Adriana Di Liberto

UCL Department of Economics

Ph.D in Economics

2004

HUMAN CAPITAL AND CONVERGENCE: THEORY, ESTIMATION AND APPLICATIONS

Abstract

In growth theory, convergence analysis tries to answer three fundamental questions "Are poor countries catching up with richer ones? How quickly? And what are the determinants of this process?" This thesis deals with issues that are relevant to all these questions. It begins by setting out the key theoretical contributions to the analysis of the role of human capital in growth and convergence. Secondly, attention is turned to the way that convergence is estimated from data. The econometric techniques used in the convergence literature usually assume that shocks are uncorrelated across countries. We claim that this is unlikely for most data sets and investigate the use of an estimator so far ignored, namely the annual panel estimator where shocks are allowed to be correlated. Our analysis indicates that this estimator is more efficient than conventional ones for plausible values of cross-country error correlation. The study then turns to the analysis of the third question. Although differences in human capital endowments and rates of investment have long been recognised as crucial elements for explaining observed GDP gaps, nevertheless, human capital proxies are rarely significant in growth regressions. In this study some possible solutions to this puzzle are explored. We estimate aggregate returns to education in Italy and Spain, and compare our results with the predictions of competing theoretical frameworks. In general, our empirical analysis identifies a positive role for human capital, and stresses the relevance of theoretical models in which human capital has a fundamental but indirect role in the catching up process. The final part of the thesis proposes a new methodology designed to estimate technology levels and to test whether part of observed convergence is due to technology convergence. The results seem to confirm the existence of technology catch-up among regions.

I would like to thank Wendy Carlin for her careful supervision and for providing constructive and detailed comments on almost every piece of the thesis, and James Symons for his continuous suggestions and thoughtful observations. Moreover, I am in debt with Angel de la Fuente, Rosina Moreno and Esther Vaya for providing me the data on Spanish regions and valuable informations on the Spanish educational system, and with Anna Maria Tosi (ISTAT), CRENoS (Università di Cagliari), PROMETEIA and Fondazione Eni Enrico Mattei (Milano) for helping me on data collection. I also want to thank Massimo Di Matteo, Francesco Pigliaru, Sergio Lodde, Luigi Pistaferri and the participants to the seminar held at UCL, Università di Siena, Università di Cagliari, AIEL Conference (Trieste), Universidad Autonoma de Barcelona, SED Conference (Alghero), ENTER Conference (ULB Brussels and Universidad Autonoma de Barcelona), ERSA Conference (Barcelona and Helsinki), Okkaido University, EEFS Conference (Bologna) and three anonymous referees for their observations and their numerous and useful suggestions.
Infine, un grazie particolare a Lorenzo, Francesco e Liliana per la pazienza dimostrata ed il continuo appoggio ricevuto.

CONTENTS

INTRODUCTION

Growth theory has been an active area of research during the last ten years due to the development of the endogenous growth literature. In particular, the theoretical contributions developed by Romer (1986) and Lucas (1988) on endogenous growth have stimulated a resurgence of interest in this field. The debate that followed focussed on theoretical and empirical aspects alike. From the point of view of theory, endogenous growth models appeared to be, or rather were simply presented by their authors as being "new" developments of the growth literature; new with respect to the "old" and still unmodified Solow-type growth model. Nevertheless, these models have their roots within the neoclassical solovian growth model. Given the availability in the mid 1980s of large international data sets with comparable GDP measures, these theoretical developments were soon followed by numerous empirical studies focussing primarily on one of the most important implications of the Solow growth model: the convergence hypothesis. By ascribing economic growth to the joint impact of exogenous technological change and capital deepening on an economy with concave short run production opportunities, the neoclassical solovian model makes very strong predictions concerning the behaviour of economies over time. In particular, the Solow growth model was initially interpreted as predicting that poorer countries should be catching up with the richer ones. This hypothesis is called in the literature the *absolute convergence* hypothesis.

Conversely, early endogenous growth models stress the presence of persistent differences in per capita income across countries: rich economies may retain a constant gap with poorer regions or may even increase it. Theoretically, these models emphasise mechanisms which generate divergence across economies. Therefore, estimating the convergence equation has become increasingly popular as the convergence hypothesis appeared to be a sort of acid test to discriminate between endogenous and exogenous theories. In other words, the convergence test was considered as the main empirical test of the validity of these modern theories of economic growth and this is why, at first, a lot of efforts have been devoted to trying to estimate the presence of a convergence/divergence mechanism across different economic areas.

In general, stylised facts derived from international data sets showed the absolute convergence prediction to be untrue[1]. Nevertheless, the debate did not conclude in favour of endogenous models for various reasons. First of all, it has been demonstrated that the Solow model predicts *conditional convergence*. That is, roughly speaking, it predicts that only economies with similar fundamentals (preferences, technology as well as institutions, economic structure etc.) actually converge towards the same level of long-run output per person. Mankiw Romer and Weil (1992) were among the first to stress the difference between absolute and conditional convergence. They found that, once we control for savings rates, population growth and other determinants of the steady state, economies with low initial income tend to grow faster than rich economies. In that case, the Solow model with exogenous technical progress was considered to be capable of explaining observed cross-country variation in per capita output. Moreover, recent endogenous growth models predict the possibility of convergence across economies. In particular, models that stress both the importance of technology in explaining long-run growth

1 See Barro (1991).

and the possibility of transfer of technology among different countries predict that countries lagging behind may catch up towards the more advanced areas.[2].
Given these developments, simple convergence tests cannot be considered fully supportive of one theory against the other and this early approach seems now to have found a sort of blind alley. However, this conclusion does not imply that empirical investigations on convergence across economies have become an uninteresting issue in growth literature. It implies rather that this literature is now called to new challenges. In particular, the three fundamental questions of any convergence analysis "Are poor countries catching up with the richer ones? How quickly? And, ultimately, what are the determinants of this process?" are of primary importance for human welfare and, thus, undoubtedly represent crucial issues for growth (and perhaps all) economists. In spite of their importance, clear-cut answers are not available yet in the literature.

This thesis deals with issues that are relevant to all these questions. The first part of the thesis relates to the first two questions. In fact, when we want to deduce if economies are converging and how fast this process is, we need to know how to estimate convergence. Chapter 2 shows how vast and heterogeneous the methodological literature on this topic is. In this study we investigate the properties of a new estimator we introduce for detecting convergence. A precise estimation of the convergence parameter is important because one is interested in inferring from the estimate how rapidly countries or regions will converge and even tiny differences in the estimated coefficient imply enormous differences in the predicted patterns of convergence. In general, despite the abundance of different econometric techniques introduced in the empirical literature on convergence, it is usually assumed that shocks are uncorrelated across countries. However, we believe that this is an unlikely assumption.

In this study we thus investigate a possibility so far ignored, namely an annual panel estimator where shocks are allowed to be correlated across countries.

---

2 Recent empirical evidence shows that the evolution of technology represents an important element in observed convergence among OECD countries. An interesting reading on the convergence hypothesis debate can be found in the "Controversy" of the *Economic Journal* (vol. 106, 1996) that includes papers by Durlauf, Sala-i-Martin, Bernard and Jones, Quah and Galor.

More precisely, we analyse by Monte Carlo the properties of a Maximum Likelihood panel estimator with an unrestricted variance-covariance matrix. Our analysis will be restricted to data sets that have more time periods than countries *(T>N)* which allows us to estimate an unrestricted variance-covariance matrix of cross-country shocks. Even if we cannot use this methodology with large international data sets, samples such as the OECD, European regions or regional data sets have more time periods than countries. We will show that, for this type of sample, our estimator is effectively unbiased and more efficient than the cross-section regression or conventional panel estimators introduced so far for estimating convergence.

The second part of this study focuses on the third question listed above. Among the determinants of the growth and convergence processes identified by the theoretical literature, human capital is certainly one of the most important. In fact, Chapter 1 stresses how differences in human capital endowments and their rates of investment have long been recognised in the theoretical growth literature as being crucial elements for explaining observed GDP gaps. Nevertheless, most of the empirical evidence is contrary to the predictions of theoretical models: empirical studies that introduce international data sets usually find human capital to be insignificantly or even negatively correlated with growth. These results have always been considered puzzling. This thesis investigates if the observed differences in human capital can explain a significant proportion of the observed Italian and Spanish regional GDP gaps. Thus, we follow the Klenow and Rodriguez Clare suggestion and perform more detailed country analysis a la Young (1995)[3].

The regional Italian and Spanish cases represent interesting case-studies. First of all, unlike in most developed countries, both Italian and Spanish regional endowments of human capital are still far from being perfectly homogeneous. Secondly, the previous empirical literature is not large and usually confirms the puzzling evidence provided by international data sets. Thirdly, these regional educational data sets are very detailed and enable us to put forward different hypotheses on the role of human capital in growth. Finally, regional data sets certainly offer one distinct advantage in the analysis on returns to schooling. Indeed, the failure to find significant and positive results in the schooling variables in studies that utilise international data sets has been often ascribed to the non homogeneity and non comparability of the different national educational systems.

Chapter 3 investigates the effect of education on growth using a sample of Italian regions while Chapter 4 replicates the analysis using the sample of Spanish regions. Since the characteristics of these two regional data sets are different, we cannot really draw parallels from the results obtained with the two samples. Nevertheless, these regional data sets enable us to test various hypotheses posited in the theoretical literature on human capital and growth. In particular, with its emphasis on technology, the so-called Nelson and Phelps approach described in Chapter 1 suggests various hypotheses that need to be tested. This literature de-emphasises the role of capital (both physical and human) accumulation for explaining growth, but stresses the importance of technological change. In particular, the growth rate of output will depend on the rate of TFP growth and, subsequently, on the level of human capital. These models allow the possibility of "beta convergence" or catch-up among countries. Human capital has a fundamental role for innovation but also an indirect role in the catch-up process, increasing the capacity to adopt and implement innovations or new technologies from abroad. The growth rate of an economy depends on its level of human capital and on its gap with the technology leader: the higher the level of human capital and the larger the technology gap between the follower and the technology leader, the faster convergence observed should be. Therefore, these studies suggest using measures of the stock of human capital instead of its rate of accumulation as usually done by the previous literature.

Following these developments and unlike in other empirical studies on Italian convergence, we focus on the stocks of human capital instead of its rate of accumulation. To this end, for the Italian regional case we have introduced census data on the educational attainment of the labour force and constructed annual measures of the regional stocks of human capital, while for Spain very detailed regional data sets on educational attainment of the labour force is readily available.

---

3 See Klenow and Rodriguez Clare (1997b): "...we think the insights gleaned from cross-country regressions have run into sharply diminishing returns. We would like to see more detailed country

These models also suggest that different levels of education could affect growth in different ways. To test this hypothesis we divide the measurement of human capital into its constituent parts: primary school, secondary school and higher education. We expect higher levels of education to be more involved in innovative activities than lower levels and, thus, we expect secondary school and higher education levels to have a greater influence on growth than, for example, primary school levels. Note that these predictions of macroeconomic models dispute the usual micro evidence on returns to education, where the latter usually finds that returns to education are higher for lower levels of schooling. Secondly, we investigate if the allocation of human capital in the public sector may affect the analysis of returns to schooling. As noted by Griliches (1997), in many countries this sector often represents the employer of most of the skilled labour force and this fact may create different sources of distortions when we estimate aggregate returns to schooling. Finally, we test if the role of education has been different in different areas of these countries considered separately. In fact, while these countries have groups of regions that may constitute different convergence clubs, previous studies on regional convergence have not investigated if returns to education are heterogeneous in different clubs.

Finally, Chapter 5 proposes a fixed-effect panel methodology to assess the existence of technology convergence. As stressed above one of the open problems in this literature is how much of the observed convergence is TFP convergence or convergence in capital-labour ratios. In fact, unlike in early studies on growth differentials, recent works show that differences in TFP levels are a major component of the observed large cross-country differences in per capita income. However, the answer to the question of whether TFP convergence is taking place is not simple and this is largely due to the fact that, given the current availability of data in most of the existing cross-country and cross-region datasets, measuring TFP levels is not an easy task. In this study we build upon a methodology in which the presence of TFP heterogeneity in cross-country convergence analysis is tested by using an appropriate fixed-effects panel estimator. Originally, this methodology was designed to measure cross-country convergence in capital-labour ratios while controlling for stationary differences in TFP levels. We show that the same methodology can be

analysis a la Young (1995)....", page 614.

extended to analyse cases in which TFP differences in levels are *not* stationary, and therefore might be converging. The robustness of our results is assessed by comparing the estimates obtained using different estimators – namely, a Least Square with Dummy Variable (LSDV) estimator, a biased-corrected LSDV estimator and a GMM (Arellano-Bond) estimator. Our case-study is Italy and its persistent regional divide. From a methodological point of view, using regional data has the main advantage that various unobservable components such as culture, institutions, geography are supposed to be far more homogeneous across regions than across countries, and this feature facilitates the interpretation of results in our empirical analysis.

This study is organised into five chapters. Chapter 1 introduces a survey of the theoretical literature on human capital and growth. In general, the aim of this survey is to pinpoint the precise meaning of the concept of convergence that we will introduce into the empirical analysis and to examine the possible links between human capital and growth identified in the existing theoretical literature. Chapter 2 includes a survey of the different econometric methodologies introduced for estimating the convergence parameter. We critically evaluate these methodologies and identify their possible advantages or disadvantages. Moreover, we propose an alternative methodology for estimating convergence. A detailed Monte Carlo analysis examines the properties of this alternative estimator. In Chapters 3 and 4 we apply our estimator to investigate the returns to education in Italy and Spain respectively. We examine the main stylised facts on both regional convergence and human capital endowments and introduce an econometric analysis that investigates the returns to education in Italian regions. Finally, Chapter 5 proposes a fixed-effect panel methodology to assess the existence of technology convergence among Italian regions. A critical summary of the main findings and results concludes the research.

CHAPTER 1

CONVERGENCE AND DIVERGENCE IN GROWTH MODELS WITH HUMAN CAPITAL

"Knowledge and skills are the product of investments and combined with other investments account for the productive superiority of the technically advanced countries. To omit them in studying economic growth is like trying to explain soviet ideology without Marx." Shultz (1962).

1.1 Modern growth theory: an introduction

The neoclassical growth model, first developed by Solow (1956) and Swan (1956), has profoundly influenced the way in which economists think of long-run interrelationships in macroeconomies. Solow's work was not the first formal model to try to explain growth[1]. He was, though, probably influenced by the empirical evidence of sustained positive growth rates in per capita output present at that time throughout industrialised countries. The Solow model cannot simply be considered as an abstract system, because the model's predictions fit some of the main empirical facts on growth. In particular, Kaldor (1961) detected the presence of certain regularities among industrialised countries and identified the following main empirical facts: a) output per worker shows continuing growth, b) capital per worker shows continuing growth, c) the rate of return to capital is steady, d) the capital-output ratio is steady, e) labour and capital receive constant shares of total income, f) there are marked differences in the rates of productivity growth, both internationally

1 For a complete survey of the early literature on growth starting from Harrod (1939) to the mid 60s contributions see Hahn and Matthews (1964).

and intra-nationally. These are almost all properties of the balanced growth path postulated by the Solow model, apart from the sixth kaldorian fact, which is not explained by the standard neoclassical Solow model. Contrary to what Solow originally intended, his model has since been used as a means to illustrate the process by which poor countries catch up the richest ones. The Solovian model's inability to explain the sixth kaldorian fact is what motivated both subsequent extensions of the Solow model and has led to further developments in endogenous growth literature.

While Kaldor's work was dedicated to studying the problem of "the tremendous differences that now divide the rich and poor nations...", where these are seen as "...the cumulative result of persistent differences in growth rates that went on over periods that may appear long in terms of a life-span, but which are relatively short in terms of recorded human history"[2], in his model Solow was probably more interested in the analysis of *within country* growth than its *across country* dimension. To quote Solow (1970):

> “The remaining stylized facts are of a different kind, and will concern me less, because they relate more to comparisons between different economies than to the course of events within any one economy.”

In this Chapter we introduce *old* and *new* neoclassical models that stress the importance of human capital. This is a limited survey, which focuses exclusively on what the different models predict in terms of the convergence hypothesis. As we shall see, different models imply different concepts of convergence. Therefore, it is important to stress how convergence has been differently defined and understood.

This Chapter may be divided into four different parts. The first part includes three sub-sections that review how the concept of convergence has evolved in literature on growth. Section 1.1.1 defines the solovian convergence equation and introduces the Solow-Swan version of the neoclassical growth model, briefly discussing its extension with utility-maximising agents. Section 1.1.2 introduces the notion of conditional convergence, while section 1.1.3 is dedicated to the early

2 Kaldor (1970). He develops a growth theory in which he argues in favour of the forces that lead to divergence instead of convergence as in the Solow model. In this respect, Kaldor's work on growth may be considered as a first step in the evolution of the "new growth theory", and, in this respect, must be considered as highly influential.

development of endogenous growth literature and to the divergence hypothesis.

The second part is divided into six sub-sections and focuses on models that stress the importance of human capital in the process of development of the economies. Sections 1.2.1 and 1.2.2 discuss the main points and predictions of the so-called Lucas approach. In this framework, human capital is introduced into a growth model as an additional input in a standard Cobb-Douglas production function. Sections 1.2.3 and 1.2.4 examine the second class of models whose roots lie in the contribution of Nelson and Phelps (1966). This literature de-emphasises the role of capital (both physical and human) accumulation as the engine of growth and highlights the importance of the process of technological change. Section 1.2.5 introduces models that stress the importance of trade for technology transfers and catch up, while section 1.2.6 shows an interesting example where too much human capital allocated in the R&D sector can be detrimental to growth.

The final part of this Chapter is dedicated to a summary of : a) the different concepts of convergence encountered during the survey (section 1.3), and b) a classification of the theoretical models examined in terms of their ability to explain observed convergence or divergence, stressing the role that human capital plays in determining either one or the other result (section 1.4). This final section serves to provide the necessary link between the theory on growth, convergence and human capital and the empirics of convergence, which will be discussed in the following Chapters.

1.1.1 The Solow model and the convergence hypothesis: absolute convergence

In the Solow model, capital deepening is at the heart of the growth process. The aim of the model is to explain the link between savings and growth, where savings are exogenous. This link is the process of capital accumulation. The model describes an economy in which the production function of the representative producer is $Y = F(K, AL)$, where Y is the flow of output, K is the stock of capital, L is the labour force and A is knowledge or, in general, "effectiveness of labour". Note that A and L enter multiplicatively, in which case technology is known as *labour augmenting* or *Harrod-neutral*. Both population growth and technological progress are exogenous. It is assumed that $F(\,.\,)$ exhibits positive and diminishing marginal products in each input, as well as constant returns to scale. The assumption of constant returns enables us to work with the production function in intensive form:

$$y = f(k) = k^{\alpha} \tag{1.1}$$

where $0 < \alpha < 1$ and, henceforth, the lowercase letters denote a quantity per unit of effective labour, with $k = K/AL$, and $y = Y/AL$. Output can be used for investment or consumption. If depreciation of capital is proportional at rate δ, and a constant proportion of income, *s*, is invested in this economy, the derivative of *k* with respect to time evolves in accordance with:

$$\dot{k} = sf(k) - (n + g + \delta)k \tag{1.2}$$

Equation (1.2) is the resource constraint, where *n* is the exogenous growth rate of the labour force and *g* is the exogenous technology (or knowledge) growth rate. The exogenous growth rate of the labour force can be considered as being a depreciation rate because it represents the fraction of resources that we need to pass on to the new generation. We can rearrange equation (1.2) to obtain the growth rate of *k* as:

$$\dot{k}/k = sf(k)/k - (n + g + \delta) = sk^{-(1-\alpha)} - (n + g + \delta) \tag{1.3}$$

If we consider a log-linear approximation of equation (1.3) around the steady state we obtain:

$$\dot{k}/k = d[\ln(k)]/dt \cong -\beta[\ln(k/k^{*})] \tag{1.4}$$

where

$$\beta = (1 - \alpha)(n + g + \delta) \tag{1.5}$$

That is, β determines the speed of convergence from k towards its steady state level, k^*. In general, when a country or region starts with k below its level of steady state we should observe positive net investment, which implies positive growth of the stock of capital. If we focus on the development of a single country over time, the model predicts that the growth rate will be high when capital per worker is low and will decline as capital per worker rises. This is due to the fact that a low value of capital per worker implies a high marginal product of capital and therefore a high interest rate and a high level of investment. Therefore, we should observe that the real interest rate declines along with capital marginal product as an economy develops. This movement to higher values of k continues as long as $k<k^*$, where k^* is the steady state level of capital. Once the capital stock gets to $k=k^*$, net investment becomes zero and k no longer changes over time. That is, capital accumulation leads for a while to growth in output, but cannot sustain growth in output forever.

