account: adding the possibility of inefficiency in the conventional partial adjustment/error correction model, and second, building partial adjustment into the frontier models discussed in Chapter 1.

Temple (1999, p.152) states "Openness to trade also appears to be a good thing, although we do not know enough about the condition under which this is true". An important aspect of this issue is the channel of how trade affects productivity. Two main problems that arise in the analysis of the link between openness and growth have been tackled in this thesis. First, although the term "openness" is widely used in the international economics and economic growth literature, there is no consensus on how to measure it. In the existing empirical studies, various measures have been tried. However, given that international trade is influenced by various factors, it is very difficult, if not impossible, to find an ideal indicator of openness (Edwards, 1998). This study has therefore focused on the exploration of the channels through which trade actually affects productivity. Second, most empirical tests of the openness-growth relationship are based on the growth accounting approach that implicitly assumes economic efficiency. If TFP is regressed on openness under the assumption of economic efficiency, the contribution of openness to technological progress may be biased: the growth of TFP can be due to gains in efficiency, as well as to technical progress (Grosskopf, 1993). Moreover, it is possible that productivity and efficiency move in different directions. The advantage of using economic efficiency measurement to analyse the role of openness is to be more specific about the details of the catch-up effect. One of the main findings of this thesis is the importance of FDI and imports of capital goods. However, these results should be interpreted with care. First, the analysis has focused on trade channels; although human capital is included into the efficiency term to provide the possibility of an alternative, other potentially important variables (e.g. R&D and patents) are omitted. Schimmelpfennig and Thirtle (1999) and Thirtle *et al.* (2002) report that R&D expenditures is importance source of productivity in agricultural sector. Second, the data are aggregate. Further insight can be expected from disaggregation by sector (Barro, 1997; Färe *et al.*, 1994), but data limitations permit to go down this route. Despite the level of aggregation, the approach taken represents a step further to the traditional approach to productivity measurement. It also constitutes a natural way to measure the details of the catching-up phenomenon. Moreover, the decomposition of total factor productivity into catch-up and technical change allows the distinction of diffusion of technology and innovation. Notwithstanding these precautions, the results obtained here are interesting and promising: "although we have not learnt as much as might be hoped, it is always worth remembering how little we knew when we started" (Temple, 1999, p.152).

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