The effect of diminishing returns implies that growth due to capital accumulation vanishes in the long-run. And this is what ultimately determines the convergence mechanism. In other words, the convergence hypothesis arises from the transitional dynamics of the Solow model. Assuming certain assumptions are satisfied, the process of convergence towards the long-run equilibrium (within country convergence) may result in a tendency towards convergence in per capita income among economies. Note that given the Cobb-Douglas production function we assumed, $Y = K^{\alpha}(AL)^{1-\alpha}$, the growth rate of *(Y/AL)* has the same form as equation (1.4):

$$\dot{y}/y = d[ln(y)]/dt \cong -\beta[ln(y) - ln(y^*)] \tag{1.6}$$

This equation indicates that when an economy starts from a level of income in efficiency units lower than its steady state level, we should observe a positive rate of growth of y where β, as before, represents the speed of adjustment towards y^*.

Equation (1.6) also implies that:

$$\ln y(t) = (1 - e^{-\beta t})\ln y^* + e^{-\beta t}\ln y(0) \tag{1.7}$$

where $y(t_1)$ is income per effective worker at some initial point of time and $\tau = (t_2 - t_1)$. Equation (1.7) can also be rearranged to deduce explicitly an equation for the growth rate of income per effective worker within a given time interval τ :

$$\ln y(t) - \ln y(0) = (1 - e^{-\beta t})(\ln y^* - \ln y(0)) \tag{1.8}$$

Equation (1.8) represents the convergence equation introduced in empirical studies.

A more complex definition of the beta parameter is found when we assume savings to be determined by optimal choices of consumption over time. The previous framework must be only slightly modified. In this framework the representative, infinite-horizon household seeks to maximize utility, given by

$$\int_0^\infty u(c)e^{nt}e^{-\rho t}dt \tag{1.9}$$

where ρ is the constant rate of time preference and the utility function takes the standard isoelastic form, $u(c) = \frac{c^{1-\vartheta} - 1}{1 - \vartheta}$, with ϑ >0, so that the elasticity of substitution between consumption at any two points in time is constant and equal to $1/\vartheta$ (the marginal utility has a constant elasticity with respect to *c*). The resource constraint is modified thus:

$$\dot{k} = f(k) - c - (n + g + \delta)k \tag{1.10}$$

where c = *C/AL*. Given the resource constraint, the first order condition for maximising *U* in equation (1.12) entails:

$$\dot{c}/c = (1/\vartheta)\left[\ f'(k) - (\delta + n + \rho + g)\ \right] \qquad (1.11)$$

The maximisation also involves a transversality condition, which ensures that the capital stock grows asymptotically at a rate less than the rate of return, $f'(k)$[3]. Equations (1.10) and (1.11) determine the dynamics of k, y and c.

As in the Solow-Swan framework, it is possible to reproduce the main findings of the convergence hypothesis from the log-linearization of the dynamic system and then obtain a relation between the initial level of y and its following growth rate as in equation (1.8). However, in that case the parameter β, which governs the speed of adjustment to the steady state, is rewritten as:

$$2\beta = (\rho - n) - \left\{(\rho - n)^2 + 4\left(\frac{1-\alpha}{\alpha\vartheta}\right)(\rho + \delta + n + g)\left[(\rho + \delta + n + g) - \alpha(\delta + n + g)\right]\right\}^{1/2} \qquad (1.12)$$

Equation (1.12) allows us to identify all the determinants of β that in the empirical analysis represent our parameter of interest. Again, the higher the value of β, the greater will be the responsiveness of the average growth rate to the gap between $\ln(y^*)$ and $\ln(y_0)$, that is, the convergence to the steady state will occur more rapidly. Firstly, it is clear from equation (1.12) that a higher δ (depreciation rate) raises the speed of adjustment. In the limit, with full depreciation, convergence to the steady state would be immediate. A higher θ (reduced willingness to substitute intertemporally) lowers the speed of adjustment towards the steady state, while a higher time-preference rate, ρ, raises it[4].

In general, the key force underlying the convergence effect is diminishing

3 This result requires $\rho > n$.

4 King and Rebelo (1993) analyzed the transitional dynamics from a quantitative standpoint. They conduct dynamics simulations using a range of parameter values that are conventional in macroeconomics. They find that it is possible to explain sustained economic growth with transitional dynamics only with extremely counterfactual assumptions such as very low intertemporal substitution and/or a very high marginal product of capital during the early stages of development.

returns to reproducible capital. In other words, the extent of these diminishing returns, that is, the size of the capital-share coefficient α in the production function, has a strong effect on β. In particular, it has been shown[5] that for small values of α, diminishing returns set in rapidly, β is large and convergence is rapid. As α approaches unity, the convergence becomes less and less rapid and, when $\alpha = 1$, diminishing returns to capital disappear, β tends to zero and we do not observe convergence. In early endogenous growth models, it is assumed that $\alpha = 1$[6].

In brief, the Solow model has many important implications. First of all, savings rates do not affect the long-run growth of per capita income. The crucial factor explaining the presence of a sustained long-run growth rate in an economy is the presence of exogenous technological progress. However, the savings rate affects the long-run *level* of per capita income. In particular, the Solow model predicts that economies converge to a steady state, where the key force that underlies the convergence effect is diminishing returns to reproducible capital; the process toward the steady state is called transitional dynamics. The steady state growth rate explained by the model is equal to zero; it is only possible to obtain continued growth in output per head if there is exogenous technical progress. If we have two economies identical in all respects, except their initial capital stocks, the one with the lower capital stock will grow faster and ultimately converge in living standards to the richer one. Thus, there should be a force that promotes convergence in levels of per capita income. Empirically, we should observe that the per capita growth rate tends to be inversely related to the starting level of output per person. This implication of the solovian model is referred to as the absolute or unconditional convergence hypothesis.

1.1.2 ...and conditional convergence

We have seen that countries would converge in the absolute sense if the only difference between them is the initial level of per capita income. One of the most convincing arguments in endogenous growth literature against the Solow model was

5 King and Rebelo (1993).

6 See Barro and Sala-i-Martin (1995).

that the latter cannot account for international differences in income[7], since there is no evidence of international convergence. However, there are two possibilities for reconciling evidence based on convergence, using the Solow model. The importance of the capital-share coefficient α lies in the fact that it may help to compensate for this weakness of the Solow model. As previously stated, for values of α close to one the transitional dynamic turns out to take a long time. Therefore, as shown by Mankiw, Romer and Weil (1992), if we see the transitional dynamics as protracted, the model becomes potentially capable of explaining sustained cross-country differences in growth rates, thus providing a Solow-type explanation of these differences.

Secondly, economies may differ not only in their capital labour ratio but also in the level of technology, savings rate, depreciation rate or population growth rate. In particular, it is important to focus attention on the determinants of the steady state. From equation (1.3) we can deduce explicitly the steady state level of both k and y:

$$k^* = [s/(n+g+\delta)]^{1/(1-\alpha)} \tag{1.13}$$

The steady state level of per capita income (not in quantity per unit of effective labour) can be found simply by substituting equation (1.13) into the production function in logarithms:

$$ln\left[\frac{Y(t)}{L(t)}\right]^* = ln\,A(0) + gt + \frac{\alpha}{1-\alpha}ln\,s - \frac{\alpha}{1-\alpha}ln(n+g+\delta) \tag{1.14}$$

Equation (1.14) states that the steady state level of income per effective worker is positively related to the savings (or investment rates) of an economy while it is negatively related to parameters *n, g* and δ. It is also positively determined by the parameter *A(0)* which, as Mankiw Romer and Weil (1992) emphasise, represents not only the initial level of technology or knowledge, as previously suggested, but also institutions, climate and resource endowments. In general, if countries differ in

7 See Romer (1986) and Lucas (1988).

one or more of these parameters, it is clear from equation (1.14) that they will end up in different steady states. In the latter case, only for given y^* can we say that the growth rate is higher the lower $y(0)$, that is, the convergence is conditional in that $y(0)$ enters in relation to y^*, which may differ across regions. Empirically, this means we would expect to observe poor countries growing faster than rich ones only if their respective steady state is similar. Yet if, for example, rich countries have a higher steady state level of per capita income with respect to poorer countries, poor economies will not necessarily grow faster. Mankiw, Romer and Weil (1992) were the first to examine empirically the conditional convergence relationship described by eq. 1.14. They examine empirically the set of countries for which non-convergence has been widely documented in past work, and find that, once differences in savings and population growth rates are accounted for, (conditional) convergence does occur, as the Solow model predicts.

1.1.3 Endogenous growth: early divergence, possible convergence

The divergence hypothesis has been explicitly formulated and tested in various studies on endogenous growth. As stated above, one of the main motivations for further studies in endogenous growth literature has certainly been the model's inadequacy in explaining the absence of convergence among countries Endogenous growth models are highly heterogeneous. A simple and unifying definition of the endogenous growth models uses their relationship with the Solow model: what distinguishes the endogenous growth literature from the solovian approach is the possibility of positive long-run growth rates without the presence of exogenous technological progress. Nevertheless, different models within this literature give quite diverse interpretations regarding the engine of long-run growth.

Following Romer (2001), we distinguish two different classes of models within the endogenous growth literature. The first class assumes that the process of capital accumulation is central for explaining long-run growth paths. These models differ from Solow's in that they assume the capital share coefficient to be $\alpha \geq 1$, that is, they assume that returns to capital are constant or increasing. Non decreasing returns are usually explained by the introduction in the production function of a broad concept of capital that may include human capital[8]. In the second class of models, technology is a standard reproducible factor of production. In this case the process of accumulation of A is the key factor for explaining long-run growth. These studies determine how the technology evolves and describe what the possible determinants of innovation will be, seen as a distinct economic activity, i.e., they focus on the input A of the production function and its evolution over time. However, the original contribution of these works is not in their simple emphasis on technology. Undoubtedly, even in Solow's view technological change lies at the heart of economic growth since it is the key factor in explaining long run growth. Nevertheless, while Solow believes that explaining technological progress is still too difficult a task for economic theory, and that the exogeneity assumption is the most reasonable one[9], this is precisely what most endogenous growth models attempt to do. As Romer notes (1990b), technology or knowledge is a nonrival good but it is not necessarily nonexcludable as assumed by Solow. In particular, excludability depends on the nature of the knowledge produced and on the legal system governing property rights (or patenting and copyrights laws). Models assuming that technology shares both of these characteristics identify the public support for basic scientific research as the driving force for growth. Thus, government decisions become important for growth as it is necessary to subsidise the R&D sector. As in Solow, technology (or knowledge) is considered to be a purely public good, not something that the private sector can provide. Yet here, unlike in Solow's model, long-run growth needs to be sustained. That is, technology is never *manna from heaven*. On the other hand, when knowledge created by R&D is excludable, it is possible to obtain mechanisms in which expenditure in R&D is motivated by the desire for private gain. In this case the developer of new ideas must have some degree of market power. Innovators can charge a fee for the use of the idea, where the fee is limited by the extent to which others are prepared to devote resources to learning the idea[10].

8See Lucas (1988) and Rebelo (1991).

9 See Solow R. (1994).

10Other forces which have raised interest because important for governing the allocation of resources to the development of technology include economic incentives and social forces influencing the activity of talented individuals and learning by doing. See Romer D. (2001).

We include Romer's model (1990b) in this framework, as it is one of the most influential studies of the *new growth* literature. Romer starts from the premise that technological change lies at the heart of economic growth. In particular, it is technological change that engenders continued capital accumulation. More precisely, the crucial input of production necessary for explaining long-run growth is the process of *knowledge creation* in an economy. Although closely linked, knowledge and technological progress are not one and the same thing. In particular, knowledge can be divided into two components: human capital and technology. While the first component cannot grow indefinitely, the second one can. This is an explicit criticism levied at the Lucas model, which identifies long-run growth (that grows indefinitely) exclusively with the growth of human capital. For Romer (1990b), the interesting case is that of a nonrival but not completely excludable good, where excludability depends on both the nature of the knowledge itself and on economic institutions governing property rights[11]. The consequence of a nonrival good when used as an input of production is that output does not have a constant returns to scale function of all inputs taken together. Therefore, technology is characterised by knowledge spillovers: the discovery of a new technology will not capture all the benefits of its investment. As a result, private efforts at technological improvements will be less than socially optimal. As an example of new technologies, Romer introduces the design of a new good: in this case technology is embodied in new capital goods. The idea is simple: this model shows that productivity increases because of ideas embodied in capital and material inputs. We will briefly introduce the main details of the model which describes an economy with four inputs of production: capital (K), labour (L), human capital (H) and index of the level of technology (A). As in (1.9) households' preferences are given by:

$$U = \int_0^\infty U(c\ )e^{-\rho t}dt \qquad (1.15)$$

11 To avoid any confusion, we prefer to distinguish between models that focus on the importance of endogenising technological change distinct from capital accumulation and models that instead focus on processes of capital deepening. However, there is a third class of models that, following Arrow (1961), introduce the possibility that accumulation of knowledge occurs in part not as a result of deliberate efforts, but as a side effect of conventional economic activity; for example, as a side effect of the

where ρ is the discount rate and *U(C)* is the usual isoelastic form. The representative household supplies skilled and unskilled labour (*H* and *L*) in perfectly competitive markets. Both the supplies of unskilled labour L, and human capital, H, are fixed. This is a three sector model including the production of the final good, technology (or R&D sector) and an intermediate good. Allocation of *H* between the research and the final good sector is endogenous. We first analyse the final good sector. Households purchase consumption goods in a perfectly competitive final goods market. Final goods production function is given by:

$$Y = H_y^{\alpha} L_0^{\beta} \int_0^A x(i)^{1-\alpha-\beta} di \qquad (1.16)$$

where *Y* is the final good, H_y is the human capital used as an input of production in the final good sector and x_i denotes the design of *K* when technology *i* is available, where the design index is assumed to be a continuous variable. We identify two crucial assumptions here. Firstly, capital in (1.16) is disaggregated in an infinite number of distinct types of capital goods, $x = \{x_i\}_{i=1}^{\infty}$, where all durables have additively separable effects on output. By assuming that each unit of knowledge corresponds to the design for a new good, Romer simplifies the technology: *A* represents a count of the number of designs and, at any moment in time there is a bundle of capital goods defined by A_t[12]. Given this assumption, the integrand in equation (1.16) implies that technology affects the production of final goods only indirectly through the list of intermediate goods used at any point in time, while knowledge affects growth via the production of new varieties of goods where the potential of developing new goods is limitless. A second important assumption is that all the *x(i)* enter symmetrically in the integrand of the final good production function so that we may assume that there is a common level of use $\bar{x}$ of all *x(i)*.

---

production of new capital.

12 Or, more precisely, at each time t there is some value A such that xi =0 for all i≥A.

Therefore:

$$\int_0^A x(i)^{1-\alpha-\beta} di = A\bar{x}^{1-\alpha-\beta} \tag{1.17}$$

The second sector is the R&D sector. In this model new technology can be created devoting human capital to research and using the existing technology. Allocation of human capital between the final good and the R&D sector is endogenously determined by $H = H_y + H_A$, and H_A. In particular, technology evolves according to the rule:

$$\dot{A} = \lambda H_A A \tag{1.18}$$

where λ is a research success parameter. Human capital is an input into idea production function characterised by knowledge spillovers: researchers generate more varieties of products (more ideas) the greater the stock of knowledge from which to learn. Moreover, there is no uncertainty in the R&D sector: Romer assumes that investments would certainly produce innovation given an exogenous success parameter λ.

We need now to describe the intermediate good sector where Romer abandons the perfect competition assumption. Following Schumpeter (1942), he characterises the intermediate goods sector by the presence of market power. Physical capital is measured in units of consumption good: capital goods are simply foregone consumption goods, with both types of goods subject to the same production function. This assumption implies that the capital goods sector may be considered as a separate sector from the final goods one but with the same technology. However, unlike in the final goods sector, for each durable good *i* there is a distinct firm, so we cannot describe the sector in terms of a representative firm. Each firm faces constant marginal costs and a constant elasticity demand curve. Therefore, the monopoly price of the intermediate good is a mark up over marginal cost. In order to produce, each firm needs to purchase the design of a good *i* from the research sector. This is a fixed cost for the intermediate good sector and represents the R&D expenditure of this economy. At the individual firm level, the failure of the perfect competition assumption is a consequence of the decreasing average total cost of producing x_i which is given by the initial investment in design costs. Once it has bought the design, firm i can convert the design and η units of Y (final output) into one unit of capital good i. That is, $x_i = {}^{1}\!/_{\eta} Y$. Note that here the developers of a new variety of capital good are separated from the suppliers thereof [13]. In other words, each time a new design is invented, its patent is sold. Potential suppliers of the new design bid to purchase the patent and become monopolists once they buy it. In this case, a new variety of good can be sold in the market at a price that is greater than its unit cost of production. But given the initial competition, the price of a new design will be equal to the present value of the net revenue that a monopolist can extract. With these assumptions, Romer develops a model that allows private profit-maximising agents incentives for making investments in the creation of new knowledge.

We now analyse the main implication of the model. First, given (1.17) and assuming that each x_i is consumed and produced in the same quantity we obtain that aggregate capital is, at any point in time t, given by $K_t = \eta A_t \bar{x}$, and the final good production function may be rewritten as:

$$Y = qA^{\alpha+\beta} H_y^{\alpha} L_0^{\beta} K^{1-\alpha-\beta} \tag{1.19}$$

where $q = \eta^{-(1-\alpha-\beta)}$, a constant. This equation represents the reduced form expression of (1.16). Although equation (1.16) is homogeneous of degree one, the final goods production function shows increasing returns (is homogeneous of degree $1+\alpha+\beta$). These are caused by the nonrival nature of knowledge, implying knowledge spillovers will occur.

Additional results can be described examining the model in the balanced growth equilibrium, g^*, that is, when $g_C^* = g_K^* = g_Y^* = g_A^*$. It can be shown that the

13 This is not an essential assumption.

balanced growth rate is determined by:

$$g^{*} = \lambda H_{A} = \frac{\lambda(\alpha+\beta)H - \alpha\rho}{\alpha\theta+\beta} \tag{1.20}$$

Equation (1.20) says that the balanced growth rate of an economy depends on the amount of human capital allocated in the R&D sector, H_A. Allocation of human capital in the R&D sector is influenced by the interest rate. In this model, the opportunity cost for H to be allocated in the R&D sector is the wage that can be earned in the final good sector, while the returns to investing H_A in the R&D sector are represented by the stream of net revenue generated by a new design. A higher interest rate leads the present discounted value of the stream of net revenue to be lower and thus results in less human capital, H_A, being allocated as well as a lower growth rate. Contrariwise, a reduction in the interest rate should speed up growth. The last equality in (1.20) represents the parametrically expressed balanced growth rate. It shows that H, total human capital, enters the growth rate equation and that λ, the research success parameter, has a positive effect on g^*, while the discount rate, ρ, has a negative effect. Moreover, in (1.20), g does not represent the efficient balanced growth rate because of the presence of a positive externality in research. There is a nonexcludable effect of R&D: when a new design is invented it increases the productivity of the R&D sector and this effect is not considered in the new design's price. The social optimum can be obtained by subsidizing the accumulation of A.

In terms of the convergence/divergence hypothesis, it must be noted that there is no convergence mechanism operating here. If we consider two economies, the one with the larger H_A will grow faster indefinitely and neither GDP per capita levels nor long-run growth rates will converge. Romer explicitly introduces this possibility in Rivera Batiz and Romer (1991), where this model is further developed. Moreover, even if human capital is important in defining the dynamics of the growth process it cannot be considered as the ultimate source of long-run growth. In order for unbounded per capita income to grow indefinitely, we need to identify another unbounded input, i.e technological progress. Nevertheless, in this study the long-run growth rate of an economy ultimately depends on the stock of human capital. This assumption may lead us to include this model within the Nelson and Phelps approach analysed in sections 1.2.3 an 1.2.4.

The influence of Romer's (1990b) model may be gauged by the many criticisms and extensions it has received. One of the first common criticisms of Romer's (1990b) model within endogenous growth literature is that it has a scale effect. Equation (1.20) implies that a country with a larger skilled labour force should grow faster, since equation (1.18) implies that the growth of technology should follow the same path of human capital over time. In practice, though, this prediction is difficult to detect in actual data. This is widely known as the Jones (1995) critique and will be dealt with later. Moreover, the model does not account for obsolescence of capital goods because it assumes additive separability of durables in the final goods production function (in eq. 1.16). More precisely, in Romer, capital goods are horizontally differentiated implying that no one capital good is better than the others. Indeed, the more capital goods we have the more each type can be used for a specific task, thus making it more productive[14]. This characterisation of the growth process has been considered unsatisfactory by advocates of the so-called Schumpeterian approach. Aghion and Howitt (1992)[15] have tried to overcome this problem by introducing the assumption of vertical differentiation of capital goods. Specifically, they introduce a mechanism of creative destruction whereby each time there is a new quality of capital good it assumes the old types to have become obsolete. In these *quality ladder* models, the variety of capital goods is fixed but the quality remains to be determined. Moreover, differently from Romer (1990b), they introduce uncertainty in the R&D sector, where uncertainty in the research process implies that the growth rate becomes stochastic. This approach is discussed in detail in section 1.2.6.

Despite their heterogeneity, all endogenous growth models are similar to Romer's (1990b) in that they do not sustain a solovian convergence mechanism.

14 Young (1928)was the first to develop the idea that growth is sustained by increased specialisation of labour due to an increase in the variety of goods produced.

15 See also Grossman and Helpman (1991).

Nevertheless, even if this literature was at first associated with predicting divergence among economies, further developments showed that endogenous models could actually produce convergence. This point will be further investigated in the following paragraphs.

1.2 Human capital, technology and growth

The emphasis of endogenous growth models for technology is an indication of the importance ascribed to human capital as one of the major forces influencing growth. This is not to say that the role of human capital for growth was neglected by economists prior to 1986[16]. From its earliest beginnings, economic theory has stressed the importance of human capital as a key factor for explaining growth. Arrow (1961) together with the works of Schultz (1962), Uzawa (1965), Nelson and Phelps (1966) are probably the most important early contributions to the theory of human capital and growth. Although Arrow (1961) does not explicitly introduce human capital in his study, his model does include externalities linked to the process of the accumulation of physical capital. It is a learning by doing model where the larger the scale of production, the greater the increase of the labour force's on-the-job productivity. We find a different approach in both Shultz (1962) and Uzawa (1965), where human capital is explicitly introduced in their analysis and is not considered as a mere by-product of production.

In general, human capital should indicate the degree of ability of the labour force and is usually measured in terms of formal education levels or on the job training. Accordingly, investment in human capital entails investment (education, training...) geared to sustaining and developing the ability of individuals. The accumulation of human capital is costly (it subtracts time available to production) but it represents a remunerative investment. In the following sections we offer a selective survey of the more recent contributions of the theory of human capital and growth. Our aim is to investigate the role human capital plays in the various growth models and to examine specifically the predictions of different models with regard to

16 Romer's (1986) model is considered as the first endogenous growth model.

the convergence hypothesis[17].

There is a substantial amount of literature on this. In order to classify the different models analysed we follow Aghion and Howitt (1998) and distinguish two different approaches that analyse the link between growth and education: the Lucas approach and the Nelson and Phelps approach. In the following sections we shall see that these two approaches include both endogenous and exogenous models. What characterises the different models is the assumed relationship between human capital and growth. What mainly characterises the Lucas approach (introduced in section 1.2.1 and 1.2.2) is the assumption that human capital enters a growth model simply as an additional input in a standard Cobb-Douglas production function and that capital accumulation is central force in generating growth. In other words, all these models imply there is a positive correlation between human capital accumulation and (long or short-run) growth rates. Therefore, empirically, we should observe that countries with different rates of investment in human capital grow at different rates.

Conversely, the Nelson and Phelps approach (see sections 1.2.3 and 1.2.4) does not emphasize the role of *capital accumulation* (both physical and human) as an engine of growth and stresses the importance of the process of technological change. Within this framework, human capital is a prerequisite for economic growth where "the growth rate of output will depend on the rate of innovation as well as on the level of human capital"[18]. Thus, (long or short-run) growth rates depend on stocks rather than on rates of accumulation of human capital. Moreover, human capital stock has two distinct roles in development processes. In particular, it has the dual role of increasing the rate of technological innovations, as well of sustaining the rate of adoption of existing technologies. The first role is generally related to technologically advanced economies or economies that may be considered at the technology frontier. The second role identifies a convergence mechanism resulting from technology transfers among economies rather than from factors accumulation as in the case of solovian convergence and, thus, should be important for less developed

17 Other important recent contributions not included in this survey are, for example, Becker, Murphy and Tamura (1990) and Benabou (1996).

18 Nelson and Phelps (1966).

economies. Stocks of human capital again play a fundamental role since they increase the capacity to adopt and implement innovations or new technologies from more advanced countries.

Finally, in section 1.2.5 we examine the models that stress the influence of trade on technological transfers, while section 1.2.6 focuses in particular on the Aghion and Howitt (1998) model, where both human capital and learning by doing appear as determinants of the growth rates.

1.2.1 Human Capital and the Lucas Approach

This framework is characterised by the assumption that the role of human capital in a growth model is simply as an additional input in a standard Cobb-Douglas production function. Therefore, we identify a new input, total capital, which represents the sum of human plus physical capital. In general, the presence of an endogenous or exogenous growth mechanism crucially depends on how returns to total capital in the production function of this economy are viewed. The presence of non-decreasing returns in this *augmented* form of capital cause, as expected, non-decreasing incentive to its accumulation as the stock of capital increases. Conversely, if total capital (human plus physical) is characterised by decreasing returns, incentives to its accumulation tend to decrease with an increase in its stock. In that case, human capital, even if it does not explain long-run growth, is still crucial for a better understanding of the process of transition towards long-run equilibrium. However, not all these models introduce augmented forms of capital. For example, Lucas (1988) assumes non-decreasing returns in the accumulation of human capital only, and identifies in this way the mechanism that causes the presence of an endogenous growth process.

Despite the presence of important differences, these models share a common assumption and a common testable prediction. First of all, this framework assumes that the process of accumulation of human capital is equivalent to that of physical capital. Secondly, all these models imply that an increase in human capital endowments positively affects an economy's growth rate. However, it affects the *long-run growth rate* in Lucas, while it influences the short run growth rate or, more precisely, *the growth rate of the transitional dynamics* in Mankiw, Romer and Weil

(1992).

We shall first examine the Mankiw, Romer and Weil (1992) model (henceforth MRW), which was already introduced in section 1.1.2 when we defined the concept of conditional convergence. In this section we propose an *augmented* version of their model. Here, the standard solovian production function is augmented by human capital, H:

$$Y = K^{\alpha} H^{\beta} (AL)^{1-\alpha-\beta} \qquad \text{with} \quad \alpha + \beta < 1 \tag{1.21}$$

and the constraints are:

$$\dot{k} = s_k y - (n + g + \delta)k \tag{1.22}$$

$$\dot{h} = s_h y - (n + g + \delta)h \tag{1.22'}$$

As in section 1.1, the lowercase letters denote a quantity per unit of effective labour. Equations (1.22) and (1.22') are identical: MRW assume the same dynamics for both physical and human capital, where s_k and s_h represent the exogenous and constant propensities to invest in both types of capital. Thus, MRW assume the same technology for producing human capital as for producing physical capital. This is a controversial assumption and has been criticised by Klenow and Rodriguez-Clare (1997a).[19]. The steady state values of physical capital, k^*, and human capital, h^*, are determined by:

$$k^* = \left(\frac{s_k^{1-\beta} s_h^{\beta}}{(n + g + \delta)} \right)^{1/(1-\alpha-\beta)} \tag{1.23}$$

19 They produce evidence showing that the technology for producing human capital is more intensive in labour than is the technology for producing other goods. Their evidence suggests factor shares of 10%, 40% and 50% for physical capital, human capital and raw labour in the production of human capital, as opposed to 30%, 28% and 42% shares used by MRW for both sectors.

and

$$h^* = \left(\frac{s_k^{\alpha} s_h^{1-\alpha}}{(n+g+\delta)} \right)^{1/1-\alpha-\beta} \qquad (1.23')$$

By augmenting the model with human capital, MRW obtain a new expression for the steady state (indicated by the asterisk) of per capita GDP:

$$ln\left[\frac{Y(t)}{L(t)}\right]^{*} = ln\,A(0) + gt + \frac{\alpha}{1-\alpha-\beta} ln\,s_k + \frac{\beta}{1-\alpha-\beta} ln\,s_h - \frac{\alpha+\beta}{1-\alpha-\beta} ln(n+g+\delta) \quad (1.24)$$

Ultimately, the steady state of per capita income, in addition to the factors of the Solow's textbook model described in (1.14), depends on s_h, the rate of accumulation of human capital. Substituting equation (1.24) in the usual convergence equation (1.8)[20], we obtain a positive relationship between the growth rate of an economy and the rate of accumulation of human capital. Note that this is not the only possible specification of the convergence regression. MRW also introduce a specification of the convergence regression in which the growth rate of an economy is a function of the level of human capital. Nevertheless, this alternative specification of the growth process involves per capita income growth as a function of the *steady state level* of human capital. In fact, equation (1.24) can be rewritten as:

$$ln\left[\frac{Y}{L}\right]^{*} = ln\,A(0) + gt + \frac{\alpha}{1-\alpha-\beta} ln\,s_k + \frac{\beta}{1-\alpha-\beta} ln\,h^* - \frac{\alpha}{1-\alpha-\beta} ln(n+g+\delta) \quad (1.24')$$

In this case, by substituting equation (1.24') within the convergence equation, we also find there to be a positive relationship between the growth rate of per capita income and the steady state level (or stock) of human capital. Note that in their empirical analysis, MRW introduce secondary school enrolment rates as a proxy for human capital. In other words, they probably consider equation (1.24) as the most

20 See also the section on beta convergence in chapter 2.

appropriate specification of steady state[21]. In fact, h^* should be considered unobservable, since in most countries it is implausible to assume that the observed human capital is at its steady state level. [22]

The MRW model has been highly influential within the growth-convergence debate. Theoretically, they have clearly illustrated the concept of *conditional convergence*, emphasizing that the Solow model predicts absolute convergence only under very restrictive assumptions. In this way, they provide a better description of cross-country data compared to the previous *unconditional convergence-exogenous growth* empirical literature, and show that it is not necessary to rely on endogenous models to explain the evident divergences among countries in international data sets. In their empirical analysis, they test for the determinants of the steady state including data on population growth rates, savings rates and secondary school enrolment rates[23] and find evidence of conditional convergence. That is, they do not predict there will be convergence in levels of per capita income among countries, since economies converge towards different long-run levels of per capita income but will converge towards the same long-run exogenous growth rate. Moreover, by augmenting the Solow growth model with human capital, they predict a larger contribution of total capital to *transitional* growth, and thus predict the existence of a prolonged transitional dynamic process. With the inclusion of a human capital indicator in their empirical analysis, they also find plausible values for the structural parameters of the Solow model[24].

Despite the differences existing between the two models, we include the Lucas (1988) model in the same class of models as MRW. Unlike the MRW one, this is an endogenous growth model where technological progress and, thus, long-run growth essentially coincides with the process of accumulation of human capital,

---

21 More precisely, during their empirical analysis they assume that actual values of human capital stocks represent a good proxy of their steady state value. However they never include in their regressions a measure of the stock of human capital arguing for a lack of data on that variable.

22 On this see Klenow and Rodriguez-Clare (1997a).

23 As a proxy for the accumulation of human capital, *sh*.

24 In particular, the value of the elasticity of output with respect to total capital, with an estimated value of approximately 0.8.

which is assumed to be unbounded[25], and to determine the long-run growth of an economy. He describes an economy where human capital is the key factor of production and where the production of human capital does not require physical capital:

$$y = k^{\beta}(uh)^{1-\beta}(h_{a})^{\gamma} \tag{1.25}$$

Differently from MRW, lowercase letters denote variables in per capita term; y is the usual GDP, h denotes the human capital stock of the representative agent, u is the fraction of time allocated to production and h_a represents the average human capital stock across individuals. Leisure is assumed exogenous and *(1-u)* denotes the time spent on education[26]. The presence of the parameter $\gamma > 0$ implies an externality in the model. In this way, Lucas stresses the possibility of the existence of "internal" and "external" effects on the accumulation of human capital: the former is simply the effect of individual human capital on its own productivity while the latter arises from a simple positive externality that the average level of human capital has on the productivity of all factors. This assumption implies that competitive equilibrium does not equate with efficient equilibrium. Therefore, optimal equilibrium will only be obtained by the social planner equilibrium. However, as we shall see, the presence of an externality in the production function is not essential in order to obtain the main results of this model. In this framework, the representative agent maximises the standard constant relative risk aversion utility function given the constraints:

$$\dot{k} = y - c - nk \tag{1.26}$$

$$\dot{h} = \xi(1-u)h \tag{1.26'}$$

25 This assumption has been criticised by Romer (1990b).

26 It is possible to relax this assumption. For a version of the Lucas model with leisure introduced endogenously see Solow (1994).

Equations (1.26) and (1.26') show that, unlike MRW, Lucas does not assume the same accumulation function for h and k. The parameter ξ in (1.26') represents the efficiency of the educational system. Equation (1.26') is the key one: it implies the presence of a process of endogenous growth. Endogenous growth is determined by the presence of constant returns to accumulation of the existing stock of human capital. In this case, the rate of growth of the stock of human capital plays the same role as exogenous technological change does in the Solow model. In fact, the Hamiltonian of this problem is:

$$H(c,u,k,h,\lambda,\mu) = \frac{c^{1-\sigma}-1}{1-\sigma}e^{-\rho t} + \lambda(Ak^{\beta}(uh)^{1-\beta}h_a^{\gamma} - c - nk) \qquad (1.27)$$
$$+\mu(\delta(1-u)h)$$

where the first order conditions are determined as usual. Rearranging the FOC's and using the relationship between k and y we obtain:

$$g_c^{*} = g_k^{*} = g_y^{*} = \frac{1-\beta+\gamma}{1-\beta}g_h^{*} \qquad (1.28)$$

where g^* denotes the steady state growth rates. It can be shown that:

$$g_h^{*} = \frac{1-\beta}{\sigma(1-\beta+\gamma)-\gamma}(\delta-\rho) \qquad (1.29)$$

Equation (1.28) is what most interests us here. In this model, the per capita income growth rate turns out to be a proportion of the growth rate of human capital. In other words, unlike MRW, Lucas endorses the idea that the *long-run growth* of per capita output is driven by the *accumulation* of human capital. Therefore this model predicts divergence across countries: economies that invest more in human capital (richer economies) should grow faster. That is to say, there is no convergence in levels of per capita income among countries because each country converges to different long-run growth rates.

However, in a more recent work, Lucas (1993) modifies this model including *a convergence in levels* mechanism. More precisely, he explicitly introduces knowledge spillovers among economies that cause the presence of a catching up process.[27] In fact, Lucas (1988) can simply be modified by introducing two countries, and transforming equation (1.26') as follows:

$$\dot{h}_1 = \delta(1-u_1)h_1^{\mu}h_2^{1-\mu} \qquad \text{with} \quad 0<\mu<1 \qquad (1.30)$$

where the subscripts, 1 and 2, represent the two countries. In (1.30) we still have constant returns on human capital for country 1 as before, but in this case note that $\dot{h}_1$ also depends on the level of human capital in country 2. More precisely, this equation captures the idea of possible interdependencies among economies because it accounts for ideas developed in one place affecting the development of new ideas elsewhere. In terms of growth rates:

$$\frac{\dot{h}_1}{h_1} = \delta(1-u_1)\left(\frac{h_2}{h_1}\right)^{1-\mu} \qquad (1.31)$$

Equation (1.31) implies that, if $u_1=u_2$, and $h_1>h_2$, country 2 should grow faster until $h_1=h_2$. Therefore, this relationship implies convergence in both per capita income levels and long-run growth rates between the two countries.

1.2.2 The Lucas Approach: multiple equilibria and clubs

The Azariadis and Drazen (1990) model introduces the existence of positive threshold externalities in education technology that lead to the existence of a multiplicity of equilibria and, thus, of steady state growth paths. They describe an overlapping generation model that allows economies with identical structures but different levels of investment in education to experience sustained differences in

27 The following example represents a further simplification of the model proposed by Lucas (1993) but it is still able to incorporate the catching up mechanism.

income per capita growth rates[28]. Individuals lives can be divided into two periods: when young, they inherit the aggregate human capital accumulated by previous generations and decide how much time to allocate to investing in education, u[29], and how much time to allocate to production activities, *(1-u)*.

As in Lucas (1988), the long-run growth rate, g^*, is a function of investments in human capital and, more specifically, it turns out to be an increasing function of the productivity of education. We focus on the equation that defines how human capital accumulates during the lifetime of an individual:

$$h_{2,t} = (1 + \gamma(u_{t-1}) \cdot u^{\vartheta})h_{1,t} \tag{1.32}$$

where the subscript 1, denotes the individual when young, 2 when old, ϑ is a parameter strictly less than one and γ represents the productivity of education and depends on the fraction of time allocated to education by the previous generation.

The existence of multiplicity of equilibria requires that there exists a positive threshold externality such that:

$$\gamma(u_{t-1}) = \begin{cases} \underline{\gamma} & if \quad u_{t-1} \leq u_0 \\ \overline{\gamma} & if \quad u_{t-1} > u_0 \end{cases} \qquad \text{with } 0<u_0<1 \text{ and } \underline{\gamma} << \overline{\gamma} \tag{1.33}$$

where u_0 defines the threshold level of u. Suppose that the previous generation invested a low fraction of his time in education such that $\gamma(u_{t-1}) = \underline{\gamma}$: in this case, investment in education will be unattractive for the current generation as well, because private rates of return on human capital investment depend on the existing average quality of h. Therefore, we will observe "...a tendency to perpetuate the successes and failures of the development process[30]". This analysis of a single

28 We will follow a simplified version of this model proposed by Aghion and Howitt (1998).

29 That is, as in Lucas (1988), u represents the fraction of time allocated to education.

30 Azariadis and Drazen (1990).

economy may be extended to a multiple economies framework. In fact, empirically this model implies the existence of convergence clubs. If two countries, A and B, have different initial human capital endowments where $u_A<u_0$ and $u_B>u_0$, they will experience indefinite growth at different growth rates with $g^*_A<g^*_B$. Without any intervention, economies that have not invested sufficiently in education in the past will find themselves in a "low development trap", that is, they will find themselves in the "poor countries" club. Moreover, we should observe different returns to education for the different clubs, with the rich countries club having the highest returns. There are no convergence mechanisms or knowledge transfers. Here, differences in actual investment rates of human capital should represent the key variable for explaining observed internationally divergent patterns of growth. And the policy implication is a simple one: in order to change club the government should subsidise education so that $u_t \geq u_0$.

1.2.3 From rates of change to levels: The Nelson and Phelps approach

An alternative approach to growth and education has its roots in the contribution of Nelson and Phelps (1966). This literature de-emphasises the role of *capital accumulation* (both physical and human) as the engine of growth and highlights the importance of the process of technological change. Within this framework "the growth rate of output will depend on the rate of innovation and, subsequently, on the level of human capital"[31] and not on the rate of change of human capital as in the previous studies.

Moreover, the majority of these models stress the importance of a catch-up mechanism in which human capital plays a fundamental role. In general, the level of human capital determines the capacity to both discover and implement innovations. That is, technological improvement is the combination of two distinct types of activities, innovation and imitation. The first can be thought as pure research and takes place mainly in technologically advanced economies. The latter describes the capacity to adopt new technologies from abroad and demonstrates the possibility of a process of beta convergence occurring, that is, of a catch up process, among

31 Nelson and Phelps (1966).

countries. The idea is that less advanced economies may be able to imitate/implement foreign technologies, since this process is cheaper than innovate.

Abramovitz (1986) was among the first to develop the idea of technological catch up as described above, though in a non-formal setting. He shares some ideas with endogenous growth models. Firstly, as were early endogenous growth studies, his studies were motivated by the search for a pattern in the observed wide variation in cross-country growth rates of output per man-hour. Secondly, he criticises the solovian approach, since catching up may explain the observed pattern of growth, but it does not represent a movement towards a steady state trend. Those who lag behind have the potential to experience higher growth rates. In particular, as in Nelson and Phelps (1966), the larger the technological and, therefore, the productivity gap between leader and follower, the stronger the follower's potential for growth in productivity. The idea is the often cited one: learning and imitating may be cheaper and faster than the original discovery and testing. Therefore, the distance between the level of development of the leader and that of a follower may be seen in terms of a stock of technological opportunities to exploit. Abramovitz distinguishes between potential and realised catching up. The former is measured by the gap between the leader countries and the backward countries, while realised catching up is the rate of exploitation of potential catching up. Actual exploitation depends on "the diffusion of knowledge, the rate of structural change, the accumulation of capital, and the expansion of the demand"[32]. More precisely, a country should have the *social capability* or the *technological congruence* to catch up with the leader; these concepts can be broadly identified with and explained in terms of technical competence, human capital and political, financial and industrial institutions. Therefore, in describing *social capability* determinants, he identifies many factors other than human capital. Despite his influence within literature on catching up, the limitation of the Abramovitz approach has been the absence of a clear theoretical background.

The following sections introduce different models that explain in a formal setting how this advantage of backwardness can lead to catch up. In particular, the

---

32 Abramovitz (1986).

higher the level of human capital and the larger the technology gap between the follower and the technology leader[33], the higher the resulting growth rate will be. Hence, it is possible to observe a convergence process: unlike in solovian convergence, this process is not produced by the existence of decreasing returns to capital accumulation but rather by the presence of knowledge spillovers or technology transfers.

1.2.4 The Nelson and Phelps approach: human capital and catching up

As in the Solow model, Nelson and Phelps (1966) describe a standard production function where technology is purely labour augmenting, that is, $Y=F(K, AL)$, where A is the usual average index of technology. Moreover, they introduce the notion of an exogenously given theoretical level of technology T. In particular, $T(t)$ can be seen as a measure of the stock of knowledge available to innovators, or as the technological frontier at time t, where T grows exogenously at a constant exponential rate, g. That is, $T(t)=T(0)e^{gt}$, where $g>0$. The major difference between this and the standard Solow model is described by the following equation:

$$\frac{\dot{A}(t)}{A(t)} = \Phi(H)\left[\frac{T(t)-A(t)}{A(t)}\right] \qquad \Phi(0)=0, \qquad \Phi'(H)>0 \qquad (1.34)$$

Equation (1.34) implies that the growth rate of A, the actual index of technology, is an increasing function of H, the level of educational attainment, and is also proportional to the gap between the theoretical knowledge, T, and A. Equation (1.34) also implies that the long-run growth rate of A is determined by the growth rate of theoretical knowledge, g, and that the long-run gap between T and A is determined by the level of H. In particular, when an economy has a positive level of H (exogenously determined) such that $\dot{A}/A > g$, we would observe a decreasing gap between T and A that causes a decrease in the current growth rate of A during the

33 Nelson and Phelps (1966) use the concept of gap between the theoretical level of technology and the level of technology in practice. A more explicit definition of leader and followers is found in Benhabib and Spiegel (1994).

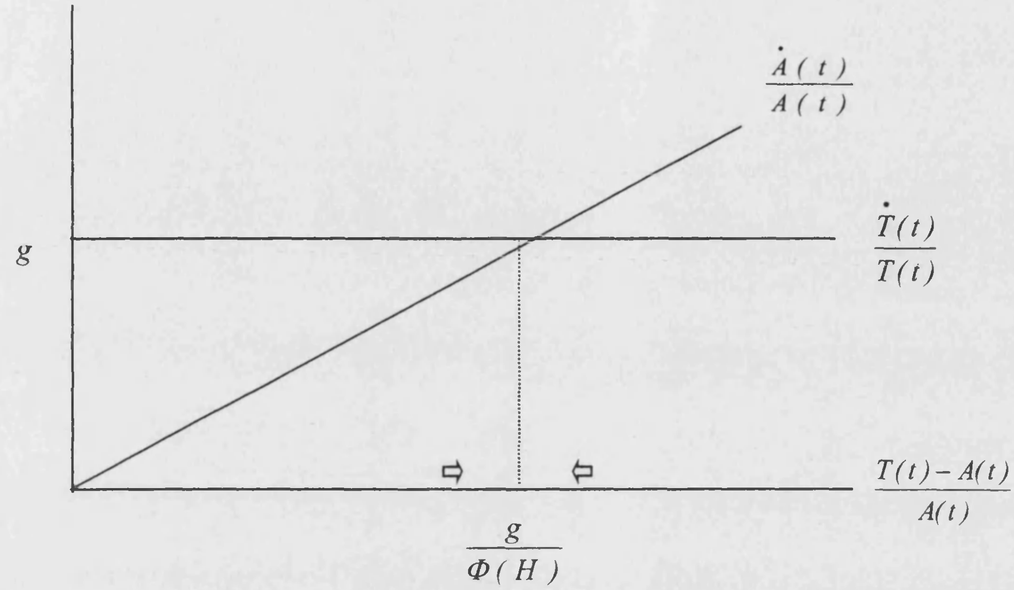

Figure 1.1

transition towards the common g. This process will continue until the growth rate of A is equal to g. Figure 1.1 describes this dynamic. We can interpret these results as implying the existence of a short run and a long-run Solow residual, where the former is influenced by the level of human capital while the latter is, as in Solow, exogenously determined. Thus, given H, in steady state the economy will grow at the rate g and will retain a constant gap between the theoretical knowledge and its actual level of technology where the equilibrium gap is given by

$$\frac{T(t)-A_a(t)}{A_a(t)}=\frac{g}{\Phi(H)} \tag{1.35}$$

where A_a represents actual technology. Equation (1.35) implies that the gap between T and A can be eventually reduced to zero by an increase in H, the human capital stock. Therefore, in terms of the convergence in levels prediction, the Nelson and Phelps model could be collocated within the conditional convergence literature. However, in this case the transitional dynamics at work constitute an explicit catching up process where the level of human capital plays the key role in defining the long-run gap that separates one country from the highest level of per capita income attainable. Even if, in comparison with Solow, the Nelson and Phelps model represents a richer framework for understanding the role of technology and human capital within the growth process, ultimately, as in Solow, the long-run growth rate of technical progress is still exogenous. Benhabib and Spiegel (1994) extend this framework considering technological progress to be endogenously determined. Therefore, as do Lucas (1988) and Romer (1990b), they stress the endogenous nature of growth and technical progress, introducing a model in which a higher level of human capital, *H*, causes a higher long-run growth rate of technical progress, where *H* is exogenously given. They extend the Nelson and Phelps model (hereafter NP) assuming an explicit process of diffusion of technology among countries. More precisely, following Nelson and Phelps (1966), they explicitly interpret *T*, the theoretical level of knowledge, as the technology level of a leading economy. The main difference with the Nelson and Phelps model is illustrated by the following equation:

$$= f(H_i(t)) + c(H_i(t))$$

$$\frac{\dot{A}_i(t)}{A_i(t)} = f(H_i(t)) + c(H_i(t))\left(\frac{\max_j A_j(t)}{A_i(t)} - 1\right) \qquad i=1,\ldots N \qquad (1.36)$$

As in equation (1.34), equation (1.36) represents the growth of total factor productivity for country *i*. Both $f(H_i)$ and $c(H_i)$ are non-decreasing functions of H_i. Thus, the growth rate of technology for a follower is given by two elements: the endogenous growth rate $f(H_i)$ plus a catch-up factor. The leader will grow at the rate $f(H_L)$, that is $A(t) = A_L(0)e^{f(H_L)t}$. This hypothesis represents the crucial difference with the previous model. In NP $f(H_i)=0$, where this assumption implies that H_i affects the growth rate of A_i only in transition. In this case, the more human capital is allocated to the R&D sector the better it will be for long-run growth. As a consequence, the dynamics among countries are here more complex, and the convergence to a common growth rate may be an extremely long process[34]. Despite the differences, both the NP model and the Benhabib and Spiegel (hereafter BS) model share the same conclusions. First, if a group of economies shares the same level of human capital we should in the long-run observe complete convergence in both per capita income and growth rates. Secondly, if we assume that H_i remain constant in each country (or that the ranking of H_i does not change across countries over time) the mechanism of technology diffusion and catch-up will at least guarantee convergence in growth rates: all countries eventually grow at the same rate as the leader, the latter acting as the locomotive. Their contribution is also of an empirical kind. In particular, their study was one of the first attempts to estimate the NP approach and to distinguish between what they call the neoclassical convergence effect and catch-up due to technological transfers. They use the standard growth accounting methodology, where the production function is given by $Y_t = A_t(H_t)K_t^{\alpha}L_t^{\beta}$ and obtain the following regression equation:

$$\begin{aligned}(\log Y_T - \log Y_0) &= c + (g-m)H_i + mH_i(Y_{\max}/Y_i) + \alpha\left(\log K_T - \log K_0\right) \\ &+ \beta\left(\log L_T - \log L_0\right) + \left(\log \varepsilon_T - \log \varepsilon_0\right)\end{aligned} \tag{1.37}$$

where the stock of human capital enters twice among regressors. Firstly, it acts as a determinant of endogenous technological progress and measures the ability of a country to innovate. Secondly, it enters the regression multiplied by the technological gap of country i from the leader, and test for the ability of a country to catch up. A positive and significant coefficient on this interactive term implies that the more educated the population the greater the catch up effect will be (or that the effect of education will be proportionately greater when the productivity gap is large). Note that, in this specification, given that technology is unobservable, BS use, as a proxy of technology gap, the difference in GDP levels between country i and the leader.

Interestingly, they find that, using a sub-sample of poor countries, only the catch up term has a significant effect on the regression, while the first term is significant and positive only for a sub-sample formed by rich countries. However, among rich (mainly OECD) countries the catch up term is not significant. While they claim that these results are consistent with their theory[35], with rich countries that innovate and

---

34 This is true if, for example, we assume that f(Hi)>c(Hi).

35 As in BS (1994) "We obtain the most striking results from the richest third of the sample,...".

poor countries that imitate, we find the absence of evidence of technology transfers among rich economies not totally convincing. Evidence of the presence of a convergence process among rich countries dates back to Baumol (1986) and, in general, one assumption that is usually found in this literature (this study included) is that technological transfers are likely among similar countries. Less convincing results also include the evidence for middle-income countries, where they do not find any significance for human capital variable. Finally, this study stresses the danger in empirical analysis of the possible observational equivalence between technology transfers and the neoclassical convergence mechanism, that is, convergence due to capital accumulation in transitional dynamics. In fact, the catch up term in eq. 1 could capture the effect of both. To evaluate this problem, they introduce initial income as a further regressor in eq. (1.37), and show that the result on the catch up term is not influenced by this new variable.

In a more recent paper, Benhabib and Spiegel (2002) examine an alternative formulation that introduces a mechanism whereby the rate of technological diffusion decreases as the distance to the leader increases. A logistic model of technology diffusion is given by:

$$\frac{\dot{A}(t)}{A(t)} = f(H_i(t)) + c(H_i(t))\left(1 - \frac{\max_j A_j(t)}{A_i(t)}\right) \qquad \text{or}$$

$$\frac{\dot{A}(t)}{A(t)} = f(H_i(t)) + c(H_i(t))\left(\frac{A_i(t)}{\max_j A_j(t)}\right)\left(\frac{\max_j A_j(t)}{A_i(t)} - 1\right) \tag{1.38}$$

The difference between eq. (1.36) (defined as the exponential model of technology diffusion) and this logistic model is the term $\left(\frac{A_i(t)}{\max_j A_j(t)}\right)$. In this formulation, the second term of the RHS includes two contrasting mechanisms. The first is the standard catch-up mechanism, but the extra term acts in an opposite direction since the positive contribution of human capital to TFP growth tends to be smaller, the greater the distance between the leader and the follower. This implies that the usual catching-up mechanism is therefore more effective at intermediate distances from the leader, while is less effective for both very laggard and advanced countries. Therefore, the logistic model further stresses the importance of investments in human capital: countries with a very low level of human capital may become unable even to exploit their advantage of backwardness and risk being "trapped in the wrong club". That is, this model identifies an explicit 'club convergence' mechanism. Assuming that the ranking of H_i does not change across countries and over time it is possible to show that if a country *i* has $c(H_i)+f(H_i)-f(H_{leader})>0$ then this country will *converge in growth rates* with the leader, while if $c(H_i)+f(H_i)-f(H_{leader})<0$ growth rates diverge, and the laggard country will continue to further distance itself from the leader.

Again, in their study BS make an interesting empirical contribution. In general, the empirical literature on convergence clubs has probably not evolved *pari passu* with its theoretical developments. Evidence of divergence and, in particular, "twin peaks" evidence in cross country analysis that use the income distribution dynamics methodology developed by Quah[36], is certainly consistent with the club hypothesis. Nevertheless, there are very few attempts to estimate what is one of the main implications of these models, which is the presence of thresholds that cause a country to settle in either the poor or rich countries club. As observed by Azariadis and Drazen (1990) for their "...model to have sharp predictions, one would need to know the location of such human capital thresholds...and if they differ across economies".[37]. Unlike Azariadis and Drazen, they use empirical analysis to derive a point estimate for the minimum initial human capital level necessary for a country to exhibit catch-up in TFP relative to the leader economy.

Instead of proxying TFP with GDP levels as in BS (1994), they estimate TFP levels as the residual in a standard level accounting framework:

$$\log A_{it} = Y_{it} - \tfrac{1}{3}\log K_{it} - \tfrac{2}{3}\log L_{it} \tag{1.39}$$

36 See Quah (1996), (1997) and (1999).

37 And they conclude that "In the absence of such information, the working hypothesis that emerges is that economic growth should be correlated with human investments relative to per capita income".

with A representing TFP. More precisely, they assume a constant returns Cobb-Douglas production function with capital share set at 1/3 and labour share at 2/3, equal for all countries. With this TFP measures they may estimate:

$$\Delta a_i = b + \left(g + \frac{c}{s} \right) h_i + \left(\frac{c}{s} \right) h_i \left(\frac{A_i}{A_{\max}} \right)^s + \varepsilon_i \qquad (1.40)$$

where a represents the log of TFP and A_{max} is the TFP level of the leader economy. They show that this specification nests both the exponential and the logistic functional form of technology diffusion. In particular, when $s=-1$ this specification corresponds to the exponential model defined by eq (1.36), while if we assume $s=1$, we obtain the logistic model of eq. (1.38).

They use a cross country dataset of 84 countries from 1960 to 1995 and estimate this nonlinear specification using maximum likelihood. The values obtained for s seem to favour using the logistic model[38]. Moreover, the coefficient of the catch up term is negative and significant while that of human capital is positive and significant as the theory would predict. These results are fairly robust to the exclusion of the constant term, the use of different proxies for h and are not dependent on the non-linear specification [39]. However, apart from the catch-up term result, other results are not robust to the inclusion of other conditioning variables. Finally, they obtain a point estimate for the minimum initial human capital level necessary for a country to exhibit catch-up in TFP relative to the leader economy. At each point in time this threshold is defined by:

$$H_t^* = \exp\left(\frac{sgh_{\max t}}{sg + c} \right) \qquad (1.41)$$

38 Their point estimate of s is equal to 2.304.

39 They use both the initial level and the average level of human capital and estimate eq.(1.40), imposing s=1.

where $h_{\max t}$ is the log of human capital of the leader at time t. Thus, if $H_{it} > H_t^*$ an economy should experience a faster TFP growth than the leader and *viceversa.* They estimate these thresholds in terms of average years of schooling for 1960 and 1995, and find $H_{1960}^* = 1.78$ and $H_{1995}^* = 1.95$. They observe that, in 1960, 27 nations had $H_{it} < 1.78$ and find that 22 out of 27 actually showed slower TFP growth than the leader nation (USA). Moreover, in 1995 only 4 nations (Mali, Niger, Mozambique and Nepal) had $H_{it} < 1.95$ and thus, are predicted to stay behind exhibiting a slower TFP growth than the leader. If confirmed, the observation that the poor club currently include only 4 nations is certainly reassuring, with eighteen nations that moved from the poor to the rich club. We will have to wait a few years to find out if this reassuring prediction is confirmed by data.

Finally, we conclude this introduction to the NP approach with the Jones (1995) critique. Jones observes that the NP approach implies counterfactual predictions. With the exception of BS(2002), in this approach the growth rate of A, an index of technology, is an increasing function of H, the level of educational attainment. Thus, we should observe in actual data that increased research effort causes an increase in the growth rate. But this is not the case. In most developed countries human capital and research effort have increased continuously in the last decades but these countries did not experience accelerating growth rates. Thus, to reconcile theory with data it is necessary to assume some form of decreasing returns in the R&D sector, with new discoveries becoming increasingly hard as the stock of existing knowledge (or human capital) increases. Otherwise, as noted by Cannon (2000), to be consistent with the stylised facts concerning human capital, the relationship linking technology to human capital should be modified. The growth rate of A should be an increasing function of the human capital to output ratio[40] with an "augmented Nelson-Phelps (NP) approach" characterised by $\frac{\dot{A}(t)}{A(t)} = \gamma\left(\frac{H}{Y}\right)$, where γ is some function with a positive first derivative. However, in this case it becomes impossible to distinguish this augmented NP approach from Lucas, as Cannon shows

[40] See Segestrom (1998) and Howitt (1999).

that the Lucas approach implies an identical relationship between A and H/Y unless we assume that there is no variation in the ratio of human capital to output. But this, again, seems a counterfactual assumption.

1.2.5 Human capital, catch up and openness to trade

The models reviewed above describe a catch up mechanism resulting from technology transfers with human capital levels acting as the main determinant. However, these models do not describe any mechanisms that may affect the existence of transfers of technology among countries. In the models analysed so far, with the possible exception of BS (2002), where human capital needs to exceed a certain threshold for catch up to take place, transfers of technology and catch up are considered as inevitable or automatic. In contrast to this approach, other studies focus specifically on the possible existence of barriers to the adoption of technology from abroad. Quoting Parente and Prescott (2000): "The relevant question is: Why don't poor countries use the existing stock of usable technology more efficiently?" [41] Many factors have been identified as important for a country to be able to imitate and implement new technologies from abroad. We saw in section 1.2.3 how Abramovitz (1986) distinguishes between potential and realised catching up and how the latter depends on the *social capability* of a country identified with its technical competence, human capital as well as the structure of its political, financial and industrial institutions. Parente and Prescott [(1994) and (2000)] have further developed this idea. They focus in particular on the existence of barriers to the adoption and efficient use of more productive technologies, where such barriers are the primary result of country-specific policies. Aghion, Howitt and Mayer-Foulkes (2003) focus on the effect of financial development on convergence and examine how financial constraints may prevent countries from taking full advantage of technology transfer.

However, among the factors influencing technology diffusion, trade policies have been identified as one of the main determinants, since they are a sort of

41" ...This is why the focus of the book is on barriers to the adoption and efficient use of more productive technologies, and not on the creation of more productive technologies." Parente and Prescott (2000) page 5.

necessary vehicle for technological spillovers to take place. For Abramovitz (1986), trade helps to explain why we observe catching up among western economies. He identifies the years following World War II as an exceptional period, where many of the elements required for rapid growth and catching up came together. There was a group of countries with similar economies, large technological gaps but with a relatively (highly) educated labour force that opened them to trade. In general, theoretical models have identified different positive channels through which trade affects an economy's productivity[42]. Firstly, the larger variety of products and intermediate capital goods available to an open economy may enhance its productivity. Secondly, trade is usually associated with cross-border learning of a) new product designs, b) new production and organisational methods and c) market conditions. In other words, we can think of technology transfers as taking place directly through flows of ideas or indirectly through flows of goods, where both are enhanced by trade-friendly policies. All these factors increase the efficiency with which domestic resources are allocated, and enable a laggard economy to learn and imitate foreign technologies. Thus, trade-induced technology transfers may lead to cross-country convergence. However, the standard international trade literature stresses also another effect of trade. In fact, in a multi-sector framework, trade may induce a country to specialise and, thus, allocate its factors of production to specific sectors, determined by its comparative advantages. As we shall see later, if different sectors have different growth potential, this allocation effect may induce divergence instead of convergence.

The idea that trade is both 1) a necessary vehicle for technological spillovers that bring about convergence and 2) a possible cause of divergence due to the specialisation induced by the working of the law of comparative advantage, was the subject of a study by Rivera Batiz and Romer (1991). They looked in particular at how two economies interact through trade and investigate the possible effects of competition, market size and trade policy on both long-run growth rates and steady state levels of per capita income. Human capital factors are of fundamental importance in explaining both the long-run growth rate as well as convergence.

42 See also the discussion in Coe, Helpman and Hoffmaister (1997).

Countries will only converge towards the same level of per capita income if they have the same stock of human capital allocated to the R&D sector. The model is based on Romer (1990b)[43]. Within this framework, we explicitly consider two different countries (1), home country, and (2), foreign country and their interactions through trade. If we extend the nonrival nature of technology to this two country-two sector case[44] we should observe the presence of increasing returns due to international knowledge spillovers. We focus here on the so-called *knowledge driven*[45] specification of the R&D process that represents a simple extension of Romer (1990b) to open economies. Moreover, we assume that countries are identical, that is, they have similar endowments and technologies. This assumption is essential since we need not be concerned with the "comparative advantage" effect that would arise in a multi-sector trade model and can thus focus on the pure scale effect of trade. Countries produce only one final good by means of raw labour, human capital and the stock of capital, where $K_t = \eta A_t \bar{x}$ in both countries as in Romer (1990b). To examine the main features of this model we focus on the R&D sector. In autarchy this process will be characterised, for both countries, exactly as in equation (1.18): $\dot{A}^i$ (with $i=1,2$) will be influenced by λ the research success parameter assumed constant between countries, H^i_A and A^i. After trade this process is characterised differently. Rivera Batiz and Romer (1991) distinguish two possibilities: 1) free trade of goods with no flows of ideas and 2) free trade of goods and ideas. The first case implies there will be a level effect of trade. In fact, given the view of technology assumed in eq. (1.18), growth rates are not affected by trade. However, free trade of goods implies that the number of machines used in each country approaches twice the number that have been produced domestically since in their pursuit of monopoly

---

43 The description of the structure of production technology in the manufacturing sector is based on equations (1.15), (1.16), (1.17), while (1.19) describes the structure of production technology in the manufacturing sector in both countries.

44 As shown in section 1.1.3, Romer's model (1990b) can be reduced to a two-sector model, where the manufacturing sector includes both the final good sector and an intermediate good sector.

45 We find similar conclusions with the so called lab-equipment specification of the R&D process. In this specification of the model it is not necessary to observe a free flow of ideas for catching up to take place. It is sufficient that there be of free trade of goods. See Rivera Batiz and Romer (1991).

rents, researchers in both countries will avoid redundancies. Therefore, trade affects the level of output produced in both countries[46] but does not have any effect on growth rates.

In contrast to the previous case, the second case involves a growth effect. In particular, if we define $A^{world}=A^1+A^2$, free flows of ideas imply:

$$\dot{A}^1 = \lambda H_A^1 A^{world} \qquad \text{and} \qquad \dot{A}^2 = \lambda H_A^2 A^{world} \tag{1.42}$$

As compared with equation (1.31), in this case the rate of growth of new ideas in each country depends not only on the human capital allocated to the R&D sector, $H^1{}_A$ and $H^2{}_A$, as before, but also on A^{world}, which represents the sum of the stock of knowledge of both countries. In other words, the entire stock of knowledge can be used in both countries[47] at the same time. But, if economies are identical then $A^{world} = 2A$. Therefore, eq. (1.42) implies the presence of knowledge spillovers and, as described, the R&D sector is characterised by the presence of a scale effect. Integration immediately raises the long-run growth rates of these countries, purely because it increases the extent of the market. In fact, economic integration with knowledge spillovers improves the efficiency of the research sector. In autarchy, we would observe redundant efforts, with one economy devoting resources to discovering a design that already exists in the other country. Finally, note that, in the long run growth rates will be equal in both countries as the technology growth rate may be rewritten as:

$$g_A^1 = \frac{\lambda H_A^1 (A_1 + A_2)}{A_1} = \lambda H_A^1 \left(1 + \frac{A_2}{A_1}\right) \tag{1.42'}$$

As in equation (1.31) the presence of the ratio of A_2 to A_1 on the RHS in (1.42') implies that the free flow of ideas/technology would finally equate the long run

---

46 See eq. (1.19).

47 And also in both sectors.

growth rates in both countries.

However, Rivera Batiz and Romer (1991) develop other interesting cases that imply different results. In particular, when countries are not similar, there is another possible effect of trade liberalisation to consider, i.e. the so-called allocation effect. This effect may explain how specialisation creates persistent growth differentials and, thus, shows when interaction among countries is not beneficial. As stated above, trade can also influence the allocation of human capital among sectors, thus affecting a country's pattern of growth. The idea is a simple one. Trade may strongly affects the reallocation of inputs of production between sectors on the grounds of comparative advantage. In these models, comparative advantage can be determined by different initial conditions. Therefore, the flow of goods that follows from the opening to trade could induce an increase in specialisation and the presence of increasing returns with specialised inputs in the manufacturing sector. In this case, we can hypothesise two different scenarios. Firstly, if trade causes H_A to expand as a result of increased specialisation, assuming the absence of knowledge spillovers among sectors, the allocation effect increases the long-run rate of growth of one country. Conversely, the allocation effect has a negative influence on growth in the other trade partner, because trade causes H_A to fall. In other words, the different allocation of basic inputs between the two sectors affects sectoral output which in turn affects long-run growth. In conclusion, it is only in the absence of the allocation effect, that the scale may turn out to be the source of large dynamic gains, uniformly distributed among countries with similar economic structures. Therefore policy implications in this case are not so simple. A country should open to trade only if the resulting allocation effects are small, and this will be true only if trade occurs among similar countries. Note that this model assumes absence of spillovers across different sectors. In this case, we may even observe two countries converging to different steady state levels of per capita income but towards the same long-run growth rate. When trading partners have different initial conditions, Lucas (1988)[48], Grossman and Helpman (1991) and Young (1991) show the conditions under which comparative advantage produces large allocation effects and growth can be larger

48 We are not referring to the model described in section 1.2.1 but to another model always described in Lucas (1988).

under autarchy.

Empirical evidence of the presence of R&D spillovers through trade among different countries may be found in Coe and Helpman (1995) and Coe, Helpman and Hoffmaister (1997)[49]. Using different samples[50] these studies find evidence of R&D spillovers where international trade plays an important role. These are present among the group of industrialised economies, but there is also evidence of developing countries benefiting from R&D investments realised in industrialised economies.

1.2.6 Human Capital, R&D and learning by doing

Finally, let us look at Aghion and Howitt's (1998) model since, unlike all the models examined so far, it introduces the interesting possibility of the role of human capital allocated in the R&D sector not being strictly positive for growth and, in addition, stresses the importance of learning by doing processes for growth[51]. In particular, they further develop the idea of the existence of many kinds of innovative activities generating many kinds of knowledge and distinguish between fundamental innovative activity, represented by the R&D sector, and secondary research, which includes all improvements in technology due to learning by doing activity. Any innovation resulting from R&D could potentially lead to a new product while innovations, resulting from learning by doing, bring about new ways to improve the quality of the goods that have already been invented. Thus, there is a clearly observable link between research and learning by doing. This is a two-sector *shumpeterian* model with a final good sector and an intermediate good sector. That is, there is a mechanism of creative destruction, where entrepreneurs continuously look for new ideas, or new products and new ideas affect the profit potential of rivals because old ideas (products) become obsolete. The final goods sector is governed by perfect competition. The unique final consumption good is produced with a

---

49 More recently, the positive role played by trade in the adoption of new technologies is also stressed in Cameron, Proudman and Redding (1999) and Comin and Hobijn (2003) among others. On this, see also Chapter 5.

50 21 OECD countries plus Israel in Coe and Helpman (1995) and a large sample of 77 developing countries in Coe, Helpman and Hoffmaister (1997).

51 This model has been firstly developed in Aghion and Howitt (1996) but it is widely discussed in their 1998 book.

continuum of intermediate goods of different vintage. In this second sector each intermediate goods producer has some monopoly power. There are only skilled workers H and each worker decides whether to engage in research or production. The flow of new products is described by $\lambda^r H^r$, where H^r represents workers employed in the research sector, and λ^r is the Poisson arrival rate of fundamental innovations, a fixed exogenous parameter. Newly invented goods are potentially better because they incorporate a higher level of general knowledge. The model is not described in detail here and we include only two explicit equations. First, the aggregate final output that is given by:

$$Y_t = \int_{-\infty}^{t} \lambda^r H^r A_\tau Z_{t-\tau} (x_{t-\tau})^\alpha d\tau = \int_{-\infty}^{t} Y_{t,\tau} d\tau \qquad (1.43)$$

where A_τ represents the general knowledge in date τ, x_a is the labour input used in production of each intermediate good of age "a" and Z_a represents the quality of the good. The second equation represents the growth of general knowledge that is given by:

$$\frac{\dot{A}_t}{A_t} = G(\lambda^r H^r, Learning - By - Doing) \qquad (1.44)$$

where G=0 if Hr=0 or LBD=0. The function G strictly increases in both arguments. In steady state, the economy's growth rate will equal $\frac{\dot{A}_t}{A_t}$, or the growth rate of general knowledge. As previously stated, one of the most interesting implications of this model is that there is a possible negative effect on the growth of human capital allocated in the R&D sector. There exists an optimal level of research, H^{r*}, that maximises the steady state long-run growth. Beyond this threshold level, H^{r*}, too many resources in terms of human capital are devoted to research at the expense of production. Therefore, because G depends also on secondary innovations, or learning by doing, we observe that, beyond this threshold level, the growth rate of innovations and ultimately the growth rate of the economy tend to decrease as H^r increase.

In conclusion, this model has many virtues since it stresses the importance of both R&D and learning by doing in the growth process and describes how an economy can risk allocating too much of its qualified labour force to the research sector. Nevertheless, originality of results has probably been achieved at the expense of plausibility. At present though, it seems that most economies are far from running the risk of allocating too much their qualified labour force in the research sector.

1.3 Summary: different notions of convergence and predictions of exogenous and endogenous models

So far in this Chapter we have seen that there is no single concept of convergence and that each possible concept of convergence is associated to dissimilar patterns. To clarify this question, this section will try to summarise some of the differences[52]. Among exogenous models, we have seen that in his influential studies Solow was probably more interested in the analysis of *within country convergence* than in its *across countries* dimension. The concept of *within country convergence* should actually relate to the transitional dynamics of the solovian model, where each economy converges towards its dynamically stable equilibrium whatever its initial condition. In other words, each economy inevitably converges towards its long-run equilibrium. At first, the notion of within country convergence was associated with the concept of *across country convergence.* Indeed, if a group of economies share the same long-run equilibrium we should observe poor countries catching up with the richer ones. We have called this hypothesis *unconditional or absolute convergence* hypothesis. However, later developments showed that the presence of within country convergence will not necessarily mean that across country convergence will take place.

The *conditional convergence* literature demonstrates that there is not necessarily a unique equilibrium among countries, since each country tends to converge to its own equilibrium level of income. In particular, this hypothesis assumes that, across countries, convergence is valid only if factors affecting the long-run equilibrium are the same. Note then that, despite the possibility of different

52 Additional definitions, prominent in empirical literature, will be examined in chapter 3. A survey of the different concepts of convergence can be found in Islam (2003).

steady states, the conditional convergence hypothesis assumes that each country converges towards its own unique equilibrium. This specification is important if we want to distinguish the concept of conditional convergence from the notion of *convergence clubs*. In fact, the two concepts are often assumed to carry the same meaning. Nevertheless, there is another possible interpretation, where, unlike conditional convergence, the convergence clubs hypothesis implies the possibility of the existence of multiple equilibria for each country.

Further, it is important to distinguish between *convergence in growth rates* versus *convergence in levels*. In general, we have seen that both the concepts of conditional and unconditional convergence imply that, in the long-run, each country converges towards the same, exogenously given *growth rate*. Therefore, it is sometimes said that conditional convergence models entail *convergence in steady state growth rates* of per capita income, while they do not assume *convergence in steady state levels* of income.

Finally, the sections above show endogenous growth models characterised by both *divergence* and *catch up*. Divergence implies that each country converges towards its own long-run level of income and its own long-run growth rate. Conversely, the catch up hypothesis implies convergence in levels and growth rates but must be distinguished from standard solovian convergence, since the first is due to technology transfers while the latter to capital accumulation. In other words, a process of *convergence in steady state levels across countries* may be due to these different mechanism:

1. Convergence due to capital accumulation;
2. Convergence due to technology transfers (catch up);
3. Convergence due to both (1) and (2).[53].

Conversely, evidence of the absence of *convergence in steady state levels across countries* may be theoretically explained by models implying:

- Divergence (or absence of convergence in both steady state levels and growth rates across countries);
- Conditional convergence (with the presence of convergence in steady state

53 See also Chapter 5.

growth rates across countries);

- Convergence clubs (with the presence of convergence towards different steady state growth rates depending on the club).

Finally, Table 1.1 offers a brief summary of some of the most important endogenous and exogenous models characterised in term of their ability to explain the observed convergence in per capita GDP levels. In general, we focus on the *across* dimension of the convergence process in terms of *per capita income levels.* This is the notion of convergence related with the first of our starting questions: Are poor countries catching up with the richer ones? This final section reviews the predictions of the different models examined so far with respect to this specific concept of convergence. We may also refer to this notion in terms of *observed* convergence as we shall refer specifically to the idea of a group of countries converging towards the same level of per capita GDP. From now on, in this Table we use the word "convergence" without any further specification with this meaning while we introduce the term divergence in a broad way as implying the absence of convergence in levels.

We identify the following four different possible categories: a) exogenous models predicting convergence, b) exogenous models predicting divergence, c) endogenous models predicting convergence, d) endogenous models predicting divergence. We should note that there are many models that can belong to more than one category. In fact, the prediction of convergence/divergence depends on initial assumptions since the same model may describe both mechanisms. Therefore, we specify the main assumptions that lead these models to predict convergence or divergence. For example, among exogenous models, the Solow model is able to explain both observed convergence and divergence. Assuming countries share the same technology and preferences (and possibly, other determinants of the steady state) the transitional dynamics of the solovian model imply convergence will occur. Nevertheless, Mankiw Romer and Weil (1992) show the assumptions required for the Solow model to explain the observed diverging pattern in per capita GDP in international data sets. In fact, when countries are dissimilar, the Solow model predicts conditional convergence, since in this case transitional dynamics cause different countries to converge towards different steady state levels. Among exogenous models we have also included NP (1966): assuming countries have the same stock of human capital, this model predicts convergence due to technology catch up. Conversely, when countries have different human capital endowments, this model implies what we have called conditional catching up: laggard countries still enjoy the advantage of backwardness and still converge towards the same (exogenously given) long-run growth rate, but they never reach the steady state level of per capita income of the most technologically advanced economies.

Within endogenous literature, models are more complex and the classification becomes more puzzling. Endogenous growth studies suggesting the possibility of convergence in per capita levels of GDP among different countries usually assume the existence of knowledge spillovers from rich to poor countries that eventually generate a catching up process. In general, these models share the idea that, unlike Solow (1956) but similar to NP (1966), the pace at which the potential for catch-up is actually realised in a particular period does not depend on the accumulation of capital. However, even in this class of models, convergence is not the only possible outcome. To be able to explain convergence, these models need to assume that different countries are somehow "similar". In particular, we would only observe convergence (and also convergence in growth rates) when different countries share the same stock of human capital. In other words, when countries are not *similar*, these models predict divergence. In general, we may divide endogenous models predicting divergence into two categories. The first is the one just described. It includes models characterised by the presence of transfers of technology but absence of convergence. The second category stresses the presence of non-decreasing returns to inputs in a standard production function. Therefore, there is no emphasis on transfer of technology or, in general, interdependencies among countries. When incentives to factor accumulation are non-decreasing, the gap between poor and rich countries stays constant or continues to increase. If a rich country invests more than a poor one, long-run growth rate of the former will be indefinitely larger than that of the latter. Among the most influential studies we can cite Rebelo (1991), Lucas (1988) and Romer (1986, 1990). A final observation concerns the hypothesis of convergence in growth rates: unlike in exogenous literature, endogenous models predicting divergence emphasise the absence of convergence in growth rates as well as that in levels.

Summarising with a play on words, we might conclude that during the last fifteen years there has been a convergence of ideas between endogenous and exogenous models with respect to the convergence hypothesis. Despite the still theoretically important difference between models that assume exogenous versus models that assume endogenous long-run growth rates, both theories predict that a mechanism of convergence is possible, but it will only be so among similar economies. In particular, most theoretical literature assumes that similar levels of human capital are fundamental for catch up to take place. Therefore, both theories are currently able to explain a stylised fact of the empirical literature on growth, namely the observed convergence among groups of homogeneous countries and the absence of convergence when large and heterogeneous data sets are introduced. This observation explains why, with current econometric techniques, it is not possible to discriminate endogenous versus exogenous models by simply using a convergence regression. The following Chapter is dedicated to the various problems relating to the empirical literature on growth and convergence.

Table 1.1

	Exogenous models	Endogenous models
Cause of observed convergence	Absolute convergence=convergence towards a unique steady state income level and growth rate → transitional dynamics or catching up. Emphasis on: Solow (1956): decrasing returns with identical technology and preferences. Nelson and Phelps (1966): technological catching up and similar countries ($H_i=H_j$).	*Possible* convergence in levels=unique steady state income level and endogenous growth rate → transfers of technology. Emphasis on: Romer and Rivera Batiz (1991): transfers of technology due to trade, similar countries ($H_i=H_j$); scale effect on R&D. Lucas (1993): catching up similar countries ($u_1=u_2$). Benhabib and Spiegel (1994): technological catching up with similar countries ($H_i=H_j$).
Cause of observed divergence	Conditional convergence=convergence towards different levels but a unique exogenous steady state growth rate → transitional dynamics or conditional catching up. Emphasis on: - Solow (1956): decreasing returns with different technology and preferences. - Mankiw Romer and Weil (1992): decreasing returns with different determinants of the steady state (human capital). - Nelson and Phelps (1966): technological catching up but ($H_i \neq H_j$).	1) Divergence=convergence towards different steady state levels and endogenous long run growth rates → non decreasing returns to reproducible factors of production ($\alpha \geq 1$). Emphasis on: Romer (1986): constant returns due to learning by doing. Romer (1990): constant returns in technology production function. Lucas (1988): constant returns in human capital production function. Rebelo (1991) *Ak* models. Azariadis-Drazen (1990): multiple equilibria due to threshold effects in *H*. 2) Absence of convergence in levels with transfers of technology = different steady state income levels and growth rates: Emphasis on: - Romer and Rivera Batiz (1991): ($H_i \neq H_j$) and, eventually, large allocation effects. - Lucas (1993): ($u_1 \neq u_2$), catching up but absence of convergence in levels and growth rates. - Benhabib and Spiegel (1994): ($H_i \neq H_j$), catching up but absence of convergence in levels and growth rates.

CHAPTER 2

CONVERGENCE REGRESSIONS: ECONOMETRIC METHODOLOGIES

> "There is some correspondence between the convergence concepts, on the one hand, and the methodologies used, on the other... This variety of concepts and methodological approaches has led to a plethora of empirical results." Islam (1998b).

2.1 Convergence regressions: an introduction

The endogenous growth literature that emerged in the mid 80s was evidently motivated by the apparent inability of the standard neoclassical growth model to explain observed cross-country growth patterns of international data sets. The ensuing resurgence of the debate on growth theory and the availability of new data sets resulted in numerous empirical studies. In particular, the convergence hypothesis became the litmus test for endogenous versus exogenous growth models. Baumol (1986) and Barro and Sala-i-Martin[1] were among the first to investigate the convergence hypothesis by regressing growth in a collection of regions over certain time intervals on the initial level of GDP per head. The equation that is estimated, usually called the *Barro* regression (henceforth B-regression) or β-convergence cross-section regression, is deduced from the transitional dynamics implied by neoclassical growth theory[2]. The B-regression approach was at first considered as the benchmark in empirical studies on growth and convergence. Its advocates stressed

---

[1] See Barro (1991), Barro and Sala-i-Martin (1991, 1995).

[2] See Chapter 1 equation (1.8).

the existence of a process of convergence at the rate of 2-3 percent per year as one of the strongest stylised facts on convergence. To quote Barro and Sala-i-Martin (1995):

> "One surprising result is the similarity of the speed of β-convergence across data sets. The estimates of β are around 2-3 percent per year in the various contexts. This slow speed of convergence implies that it takes 25-35 years to eliminate one-half of an initial gap in per capita incomes."

However, the B-regression is no longer considered as the benchmark. As we saw in Chapter 1, during the last decade the concept of convergence has evolved continuously over time, and econometric methodologies applied for estimating the convergence parameter have consequently evolved with it. Despite methodological differences, these studies usually stress the same general stylised facts that a process of convergence in levels tends to exist for homogenous regions (the states of the U.S., Japanese Prefectures, European regions) but not for more heterogeneous units (the world as a whole). Nevertheless, there is no wide consensus on these conclusions. Not surprisingly, general consensus on the more appropriate methodology for estimating convergence is lacking and, therefore, so is any agreement on the most reliable values of estimated convergence rates. In general, there is now a vast amount of literature on this topic[3], and a number of econometric techniques have emerged. It is natural to ask which of these methods gives the best results in estimating convergence rates because of the need to infer from the estimate how rapidly countries or regions will converge; even tiny differences in the estimated coefficient imply enormous differences in the predicted patterns of convergence and, possibly, even different interpretations of the convergence process.

This Chapter examines the main features, and, thus, the main advantages/disadvantages, of some of the (possibly) most influential econometric techniques proposed for estimating the convergence parameter. In order to compare these different methodologies we need to introduce some additional concepts of convergence. In the final section of Chapter 1 we looked at a survey of different notions of convergence that can be found in theoretical growth literature. We can now increase the list with three further possible distinctions important for empirical

[3] See e.g. the survey by de la Fuente (1995) and, more recently, Durlauf and Quah (1998).

analysis: stochastic convergence, β-convergence and σ-convergence. The concept of β-convergence is related to the methodology that investigates convergence across countries and attempts to deduce how fast economies will converge. Most current research in this field uses this approach. In particular, both cross-section and panel methodologies examined in this survey introduce this so-called *classical approach*[4]. The concept of stochastic convergence is related to the time series approach for estimating convergence. We then examine an alternative approach that investigates convergence across countries. This is known as the distribution approach and is strictly related with the concept of σ-convergence. Similarly to the time series approach but unlike in β-convergence, the distribution approach does not claim to produce answers regarding structural parameters of the growth models. As we will see, this line of research has almost exclusively been developed by one researcher, Danny Quah.

Finally, in this study we investigate a possibility so far ignored in the convergence literature, namely the annual panel estimator where shocks are allowed to be correlated across countries[5]. Indeed, while panel methodologies are widely used in the growth and convergence literature, they usually assume that shocks are uncorrelated across countries, surely wrong for most of the macro data sets considered.

This Chapter may be divided into two parts and is structured as follows. The first part includes a survey of the different econometric methodologies proposed to estimate convergence. Section 2.2 specifies the concept of β-convergence and deals with the cross-section approach to β-convergence. Sections 2.3 to 2.5 introduce the panel approach. As we will see, different sections are necessary to survey this heterogeneous framework and in Section 2.6 we focus on the main criticisms that the panel literature has received. We then introduce the σ-convergence approach and the distribution approach developed by Quah in section 2.7, while Section 2.8 analyses early time series approaches used to estimate convergence. In the second part of this Chapter we propose a new estimator to analyse convergence namely an annual panel

---

[4] This definition is given by Sala-i-Martin (1996) as an alternative to the so-called, *non classical* approach pursued by Quah.

[5] A first version of this work may be found in Di Liberto and Symons (2003).

estimator where shocks are allowed to be correlated across countries. Sections 2.9 and 2.10 describe the characteristics of this estimator, while sections from 2.11 to 2.15 present a Monte Carlo analysis that examines its robustness against possible misspecifications The last section presents a summary of the results and makes some concluding observations.

2.2 The β-convergence approach: early cross-section regressions

β-convergence is currently the prevailing approach for investigating across countries convergence. In general, the β-convergence approach entails estimating *growth-initial level* regressions. We saw in Chapter 1 that the transitional dynamics of the Solow model implies there is a clear relationship between the growth rate of income and its initial level. In particular, from equation (1.8), we may rewrite our convergence regression equation as:

$$y_{i,t2} - y_{i,t1} = (1 - e^{-\beta\tau})(y^{*} - y_{i,t1}) + u_{i,t1} \qquad (2.1)$$

or

$$y_{i,t2} = (1 - e^{-\beta\tau})y^{*} + e^{-\beta\tau}y_{i,t1} + u_{i,t1} \qquad (2.1')$$

where $y_{i,t1}$ is the logarithm of per capita GDP in the initial year and y^* is the logarithm of the steady state per capita income and u_i is the error term. This specification assumes absolute β-convergence, with countries sharing the same steady state level of income. Equation (2.1) introduces the average growth rate within the given period as a dependent variable, while equation (2.1') represents the usual regression equation in levels. Beta is the parameter governing the speed of convergence (see equations (1.5) and (1.12)) and can be deduced by the estimated coefficient of the lagged dependent variable[6]. Therefore, a β-convergence test assumes that data under study are generated by economies far from the steady state. We obtain evidence of convergence if we find that the convergence coefficient is

[6] The convergence parameter beta is computed using the formula $b = -(1 - e^{-\beta T})/\tau$. Otherwise, it is also possible to estimate beta directly by Nonlinear Least Squares.

negative and significant. We will see in the following sections that both cross-section and panel methodologies reviewed in this Chapter use this approach.

Most of the early empirical literature on convergence introduces cross-section analysis to estimate a parameter that captures the existence of convergence among different economies. The estimation of a process of absolute or conditional convergence is the goal of the cross-section approach. That is, this literature is usually linked with Solow-type explanations of the convergence process. Equation (2.1') is rearranged to obtain:

$$y_{i,T} - y_{i,0} = (1 - e^{-\beta T})(y_i^* - y_{i,0}) + u_i \tag{2.2}$$

or:

$$y_{i,T} - y_{i,0} = a^* + by_{i,0} + u_i \tag{2.2'}$$

with $a^* = (1 - e^{-\beta T})y_i^*$, $b = -(1 - e^{-\beta T})$. For a given T a higher estimated parameter implies a higher convergence coefficient. With respect to conditional convergence we can identify two approaches: Barro's semi-structural approach and Mankiw, Romer and Weil's (1992) (henceforth MRW, as in Chapter 1) structural approach[7]. Starting from equation (2.2'), Barro simply assumes that the steady state levels of income, y_i*, depend on country specific factors (such as schooling, institutions or political stability[8]). Therefore, to investigate conditional β-convergence he simply introduces into equation (2.2) the relevant conditioning variables to control the existence of different steady states. The estimated equation becomes:

$$y_{i,T} - y_{i,0} = a^* + \sum_{j=1}^{M} \varphi_j X_j + by_{i,0} + u_i \tag{2.3}$$

with X being a vector of additional explanatory variables. Regressors are assumed to be independent of country specific factors shifting the production function, so that this equation can be estimated by OLS.

---

[7] See Mankiw, Romer and Weil (1992).

[8] They test for many additional factors. See Barro and Sala-i-Martin (1995).

The MRW structural approach is very similar, but implies the substitution of equation (1.14), which precisely defines the steady state, into the solovian convergence equation (1.8). They estimate the following specification:

$$y_{i,T} - y_{i,0} = a - b\frac{\alpha}{1-\alpha}ln(s_i) + b\frac{\alpha}{1-\alpha}ln(n_i + g + \delta) + by_{,0i} + u_i \qquad (2.4)$$

This is a cross-section regression specification where technological progress, g, is constant across countries: that is, gt in equation (1.14) is just a constant. Equation (2.4) is again a conditional convergence equation, where the conditioning factors are the saving rates and population growth. In Chapter 1 we also saw the augmented version of this regression equation that includes human capital[9]. As in Barro, they assume $lnA_{i,0}=a+u_i$ where a is a constant and u_i is the idiosyncratic shock term. In MRW the term $A_{i,0}$ represents the combination of technology, resource endowments, climate and institutions. These country-specific factors are considered as part of the error term. Assuming that u, the error term, is independent from explanatory variables, s and n, equation (2.4) may be correctly estimated by OLS.

The main advantage of the MRW approach compared to Barro's is that it enables us to directly estimate the structural parameters of the Solow model and tests if these estimated parameters satisfy the model assumptions. For example, we might test if the coefficients on the saving rate, s_i, and on population growth, n_i, are equal but have opposite signs as expected. Moreover, from the estimated coefficients of equation (2.4) it is also possible to deduce the value of the elasticity of output with respect to capital, α. As we saw in Chapter 1, the value of this parameter is strictly linked with the convergence hypothesis: for small values of α, diminishing returns set in rapidly, while as α approaches unity, the convergence slows considerably. Empirical studies deduce α from the estimated value of the convergence parameter. In particular, early empirical analyses on unconditional convergence usually find a rate of convergence of 2 percent together with counterfactual high values of the elasticities of output with respect to capital. This evidence has always been considered a problem of cross section unconditional convergence estimates. In fact, only protracted transitional dynamics are able to explain observed cross-country differences in growth rates. MRW (1992) argue in favour of the use of their augmented version of the Solow model because it produces more plausible values of the parameter α. In other words, this implausible result has always represented a source of embarrassment for the B-regression advocates. In fact, the next section shows how this particular point has been one of the main criticisms of the panel literature against the cross section approach[10].

2.3 Panel studies of β-convergence (1): heterogeneous intercepts

Recent empirical studies on convergence exploit both the time series and cross-section nature of data sets. One of the reasons for implementing a panel approach is to improve estimates. The use of panel data enables us to examine a combination of cross-section and dynamic information, thus providing greater precision in the estimation of parameters. Nevertheless, this is not the main motivation that we observed in panel studies on growth and convergence. We can distinguish two different approaches within this literature. The first approach employs standard microeconometric panel techniques. It usually introduces five-year averages in the estimation and completely ignores the possibility of the non-stationarity of the series introduced. Conversely, the second approach is more *time series oriented* and stresses the non-stationary time series panels methodology as the most appropriate for estimating convergence.

This section introduces what we have called the *microeconometric approach.* Advocates of this approach stress that the advantage of the panel methodology is that it can control for possible bias present in the cross-country approach. We have seen above that cross-section models, including conditional convergence models, assume parameter homogeneity in the production function across countries. However, both Barro and MRW do not exclude the existence of country-specific factors. They simply assume that these factors are part of the error term, where the latter is

---

[9] See equations (1.24) and (1.24').

[10] This approach has been also criticised since it assumes that the β term is constant across countries, while as specified in equation (1.5) it involves the term n_i that causes the model to be mis-specified. On this see Dowrick and Rogers (2002). See also section (2.5) on the econometric problems related to the existence of a β parameter heterogeneous across countries.

independent from included regressors. The panel framework considers this hypothesis unlikely. First of all, they assume that permanent cross-economy differences in per capita output (representing, for example, differences in technology, institutions or tastes) are difficult to measure or completely unobservable. Secondly, they consider these characteristics as correlated with included regressors. Therefore, a cross-section (or a simple OLS pooling analysis) would produce estimates plagued by omitted variable bias[11]. By introducing a fixed effects Within Group estimator, or Least Square with Dummy Variables (henceforth LSDV) estimator, it is possible to relax the assumption of strict parameter homogeneity introducing individual effects that account for this problem. In this case, parameters are estimated by OLS, but, unlike in cross section analysis, they account for unobservables with individual intercepts. Thus, this panel specification of the convergence equation is given by:

$$y_{i,t} - y_{i,t-\tau} = a_i + by_{i,t-\tau} + dx_{i,t-\tau} + \upsilon_{i,t} \qquad (2.5)$$

where, as usual, $b=-(1- e^{-\beta t})$, while τ determines the time span considered. For example, $\tau=1$ implies the estimation of an annual panel. Again, equation (2.5) is based on the usual approximation around the steady state of the Solow model and should thus capture the dynamics around the steady state. Assuming that the character of the process remains stable, it must be valid for short periods as well[12].

However, this estimation procedure is not free of possible mis-specifications and problems. The estimate of equation (2.5) by OLS involves problems of consistency typical of a dynamic panel framework[13]. In fact, in a typical microeconometric panel where the temporal dimension is assumed as fixed, the LSDV estimator is a consistent estimator only assuming strictly exogenous regressors. But the presence of a lagged dependent variable on the right hand side of the convergence equation implies that this assumption is not valid.

---

[11] The extent and direction of the bias will depend on the precise nature of the relationship between the individual specific effect and the lagged dependent variable regressor.

[12] Therefore, from the estimated parameter of the lagged dependent variable we can, as usual, calculate our beta "speed of convergence" parameter defined in section (1.1.1).

[13] See Baltagi (1995).

For the sake of simplicity we can rewrite equation (2.5) in levels as:

$$y_{i,t} = a_i + \rho y_{i,t-\tau} + dx_{i,t-\tau} + \upsilon_{i,t} \tag{2.6}$$

where $\rho = (1+b) = e^{-\beta t}$. In this case, when asymptotic is considered in the direction of $N \rightarrow \infty$, equation (2.6) produces inconsistent estimates of the parameter ρ. This problem is usually solved using alternative estimation procedures[14]. Nevertheless, Amemiya (1967) showed that, when the relevant asymptotic is in the direction of $T \rightarrow \infty$, the LSDV estimator is in fact consistent and asymptotically equivalent to the Maximum Likelihood Estimator[15]. These studies exploit this result. It is true that within the growth literature framework, data sets are different from the typical microeconometric panels in which T is usually short. Here, both N (the number of individuals) and T (the number of time periods) are considered sufficiently large. In this case the asymptotic analysis must be considered in the time series dimension of the data, while N (the number of countries) should be considered as fixed[16]. However, as shown by Nickell (1981), while the LSDV estimator is consistent for large T, small sample problems may still badly affect these estimates. Later in this Chapter, we shall use Monte Carlo to analyse at length the extent of this possible small sample bias.

This approach was first applied to the convergence framework by Knight, Loayza and Villaneuva (1993). This survey though, focuses on two later but more influential studies of this microeconometric panel approach, namely, the contributions of Islam (1995) and Caselli, Esquivel and Lefort (1996). Islam (1995) was among the first to introduce an LSDV technique for estimating the convergence parameter. He builds on the MRW structural approach described by equation (2.2) in which the saving rate and the population growth rate are assumed to vary across countries.

---

[14] A possible solution is to use the Anderson-Hsiao estimator, or a Generalised Method of Moment procedure. See Caselli, Esquivel and Lefort (1996).

[15] See Amemiya (1967) for the proof.

[16] On dynamic panels when T is large see also Pesaran and Smith (1995).

His dynamic panel data model can be represented thus:

$$y_{i,t} - y_{i,t-5} = a_i + by_{i,t-5} - b\frac{\alpha}{1-\alpha} ln\, s_{i,t-5} + b\frac{\alpha}{1-\alpha} ln(n_{i,t-5} + g + \delta) + \eta_t + u_{i,t} \qquad (2.7)$$

where u_{it} is the transitory term that varies across countries and periods, ηt is the time trend component and b is the usual speed of convergence coefficient as in (2.5). Data are in five-year time intervals[17], to account for business cycle fluctuations and serial correlation, more likely in a yearly data set-up. The only difference with the MRW specification lies in the time trend component and the constant term that Islam assumes country specific. In fact, $a_i = (1-e^{-\beta t})\ln A_{i,0}$ is a time-invariant component that varies across economies. This term should account for various unobservable factors like institutions or climate.

Nevertheless, he does stress the importance of technology. Technology is unobservable and likely to be correlated with regressors and, in particular, lagged per capita GDP. This is why Islam proposes the LSDV methodology as an alternative to standard growth accounting methodologies and considers estimated fixed effects as a good proxy for TFP[18]. The presence of a significant coefficient in the country specific intercepts should reveal the presence of different steady states among economies, where long-run equilibria are determined by these unobservable fundamentals.

During his analysis, Islam introduces two different econometric techniques: he applies an LSDV estimator and Chamberlain's Minimum Distance estimator [19]. To test for this hypothesis, he compares the results obtained by these procedures, but does not find significant differences. While the LSDV estimator directly introduces individual specific dummies and is based on the direct estimation of equation 2.7, Chamberlain (1982) formalizes the idea of the fixed effect models and assumes that:

---

[17] During his econometric analysis Islam (1995) introduces other variables and uses both series in levels at the beginning of the period or five year averages.

[18] On this see also Chapter 5.

[19] See Islam (1995). In general, unlike in the LSDV procedure, the Minimum Distance estimator allows for individual effects to be correlated with the included exogenous variables.

$$\alpha_i = \lambda_0 + x_{i1}\lambda_1 + x_{i2}\lambda_2 + \ldots + x_{iT}\lambda_T + \xi_i \tag{2.8a}$$

and

$$y_{i0} = \phi_0 + \phi_1 x_{i1} + \ldots + \phi_T x_{iT} + \psi_i \tag{2.8b}$$

where the fixed effect depends linearly on all leads and lags of the exogenous variable x, $E\left[\xi_i \middle| x_{i1} \ldots x_{iT}\right] = 0$, and $E\left[\psi_i \middle| x_{i1} \ldots x_{iT}\right] = 0$. If we consider $x_{it} = \ln(s) - \ln(n + g + \delta)$ it is possible to substitute α_i in eq. (2.7). Moreover, the lagged dependent variable in eq. (2.7) can be replaced (by repeated substitutions) by the initial value, y_{i0}, and then by eq. (2.8b). Chamberlain (1982) suggests reducing the problem of estimating eq. (2.7), a single equation model involving two-dimensions, into a one-dimensional problem of estimating a T-variate regression model with cross-sectional data, that is combining all equations of a single individual into one system of equations. In order to obtain Chamberlain's minimum-distance estimator we must first obtain the unconstrained reduced-form coefficient matrix, called the Π-matrix. Each element of this matrix is a function of the structural-form coefficients that can be summarized by a vector θ. To estimate θ from the elements ϕ of the Π-matrix, we must impose restrictions by using a minimum-distance estimator[20].

Both the Minimum Distance and the LSDV estimator reveal a much higher rate of convergence in comparison to the simple cross-section OLS estimator. The speed of convergence coefficient jumps from a value of 0.0161 for the OECD sample in the simple pooled regression to a value of 0.0926 when a LSDV model is introduced. Similar results have been found for two additional samples, non-oil producing countries (98 countries), where the parameter increases from 0.0048 of the cross-section estimates to 0.0467 using the fixed effect model, and a subsample of this group (comprising 74 countries) in which the relevant parameter shifts from 0.0074 to 0.0458. Moreover, unlike in the cross section approach he obtains values of the elasticity of output with respect to capital which are nearer to their usually

[20] More on this estimator in Chamberlain (1982), and Hsiao (1986).

accepted empirical values[21]. In general, he suggests that both his convergence parameter and elasticity values are plausible: that is, his econometric methodology for conditional convergence solves one of the problems affecting cross-section convergence estimates.

Caselli, Esquivel and Lefort (1996) stress the importance of more than one source of inconsistencies in cross-country regressions. First, as does Islam (1995), they conclude that cross-section regressions are plagued by omitted variable bias. However, they argue that a second problem makes even Islam's estimates inconsistent[22]. In fact, they emphasise the possibility that most regressors introduced in growth studies are predetermined but not strictly exogenous regressors. This characteristic would cause the MD estimation procedure introduced by Islam to produce inconsistent estimates because it requires strictly exogenous regressors. The procedure in question substitutes out a_i using both past and future values of included regressors[23].

Following Arellano and Bond (1991), Caselli et al. suggest to control for both omitted variable bias and endogeneity problems using a procedure based on a Generalised Method of Moment (GMM) estimator. Basically, the idea is the same as that of the Anderson-Hsiao estimator, i.e. to check for the presence of fixed effects by taking data in first difference and then to use the instrumental variables technique to purge the correlation between the dependent variable and its lag. However, unlike Anderson-Hsiao, who favour the use of $\Delta y_{i,t-2}$ or $y_{i,t-2}$ as instruments, Arellano and Bond (1991) suggest exploiting all the orthogonality conditions existing between $y_{i,t}$ and the disturbances $\upsilon_{i,t}$[24].

Specifically, they use the Summers and Heston international data set and focus on a sub-sample of 97 countries. As in equation (2.6) they rewrite the growth equation as a dynamic model in levels:

---

[21] The values are respectively: OECD sample α =0.067, NONOIL countries α=0.4397, 78 countries α =0.4245.

[22] This is true also for the Knight, Loyaza and Villaneuva (1993).

[23] In a more recent paper Islam (2000) introduces a modified version of the MD estimator that account for this problem .

$$\tilde{y}_{i,t} = a_i + \rho\, \tilde{y}_{i,t-\tau} + \sum_{j=1}^{M} \lambda_j (\tilde{x}^{j}_{i,t-\tau}) + \upsilon_{i,t} \qquad (2.9)$$

where $\tilde{y}_{i,t} = y_{i,t} - \bar{y}_t$, and $\bar{y}_t = \frac{\sum_{i=1}^{N} y_{it}}{N}$.

The use of demeaned value of per capita output allows time specific constants to be eliminated[25]. The coefficient ρ allows us, as ever, to deduce the convergence parameter, while the M included variables are additional determinants of the growth rate. They apply a first-difference transformation in order to eliminate individual effects[26] and subsequently rearrange equation (2.9) to obtain:

$$\Delta \tilde{y}_{i,t} = \rho \Delta \tilde{y}_{i,t-\tau} + \sum_{j=1}^{M} \lambda_j \Delta \tilde{x}^{j}_{i,t-\tau} + \Delta \upsilon_{i,t} \qquad (2.10)$$

Equation (2.10) cannot be estimated as it stands since $E(\Delta y_{it} \Delta \upsilon_{it}) \neq 0$; that is, the lagged dependent variable is correlated with the error term through the contemporaneous terms in period t-τ. However, assuming the absence of τ-order serial correlation (where τ=5 in their study, as in the previous study) in the transient errors of the equation in levels we have

$$E(y_{it-s} \Delta \upsilon_{it}) = 0 \qquad \text{for t=3,..., T and } s \geq 2$$

so that it is possible to use the lagged levels dated t-2 and earlier of the dependent variable as instruments. With respect to the other regressors, Caselli at al. (1996) distinguish between stock variables and flow variables. The former, measured at the beginning of the period, are assumed as predetermined variables, while the latter

---

24 See Baltagi (1995).

25 On this see also Evan and Karras (1996) in the following section.

26 The use of a first-difference estimator also allows us to test for the presence of permanent additive measurement errors that are eventually absorbed into the fixed, time-invariant effects. See Bond S., Hoeffler A. and Temple J. (2001).

(usually measured as averages within the time span considered) are not predetermined for υ_{it} but are assumed to be predetermined for $\upsilon_{i,t+\tau}$. In that way they conveniently instruments the right hand side of equation (2.10) using all past values of regressors assumed exogenous. The consistency of their estimation procedure crucially depends on the identifying assumption that lagged values of both income and other explanatory variables are valid instruments in the growth regression. Specification tests suggest their methodology is correct. Following this procedure, Caselli, Esquivel and Lefort find a speed of absolute convergence coefficient 20 times larger than the usual cross-section result. In addition, they introduce an augmented version of the Solow model (including both a set of variables accounting for the economy's initial conditions and a second set capturing the differences in steady states across countries) and find results similar to Islam's, with a convergence coefficient of about 10 percent a year.

However, recent studies criticise the use of the GMM-Arellano and Bond (henceforth GMM-AB) estimator in frameworks such as the standard growth-convergence analysis. Blundell and Bond (1998) and Bond-Hoeffler-Temple (2001) stress that the GMM-AB estimator may perform poorly with datasets that use either a small number of time periods or persistent time series. Unfortunately, these are typical features of growth datasets. In this case, these authors suggest that, with persistent and relatively short time series, the Arellano-Bond estimator may be plagued by weak instruments bias and would produce large finite sample biases. In particular, they show that when T is small, and a) the autoregressive parameter is close to one (highly persistent series) or b) the variance of the individual effect is high relative to the variance of the transient shock, the lagged levels of the series will tend to be only weakly correlated with subsequent first differences and the GMM-AB estimator may produce downward biased estimates[27]. Bond, Hoeffler and Temple (2001) stress that a sign of the bias in the GMM-AB estimates is an AR(1) coefficient close to the LSDV one. Thus, to detect the bias, they suggest using the following "rule of thumb". Given that we know the OLS is biased upwards in dynamic panels and LSDV is biased downwards, a consistent estimate should therefore lie (somewhere) between the two. In other words, we may expect that the true parameter values lie somewhere between $\hat{\rho}_{ols}$ and $\hat{\rho}_{LSDV}$. Note that this is not the case in Caselli et al. (1996), given that the estimated AR(1) parameter is close to the LSDV value. When there is evidence that lagged levels of the explanatory variables provide weak instruments for the model in first difference as in equation (2.10), the inclusion of additional explanatory variables among regressors and the inclusion of additional lags of these regressors among instruments may improve the performance of this estimator[28]. Moreover, Bond, Hoeffler and Temple (2001) suggest employing a system-GMM estimator in growth regressions. In very simple terms, this estimator specifies a system of equations in both first difference and levels where the instruments of the levels equations are the lagged first-differences of the series[29].

Kiviet (1995) advocates a more direct approach to the problem of the finite sample bias in dynamic panels by estimating a small sample correction to the LSDV estimator. As noted by Kiviet (1995), although Anderson-Hsiao and GMM-AB are consistent estimators, their small sample properties are far from reassuring. In his study he performs a Monte Carlo analysis comparing the finite sample performance of his corrected LSDV estimator with the GMM-AB and Anderson-Hsiao IV estimators. The main conclusion is that for very small T (as we find in convergence literature) corrected-LSDV seems more attractive than GMM-AB. But the most cited evidence in favour of the Kiviet correction is found in Judson and Owen (1996). They explicitly analyse a typical macro-panel and found that for samples with relatively small T and N (T<20 and N<50) LSDV and Anderson-Hsiao estimators consistently outperform GMM-AB. Moreover, despite having a higher average bias, LSDV is even more efficient than Anderson-Hsiao and the authors conclude that when T is small, the corrected LSDV estimator should be preferred to other estimators.

---

[27] See Bond-Hoeffler-Temple (2001).

[28] See Blundell and Bond (1998).

[29] To estimate equation (2.10) by system GMM, it is necessary to make additional assumptions on the series. See also Chapter 5.

2.4 Panel studies of β-convergence (2): stochastic and deterministic convergence

As in previous studies, the second *panel* approach to estimate convergence considers OLS estimates of equation (2.2') as being incorrigibly biased. However, this approach differs from micro-econometric panel techniques in that it explicitly investigates the stationarity of the series included and employs recently developed panel unit root methodologies for investigating cross-countries convergence. Examples of this approach include Evans and Karras (1996) and Lee, Pesaran and Smith (1997) among others[30].

This section distinguishes the concepts of deterministic and stochastic convergence as defined by Evans and Karras (1996). Formally, the Solow model with a common exogenous technological progress, as described in Chapter 1, implies that a set of N countries will exhibit the presence of a process of conditional convergence if:

$$\lim_{r\to\infty}(y_{n,t+r} - a_{t+r}) = \mu_n \qquad n=1,2....N \qquad (2.11)$$

where y_{it} is the logarithms of per capita output in country i, a_t is the common trend[31] and μ_n is the country's n long-run equilibrium. We have absolute convergence if μ_n is equal to zero for all countries. Otherwise, different countries converge towards different steady states levels determined by μ. Moreover, when a group of countries shares common or identical structures they will converge towards the same steady state. This assumption is related to the convergence club hypothesis. Contrariwise, in a stochastic framework, a group of countries is said to converge if and only if a common trend and finite parameters μ_1, μ_2,.... μ_N exist such that:

$$\lim_{r\to\infty} E_t(y_{n,t+r} - a_{t+r}) = \mu_n \qquad (2.12)$$

---

[30] See also Bernard and Durlauf (1996), Bernard and Jones (1996), Pedroni (1997) and, more recently, Gerosky *et al* (2003).

[31] Within the Solow model, *at* can be thought as the logarithm of an index of Harrod-neutral technology.

In that case a_t is unobservable. Therefore, it is necessary to account for this problem. One possibility is demeaning each single series. That is, we calculate average values over the N countries:

$$\lim_{r\to\infty} E_t(\overline{y}_{t+r} - a_{t+r}) = \overline{\mu} \tag{2.13}$$

where $\bar{y}_t \equiv \sum_{i=}^{N} y_{i,t} / N$, and $\bar{\mu} \equiv \sum_{i=}^{N} \mu_i / N$. Consequently, the appropriate series introduced in the empirical analysis is:

$$\lim_{r\to\infty} E_t(y_{n,t+r} - \overline{y}_{,t+r}) = \mu_n \tag{2.14}$$

Other researchers prefer to take data in difference from a reference economy but these two methodologies for transforming data are equivalent. More precisely, this analysis suggests that, even if series are non-stationary, if the difference $(y_{n,t+r} - \overline{y}_{,t+r})$ or $(y_{n,t+r} - y_{1,t+r})$ with $y_{1,t}$ as the reference economy is stationary, series are said to be converging towards their steady states. As before, we obtain a process of unconditional convergence if μ_n is equal to zero[32] for each n.

In their convergence analysis Evans and Karras (1996) introduce an annual panel of demeaned data. They propose a four-step procedure as the correct test for estimating convergence. They firstly consider 1,2...N countries in their sample and apply OLS to the equation:

$$\Delta \tilde{y}_{i,t} = a_i + \delta_i \tilde{y}_{i,t-1} + \sum_{j=1}^{p} \varphi_{i,j} \Delta \tilde{y}_{i,t-j} + \upsilon_{it} \tag{2.15}$$

on each series to obtain, $\hat{\sigma}_i$ the standard error of estimate for the i=1...N series. Again, $\tilde{y}_{it} = (y_{it} - \bar{y}_t)$, and $\bar{y}_t = \frac{\sum_{i=1}^{N} y_{it}}{N}$. Lagged values of the dependent variable are

[32] See Evans and Karras (1996) for further details.

introduced to control for autocorrelation. Moreover, they calculate the normalised series $\hat{z}_{it} \equiv (\tilde{y}_{it}) / \hat{\sigma}_i$ for each country. As a second step they apply OLS to the following annual panel of N countries:

$$\Delta \hat{z}_{it} = \hat{a}_i + \hat{\beta} \hat{z}_{i,t-1} + \sum_{j=1}^{p} \varphi_{i,j} \Delta \hat{z}_{i,t-j} + \hat{\upsilon}_{it} \tag{2.16}$$

where $\hat{a}_i \equiv a_i / \hat{\sigma}_i$ and $\hat{\upsilon}_i \equiv \upsilon_i / \hat{\sigma}_i$, and obtain the convergence parameter $\hat{\beta}$ and its t-statistics. Thirdly, if the t-statistic exceeds an appropriately chosen (by Monte Carlo)[33] value, they reject $H_0 : \forall_i \beta_i = 0$ in favour of $H_1 : \forall_i \beta_i < 0$. In that case, they obtain evidence of convergence[34]. Finally, if the convergence hypothesis is accepted, a test for conditional convergence is given by the estimate of the F-ratio:

$$\Phi(\hat{a}) = \frac{1}{N-1} \sum_{i=1}^{N} [\tau(\hat{a}_i)]^2 \tag{2.17}$$

where $\tau(\hat{a}_i)$ is the t-ratio of the estimator of α_i obtained by applying OLS to equation (2.15) for each country. If $\Phi(\hat{a})$ exceeds an appropriately chosen (by Monte Carlo) critical value they accept the hypothesis of significant individual effects and conclude in favour of a conditional convergence process. Otherwise, absolute convergence is accepted. Using this procedure and introducing two different samples (48 contiguous US states and 54 countries from the Summer and Heston data set), Evans and Karras (1996) find evidence of conditional convergence in both samples. The estimated convergence parameter increases from $\hat{\beta}$=-0.011 (using cross-section) to $\hat{\beta}$=-0.0826 (with their procedure) for US States and from $\hat{\beta}$=-0.012 to $\hat{\beta}$=-0.0430 for the international data set.

---

[33] Because of the presence of small sample bias. See next Chapter for more details.

2.5 Panel studies of β-convergence (3): further parameter heterogeneity

In Chapter 1 we distinguished between the concept of convergence in levels and convergence in growth rates. We observed that while conditional and unconditional convergence models always predict convergence in growth rates, part of the endogenous growth literature is characterised by divergence in both: each country converges towards its own long-run level of income and its own long-run growth rate of income. However, the empirical literature we have surveyed above assumes convergence in long-run growth rates of income. The study carried out by Lee, Pesaran and Smith (1997 and 1998) (henceforth LPS) differs from these studies because they test for an unrestricted specification of the transitional dynamics of the Solow model. In particular, they criticise previous methodologies for their cross-country parameter homogeneity, where the simple cross-section approach represents an extreme, assuming complete parameter homogeneity. Conversely, starting from the usual conditional convergence framework[35], they allow not only for individual intercepts, as do previous panel studies, but also for both the convergence parameter and exogenous long-run growth rates to differ among countries. Their unrestricted version of the convergence equation is thus given by:

$$y_{it} = a_i + \vartheta_i t + \rho_i y_{i,t-1} + \upsilon_{it} \tag{2.18}$$

where, $\rho_i = 1 + b_i$, $\vartheta_i = (1-\rho_i)g$, and the country-specific intercept is now defined by:

$$a_i = (1-\rho_i)\left[g + \ln A_{i0} - \frac{\alpha}{1-\alpha}\ln(n_i + g + \delta) + \frac{\alpha}{1-\alpha}\ln s_i \right] \tag{2.19}$$

If, as implied by the theory, different countries share a common steady state growth rate, the ratio $\vartheta_i/(1-\rho_i)$ should be identical across countries. Assuming series are trend stationary processes, they apply Exact Maximum Likelihood[36] to equation

---

[34] This is the panel unit root test developed by Levin and Lin (1993).

[35] See the Mankiw Romer and Weil (1992) structural approach.

[36] Thus, constraining the coefficient ρ to be less than unity.

(2.18). Therefore, LPS compare results arising from both the restricted (homogeneous parameters) and unrestricted version of the Solow model using three different samples: 102 non-oil producing countries of the Summer and Heston data set, a subsample of 61 countries[37], and the OECD data set (22 countries). More precisely, they compare four different specifications of equation (2.18): a) an unrestricted model, with heterogeneous parameters, b) g constrained to be equal across countries, c) ρ constrained to be equal across countries, d) both g and ρ equal across countries. They find evidence of heterogeneous growth rates g_i in all samples, while the hypothesis of homogeneity in the speed of adjustments, ρ, was not rejected only by the OECD sample. In conclusion, the unrestricted version of the model should be considered as the correct one. In that case their estimated speed of convergence is approximately 30 percent per year, a very high value even compared to other panel studies.

Given these results, the LPS study is highly critical not only towards the cross section approach but also towards previous panel studies. In particular, they argue that in dynamic models if we ignore the presence of coefficient heterogeneity we may obtain inconsistent estimates. When regressors are serially correlated, coefficient heterogeneity induces serial correlation in the disturbance term, causing estimates to be inconsistent even as $T \rightarrow \infty$. For example, assuming $b_i=b$, that is, assuming a unique long-run growth rate, the false imposition of a common growth rate g would produce inconsistent estimate of b because it adds a term $(g_i-g)t$ to the disturbance for each country, where this term is serially correlated[38].

Finally, we briefly introduce the second argument put forward by the LPS study. i.e. that possible non-stationarity of the series could further complicate this analysis. In particular, they stress that it should be necessary to test the possibility for the series to be difference stationary because, under a stochastic version of the Solow model, the convergence coefficient as deduced from the log linearisation around the steady state no longer has its usual interpretation[39]. As in Evans and Karras (1996), to

---

[37] They exclude countries for which quality of data is thought to be poor.

[38] They show that in that case the estimate of $\rho=(1+\beta)$ in (3.15) would tend to unity as N and T grow irrespective of its true value.

[39] See Lee Pesaran and Smith (1997).

overcome the problem of the low power of standard unit root tests they propose an alternative test that exploits the panel structure of the data: the so called t-bar test. This test is based on the average value of the DF or ADF statistics obtained across countries and inference is built on H_0: $\rho_i=1$ against H_1: $\rho_i<1$ for $i=1,2...N$.[40] They apply the t-bar test to demeaned data to eliminate common technological trends and shocks influencing all countries in the sample. They find that none of the sample rejects the null.

Nevertheless, they stress the presence of possible problems. In particular, this test is very sensitive to underestimation of the degree of augmentation and the likely presence of a moving average component could further complicate the analysis. Their conclusion is that all unit root tests (including their panel test) are not conclusive[41]. In summary, this study endorses two main arguments. First of all, it is unlikely that the parameters of the convergence equation are homogeneous across countries. The correct model specification is the unrestricted one with heterogeneous parameters and previous studies on convergence all produced inconsistent estimates. Moreover, it is necessary to take into account the possible nonstationarity of the series introduced. However, given the low power of standard unit root tests and panel unit root tests, it is first necessary to find better tests able to discriminate between difference and trend stationary series.

Finally we briefly introduce the methodology proposed by Canova and Marcet (1995). Using a Bayesian procedure to estimate convergence rates and steady states, Canova and Marcet (1995) obtain results similar to LPS. Like both Evans and Karras and LPS, they estimate an annual panel, that is, they use information available for all

---

[40] Assuming no autocorrelation (and thus no need to augment the DF test) the t-bar statistic is defined by:

$$\overline{z_{NT}} = \frac{1}{N}\sum_{i=1}^{N} t_{iT} - E[t_T] \Big/ \sqrt{\frac{1}{N} V[t_T]}$$

Under the null, each of the DF statistics, t_{iT} can be viewed as a random draw from DF distribution, where the underlying DF regression contains an intercept and a trend and is based on T observations. The DF distribution relevant to each draw has mean and variance $E[t_T]$ and $V[t_T]$. They show that, under the null hypothesis, for large N and $T>6$, this is an exact test with a standard normal distribution.

[41] "In these circumstances, trying to determine whether there is a unit root against the alternative of a root very close to unity is likely to be impossible with available samples and techniques." See Lee Pesaran and Smith (1997).

periods and all cross-sectional units. Moreover, as do LPS, they estimate a flexible statistical model allowing for parameters on both the lagged dependent variable and the intercept to vary among cross-sectional units, thus allowing the presence of heterogeneous convergence parameters. However, unlike LPS, they do not introduce the possibility of heterogeneous long-run growth rates into the regression equation. That is:

$$y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \varepsilon_{i,t} \tag{2.20}$$

They argue that equation (2.20) cannot be estimated by standard econometric methodologies. In fact, standard procedures have too many parameters relative to the number of time series observations for each cross-sectional unit. To solve this problem they introduce a Bayesian approach. Since Bayesian estimates are exact regardless of the sample size, they impose a Bayesian prior on parameters and combine it with sample information to construct posterior estimates. In other words, they do not impose the equality of the coefficients but they impose possible differences among parameters. Their prior distribution is based on the belief that parameters in the different units are similar but not identical. The main point within this framework is how to select these differences. We do not describe their procedure in details but we focus on their results. Their empirical analysis introduces two data sets: the first consists of regions of the 14 EEC members, while the second includes 17 western European countries. Therefore, unlike in previous studies, they do not extend their analysis to large international samples because they want focus on quite homogeneous samples in terms of institutions and economic structure. Following standard procedures, they compare results arising from standard cross-section methodologies with the results generated by their bayesian approach. The European Regions sample shows that when the equality in the parameters is imposed to equation (2.20) the average rate of convergence is around 2 percent per year, the usual Barro-Sala-i-Martin result. However, using their bayesian methodology and allowing for some difference among both individual constants and intercepts in equation (2.20), the average rate of convergence increases from 2 percent a year to 23 percent a year. This result is similar to LPS's result and much higher compared to the 9 percent result found in other panel studies.

2.6 Panel literature: some criticisms

In general, the survey on the panel literature discussed above shows that, despite consistent differences, a common feature of all panel data methods is the estimate of a very high rate of *conditional* (to country specific steady states) convergence, with values reaching 30 percent per year. This conclusion is different in comparison with previous cross-country *absolute/conditional* convergence type estimation procedure, with its 2 percent result. The former findings have always been interpreted as evidence in favour of the persistence of inequalities among countries, where poor countries do not converge towards the rich. More precisely, high values of the convergence parameter would imply that countries are almost in their long-run equilibrium (indeed, they will reach their long-run equilibrium in a very short period of time) and that differences tend to remain in the long-run. Further, rates of convergence of 23 percent or 30 percent per year as found in this literature have also been interpreted by their advocates as favouring open economy versions of the neoclassical growth models[42]. However, we have previously seen that they have also been interpreted as a sign of the presence of a small sample bias.

The use of the panel approach for estimating growth has been strongly criticised for several reasons. For example, one of the problems of assuming complete parameter heterogeneity as in LPS, is that this procedure assumes that actual growth rates (the g_i introduced in the regressions) represent a good proxy of steady state growth rates. However, this is not necessarily the case. In particular, Islam (1998a) observes that actual g_i are usually a combination of steady state and transitional growth rates. This observation introduces more than one doubt in LPS's results of heterogeneous *steady state* growth rates. Secondly, Durlauf and Quah (1998) argued that the panel fixed effect (within group) approach, introducing deviations from time-average sample means for each country and then applying OLS to the transformed data, may discharge the long-run variation across countries. This may be seen as a gross mis-specification because, when we examine intra-countries convergence, we need to examine the variation across countries with some precision. Thus, the implied transformation of the fixed effect model would probably eliminate the phenomenon we want to analyse when we consider convergence. Finally, high rates of convergence would imply implausible low values of the parameter α, the capital share parameter of the Solow model. That is, one of the problems of the cross-section approach is once again evident.

Finally, there is another important criticism that has cast some doubts on the economic interpretation of panel results. Again, Durlauf and Quah (1998) noted that this evidence says nothing about the possibility of catch-up (or not) of the poor countries towards the rich. Basically, these results are unable to capture the presence of a catching up relationship among countries. This problem is more obvious when we allow differences in the steady state growth rates and/or convergence rate parameters as in LPS or Canova and Marcet. In this case, estimates rely solely on each country's individual history. That is to say, "...this leads to a virtual collapse of the concept of convergence, so far as its across-dimension is concerned[43]". Durlauf and Quah (1998) conclude that this approach renders the concept of convergence hollow. In short, when we allow individual intercepts to capture the possibility of individual steady state for each country and heterogeneous convergence parameters to capture the individual speed of convergence, it becomes very difficult to interpret the results within standard convergence literature. Thus, for these authors, if we want to investigate how different economies perform relative to each other or if we want to focus on the analysis of convergence clubs it is better to introduce alternative approaches.

2.7 Further methodologies: σ-convergence and the Quah approach

We saw in the previous sections that β-convergence should relate to mobility of different individual economies within the given distribution of income. As is clear from equations (2.3) and (2.4), these regressions examine the cross-section correlation between initial per capita output levels and subsequent growth rates for a

---

[42] See Caselli, Esq uivel and Lefort (1996).

[43] See Islam (1998).

group of countries. A negative correlation is taken as evidence of convergence as it implies that, on average, poorer countries are growing faster than the richest ones. In other words, if we estimate a negative and significant β we should conclude that poor economies were growing faster with respect to economies with a higher level of per capita GDP in the initial year. However, this evidence does not necessarily imply a well-behaved process. Well-behaved in this framework means the concomitant presence of a catching up process. In particular, evidence of β-convergence implies an explicit catching up process only if there is also a reduction in the dispersion of GDP levels among the different countries. That is, β-convergence is a necessary but not sufficient condition for catching up.

Friedman (1992) was the first to observe that these tests turn out to be plagued by Galton's fallacy of regression towards the mean. He shows that the right sign on the initial-condition coefficient does not indicate a collapsing cross-sectional distribution. Using the same argument, Quah (1993) showed that we can find a β-convergence result (that is, a negative β-coefficient) even when the cross-section distribution of per capita income remains invariant over time or even if it diverges. Moreover, cross-country methodology is inappropriate when we have the presence of converging clubs in the sample. It is indeed possible to have a group of countries for which only a subset of them is truly converging while others are completely independent from the attractor and still obtain a negative β. But we could also observe the opposite situation i.e. a non-significant coefficient that hides the presence of a small subset of converging countries. In general, when the existence of convergence clubs is evident, the cross-country regression is not the appropriate approach to employ. Quah (1995) concludes that β-convergence, or, more generally, looking at coefficients in a cross-section regression, is uninformative for a distribution's dynamics and is thus uninformative on the presence of convergence.

Friedman (1992) argues that a good description of the existence of a catch up process across economies is given by sigma convergence analysis. In fact, σ-convergence measures the standard deviation of the logarithm of per capita GDP. A group of economies is converging in the sense of sigma if the dispersion of their real per capita GDP levels tend to decrease over time. σ-convergence is thus a synthetic measure of the behaviour of cross-country income dispersion. However, this methodology has also received some criticism. First, whether dispersion increases or decreases towards its steady state value depends on whether initial dispersion is less or greater than the steady state dispersion. Moreover, the presence of σ-convergence can be interpreted as evidence in favour of catching up only if we are assuming that countries are converging towards the same equilibrium. In other words, as in β-convergence methodology, this measure is not a good representation of a convergence process when we have convergence clubs. In fact, we could observe that countries are converging to their own equilibrium but cross-country equilibria are diverging. In sum, σ-convergence relates to whether or not the cross-country distribution of different economies shrinks over time but it does not provide an exhaustive description of the phenomenon we want to capture. In fact, from the time path of this measure we can infer nothing about the presence of a process of catching up of the poorest country toward the richest.

Departing from standard techniques of econometric analysis Quah (1997) further develops the σ-convergence approach. Instead of exclusively concentrating on the variance of the cross-countries distribution over time, he studies the entire shape of the distribution and intra-distribution dynamics. The focus of this study is more on what Sala-i-Martin (1996) called the non classical approach to convergence analysis. Thus, we follow Islam (2003) and include just a brief introduction of this approach. Quah's research focuses on the determinants of the dynamics of cross-economy income distributions. In simple terms, defining F_t as the cross-section distribution at time t and F_{t+1} at time $t+1$ he describes:

$$F_{t+1} = MF_t \qquad (2.21)$$

where M is the operator that maps F_t onto F_{t+1}. Assuming that M does not change over time we obtain:

$$F_{t+s} = M^s F_t \qquad (2.22)$$

Modelling M as a Markov transition matrix, Quah (1997) calibrates it introducing actual data and finds that the distributions tend towards shapes that stress the presence of clusters[44]. In particular, he identifies two main stylised facts. The first concerns mobility and states that countries tend to stay in the same position as the distribution. Moreover, despite this observed persistency, the distributions show polarisation or, more precisely, tend to "thin out the middle". In sum, this analysis of the cross-economy income distributions stresses the presence of an "emergent twin peaks in the cross-country distribution"[45], where the implied limit distribution F_{t+s}, $s \rightarrow \infty$, would then be bimodal: in other words, he shows a tendency for economies to join one of two clubs, either rich or poor countries.

2.8 Further methodologies: a brief look at time series methodologies and within countries convergence

Early empirical studies on convergence that use a time series methodology usually assume that series are already in their steady states. More precisely, these tests assume that series have already converged and then convergence is interpreted with the meaning that initial conditions have no effect on the expected value of output differences. This assumption is not present in the cross-section literature where data are seen in transition towards a limiting distribution. In fact, as we will see below, β-convergence tests assume data under study are generated by economies far from the steady state, Most of these time series studies are based on the estimate of a cointegration relation[46]:

$$y_{it} = \alpha + \beta y_{jt} + \varepsilon_t \tag{2.23}$$

where i and j are two different countries (where j can be explicitly considered the attractor). First, stationarity of the series is investigated using standard Dickey-Fuller (DF) or Augmented DF statistics for testing the presence of unit roots in per capita GDP series. Second, stationarity of the error term in (2.23) is investigated within the cointegration framework, while convergence may be tested through the value of the

[44] On this see also Islam (2003).

[45] See Quah (1997).

[46] See Bernard and Durlauf (1996). Cellini and Scorcu (1997) apply this methodology to estimate convergence among Italian regions

long-run parameters. We say that y_{it} converges towards y_{jt} if α=0 and β=1. Note that if the relationship:

$$y_{it} - y_{jt} = \varepsilon_t \tag{2.24}$$

is not stationary it is impossible to conclude in favour of convergence since the series may evolve further apart from the relationship, even if they satisfy it on average[47]. Further developments of this approach introduce a multivariate Johansen procedure.

The main problem of this approach is that it cannot be considered a good methodology if series have not yet converged. For example, an estimate of α and β different from these expected values does not necessarily imply a lack of convergence but could be the result of the fact that countries are converging towards their steady state. More precisely, α and β can be evolving over time tending toward the expected values of $\alpha=0$ and $\beta=1$. To take into account this possibility, more recent studies try to model this transitional dynamics[48]. However, an even more damaging problem within the time series framework is represented by the low power of DF or alternative unit root tests against the alternative[49]. The short time dimension of GDP and other relevant series mainly for developing countries makes this a relevant problem. As we have seen in the previous sections, one alternative is to introduce more powerful unit root tests that exploit the panel structure of data sets.

2.9 An alternative Methodology

In this study we investigate a possibility so far ignored in the convergence literature, namely the annual panel estimator where shocks are allowed to be correlated across countries. As we have seen in sections 2.3 to 2.5, other authors have used panel methods but have assumed effectively that shocks are uncorrelated across countries, surely wrong for most of the data sets considered. In particular, we consider this

[47] See Bernard and Durlauf (1995).

[48] For example, Hall and St. Aubin (1995) introduce Kalman filter techniques for estimating this evolving relationship of the parameters

[49] Lee Pesaran and Smith (1995) stress this problem. Bernard and Durlauf (1995) try to overcome this problem using a small sample of 15 industrialised countries: for this sample GDP series are available from 1900 to 1987.

assumption unlikely, mainly when convergence is investigated across groups of relatively homogeneous economies such as OECD countries or regional data sets. In principle, panel data approaches exploit more data than the Barro's type regression or cross-section regression[50] (henceforth B-regression) and hence might be expected to be more efficient. Against this, the B-regression is likely to be more robust against certain possible mis-specifications. There have been some suggestions that panel estimates are incorrigibly biased[51] together with recent arguments in favour of the B-regression[52]. Indeed, we show below that estimating the B-regression is more efficient than maximum likelihood on the full panel, provided that shocks are not too correlated across regions or countries. For cross-correlations of the order that arise in OECD countries, however, maximum likelihood dominates the B-regression. It is also true that maximum likelihood is more efficient than panel methods which do not allow for correlations in cross-country shocks. Ignoring cross-sectional correlation leads not only to efficiency losses: it means also that inference is distorted, given that, as is easily demonstrated, important cross-correlations exist in OECD data. It is fair to say that there is hardly a consistently estimated standard error in this entire literature. The study examines these issues by Monte Carlo. We apply our findings to a panel of OECD countries. On balance we find some evidence against convergence. Our analysis will be restricted to the case that there are more time periods than countries *(T>N)* which allows us to estimate an unrestricted variance-covariance matrix of cross-country shocks. In the opposite case, $N>T$, some restriction of the covariance matrix is necessary for the analysis. We do not discuss this case. [53]

Our main contribution is to show that, for data-sets such as the OECD, maximum likelihood is effectively unbiased and more efficient than the B-regression or conventional panel estimators. Our analysis indicates moreover that both the B-regression and maximum likelihood estimates are robust to plausible measurement error and variation of convergence rates across countries. We show the reason these estimators are so well behaved is that many OECD countries were far from their

[50] See equation (2.2') in Chapter 3.

[51] See sections (2.5) and (2.6).

[52] See Shioji (1997a) and (1997b).

[53] This case is analysed in Robertson and Symons (2000).

equilibrium values in 1950. Our contribution here is consider in detail the relationship between the distribution of the maximum likelihood (henceforth ML) estimator and the initial conditions[54]. We show that, unless initial conditions are sufficiently extreme, confidence intervals for the convergence rate are unsatisfactorily wide. We offer a likelihood ratio test of the fixed-effects model (a general test of the convergence hypothesis), and show why, in small samples, the true size of the test is much lower than nominal levels. We construct tests of correct size by Monte Carlo. This analysis is similar in some respects to a test proposed by Evans and Karras (1996), except that we allow for a general cross-sectional covariance matrix.

2.10 Econometric Issues in Convergence Regressions: testing absolute β-convergence

In this study we analyse unconditional convergence, having in mind the OECD economies or the regions of a given country. The general point that efficiency and inference are improved by exploiting the cross-sectional correlations of groups of economies applies also to studies of conditional convergence and it may well be that our findings provide a useful direction for future work in this area. Thus the convergence discussed in this study is absolute β-convergence.

As in Evans and Karras (1996), to estimate the β–parameter we argue for the use of demeaned data as the correct convergence test. It is also possible to choose at random a comparator country j and replace the logarithm of per capita GDP, y_{it}, by[55]:

$$y_{it}^{\bullet} - y_{it-1}^{\bullet} = -\beta y_{it-1}^{\bullet} + v_{it} \qquad (2.25)$$

where $y_{it}^{\bullet}$ is output in i less output in j and $v_{it} = u_{it} - u_{jt}$. Note that absolute β-convergence, as we have defined it, amounts to asserting β>0. If N<T, (2.25) can be estimated by maximum likelihood (henceforth ML) techniques with an unrestricted covariance matrix, allowing shocks to be correlated across countries, which is almost certain to be true. Expressing the data as deviation from a comparator country will

[54] Shioji (1997b) has considered the importance of the initial conditions in bias reduction.

[55] See also Section 2.4.

eliminate some of the cross-sectional error correlation but not all, unless $v_{it} = \eta_t + \varepsilon_{it}$, where η_t is a time-varying common stochastic component[56]. This could not hold when international shocks impinge differently on different countries.

2.11 Possible mis-specifications

The B-regression has a number of things in its favour. First, the method has no difficulties with $N>T$ where an ML attack on (2.25) will encounter problems in this case[57]. Second, as we shall see below, the method is robust to a number of plausible specification errors. The obvious weakness with the approach is that it is a non-standard method of estimating the family of time-series given by (2.25) and is hardly likely to be efficient. A development of this method, presumably to increase efficiency, is to construct observations for shorter time periods, decades say. As we have previously seen in this Chapter, a related method is to average (2.25) over time periods and estimate using the initial value as an instrument for the period-average GDP.

Using the ML approach, we shall regard the vector process y_t as having commenced at $t=0$ and conduct inference conditional on y_0. We do not regard the data as a realisation of a stationary vector process commencing in the distant past. For our sample, and in most samples in this literature, the presence of undeveloped regions which are many standard deviations from the assumed long-run mean makes this assumption essential. Thus many of the i processes in (2.25) are not even approximately realisations of a stationary time-series but are best thought of as exponential decay. As it happens, as we shall see below, this leads to increased efficiency in estimation.

The problem with estimating (2.25) is that one is trying to obtain precise estimates of the autoregressive parameter of a process close to the unit circle. Usually this is tricky because the estimator is badly behaved in small samples. For example, in the univariate case, the OLS estimator $\hat{\rho}$ of

---

[56] As assumed by Lee, Pesaran and Smith (1997).

[57] A possible argument against the adoption of an ML or SUR approach is that, assuming series are stationary, the SUR estimator has low power unless N is appreciably less than T, while it does not even exist when $N \geq T$. See Evans and Karras (1996) on this point.

$$z_t = \rho z_{t-1} + \varepsilon_t \qquad (t = 1,\dots T,\ z_0 \text{ fixed}) \qquad (2.26)$$

is biased down by $2\rho/T$ for $\rho < 1$[58]. This is a large T result. For given moderate T and ρ close to unity, the distribution of $\hat{\rho}$ will be indistinguishable from the Dickey-Fuller distribution (for which this bias formula is a little different). What is mitigating in the cases we have in mind is that considering a panel of countries reduces bias considerably. Thus with, for example, $N=20$ and $T=40$ we have effectively 800 observations so that such bias is of the order of .002, non-trivial but unimportant in context. One should note however that if included regressors have genuinely different parameters then the false imposition of equality in estimation can bias β in the opposite direction, that is towards 0[59]. It is likely that the B-regression (2.25) is more robust against this mis-specification.

A second mitigation is the initial conditions: z_0 in (2.26) or the set y^*_{i0} in (2.25). The bias estimates discussed above are for large T and the contribution of the initial conditions is of lower order than $1/T$. However, for fixed T, the distribution of $\hat{\rho}$ in (2.26) concentrates on ρ with variance proportional to $\sigma^2/z_0 2$ as z_0 grows[60]. Thus the relevant parameter is the initial condition measured in units of the innovation standard deviation and, for typical samples, values of this can be 40 or more. In these circumstances the estimate will be accurate and precisely determined. It follows that the small sample properties of the ML estimator of β are subject to two conflicting influences : the closeness to the unit circle induces the distribution to behave like a multivariate Dickey-Fuller distribution, while the extreme initial conditions induce normality. In such circumstances, Monte Carlo seems the only way to deduce the properties of the distribution.

Finally one might want to test H_0: $\beta=0$ in (2.25). In these circumstances, (2.25) is a family of random walks and a version of the Dickey-Fuller test would

---

58 See Grubb and Symons (1987) for a general discussion.

59 Robertson and Symons (1992) discuss this possibility. In the event that the forcing variable is a random walk, the false imposition of parameter equality across countries will produce an estimate $\beta=0$ in large samples.

60 Evans and Savin (1983).

need to be performed. If one took seriously the possibility that the v_{it} are correlated across i, critical values could be calculated by Monte Carlo, wherein the artificial random vector v_t would be selected with contemporaneous covariance matrix given by the sample covariance matrix of $y^*_{it} - y^*_{it-1}$. In the case we shall study, and in like work, one is certain to reject the null, because under H_o:$\beta=0$, the B-regression (2.25) should return an estimate on y^*_{io} of zero and the graph of growth against gap should reveal no systematic relationship. Neither is remotely the case.

2.12 ML versus the B–Regression and Pooling: a Monte Carlo analysis

Table 2.1 sets out some Monte Carlo experiments to investigate the properties of the estimators of β. We consider three values of β (.04, .02, .00) and four sets of initial conditions for the y_{it}, $-\lambda(1,2,...,20)$ for λ = .5, 1, 2, 4. A value of λ somewhere between 2 and 4 would characterise differences from US GDP (per head) in OECD data. Each of the 12 cells reports the results of 5000 experiments. The first entry in each cell gives the average of 5000 estimates of the cross-section equation (2.25), the second entry the corresponding average for method (2.2'), while the final entry gives the relative root mean squared error for the two methods. By construction, the v_{it} are orthogonal at different i and different t. In general both estimators are negligibly biased over the range of parameters considered but it is possible to identify several patterns.

Bias and estimate imprecision are increasing in β and decreasing in λ. For $\beta=.04$ the B-regression is always worse in Root Mean Square Error (RMSE) terms. For $\beta=.02$ or smaller this result is reversed except for small λ. Thus neither method is unambiguously superior. For λ=2, more or less the OECD value, ML is slightly better for $\beta=.04$ but becomes decidedly worse for smaller values. The reason for the relative diffuseness of the ML estimates is that they entail calculation of a large (20 $\times$ 20) covariance matrix of errors. If it is assumed in estimation that this covariance matrix is scalar (as is true in fact for the generated errors v_{it}), ML becomes better in terms of root mean square error, only by 10 - 14% for the values tabulated of λ and β.

However ML improves its performance when the v_{it} are correlated across i. Table 2.2 sets out some experiments varying the correlation (ψ) between the v_{it}. We find that ML dominates the B-regression once the average cross-correlation becomes greater than .25. Correlation of this order and greater characterizes many data sets, including per-capita GDP. We also include in Table 2 some experiment with a conventional pooling estimate of (2.25) (that is, stacking and OLS, thus ignoring cross-sectional correlation). ML dominates pooling once cross-country correlation becomes greater than .25 .

2.13 Serial Correlation

We have noted above that the B-regression is more likely to be robust against the false imposition in estimation of parameter equality across conditioning variables. Robustness against mild mis-specification is a very useful property in this context. One likely form of mis-specification is the presence of serial correlation in v_{it} in (2.25). Indeed, Barro (1997) argues against panel estimates of (2.25) on the grounds that (2.25) pertains, not to GDP itself, but to GDP purged of its business cycle component. In this case, if observed GDP is used in estimation, bias is expected because of measurement error[61]. Specifically, assuming $y_{it} = \hat{y}_{it} + w_{it}$ where $\hat{y}_{it}$ is the value of per capita GDP appropriate to equation (2.25), the error term in (2.25) becomes

$$\varepsilon_{it} = v_{it} + w_{it} - (1-\beta)w_{it-1} \tag{2.27}$$

where w_{it} is the business cycle component of output. Thus if v and w are independent white noise processes, serial correlation in ε is negative and fitting (2.25) will lead to estimates of β being biased upwards. If one is willing to assume a value of β, the serial correlation of

$$\hat{\varepsilon}_{it} = y^*_{it} - (1-\beta)y^*_{it-1} \tag{2.28}$$

may be directly investigated. For real OECD data and values of β in the internal (0, 0.1), $\hat{\varepsilon}_{it}$ is well represented by an AR(1) with parameter ranging from about 0.2 to

---

[61] Note however that, since y^*_{it} is a difference from a comparative country, common business cycle components are automatically eliminated.

0.3. The implication is that estimates of β would tend to be biased down if anything[62].

To deal with measurement error Shioji (1997a) proposes a "skipping" estimator[63]. The skipping procedure consists of estimating

$$y^*_{it} = (1-\beta)^m y^*_{it-m} + e_{mit} \qquad (2.29)$$

by OLS, where $e_{mit} = v_{it} + (1-\beta)v_{it-1} + \ldots + (1-\beta)^{m-1} v_{it-m+1}$. A decreasing pattern on the estimated coefficient as m increases suggests the presence of an important measurement error bias.

Another mis-specification that could have important effects occurs when β varies across countries or regions, a point made by Lee, Pesaran and Smith (1997). If the variation is random then estimates of the average β deduced from (2.2') will not be importantly biased[64]. If however there is correlation in the sample between β_i and y^*_{i0} then bias can be expected for both methods. The ML estimate of β deduced from (2.25) may be thought of as a weighted average of OLS estimates of each i equation taken singly, wherein the weights are proportional to the sample variance of y^*_{it} (if the v_{it} are orthogonal). Thus, if slow adjusters (low β) tend to be undeveloped regions (low y^*_{i0}), as seems quite plausible, the estimate of β will be biased towards 0.

We study the effect of serial correlation on the β–coefficient by Monte Carlo in Table 2.3. The error processes are scaled to have unit unconditional variance (not unit innovation variance) and we denote the autoregressive parameter by α. Both estimators are relatively immune from bias, with the estimates derived from the B–regression somewhat more efficient. Note that, if the series y^*_{it} were realisations of stationary AR(1)s, we could expect strong biases in ML estimates of β in the

---

[62] Thus, if v and w are independent AR(1)s, it must follow that the serial correlation in v_{it} is of the order of 0.2.

[63] See Shioji (1997a) on this point. Using a skipping procedure, he finds evidence of possible measurement error in the US states and the Japanese prefectures. Evidence is less clear cut for the OECD.

[64] Though see Lee, Pesaran and Smith (1997).

presence of autocorrelated errors. The lack of bias in Table 2.3 is due completely to the initial conditions.

Table 2.4 gives the results of variability across i in the parameter β. We have taken 20 different values of β_i, evenly spread between .01 and .03. In terms of the usual economic interpretation, this is fairly extreme variability since at the lower end, gaps have a half-life of 70 years versus 23 years at the higher end. The first cell assumes the order of the βs corresponds to the initial conditions, that is, the lowest β is the least developed etc. Note that β is biased towards zero by about 0.005. The second cell reverses the assignment: the lowest βs go with the most developed. In this case the bias is reversed. It seems to us that these results are quite reassuring since the tabulated biases are very much worst case outcomes.

Finally, Table 2.5 investigates the relationship between the initial conditions and the distribution of the ML estimator $\hat{\beta}$. We compute indices of skewness and kurtosis. We compute also confidence intervals for $\beta = .02$, defined as the points between the 2.5 percentile and the 97.5 percentile of these empirical distributions. It will be observed that $\hat{\beta}$ is effectively unbiased once λ rises above about 2.0 but the distribution still manifests skewness and excess kurtosis. Even for λ as high as 8.0, the distribution is leptokurtic. For low values of λ, *95%* confidence intervals for λ are quite wide, indicating that tight estimates of convergence rates require wide variance in initial conditions.

2.14 Bias and fixed effects

A natural test in the general convergence proposition is to insert constants on the right in (2.25), that is to allow for fixed effects. In Chapter 3 we have seen that, if such constant are present in the true model, different countries will differ in per capita income in the long-run, perhaps due to semi-permanent aspects of institutional and technological structure[65]. In this case estimates of β from (2.25) will be biased towards zero if constants are not included. On the other hand, if constants *are* included, estimates of β will be biased up, whether the constants are present in the

[65] See Islam (1995), section 2.3.

true model or not[66]. In the univariate case, (2.26) bias is $(1+3\rho)/T$ when a constant is included. With K extra regressors on the right, the maximum bias is $[K(1+\rho) + 2\rho]/T$. In the multivariate case, allowing each country to have its own constant will bias β by approximately 4/40 = .10 given that the constants are in fact absent.

We analysed this latter bias by Monte Carlo. In the notation of Table 2.1 with β=.02, λ=2 and orthogonal v_{it}, we found with 5000 Monte Carlo replications an average estimate of .102 with sample standard deviation of .086 when each country was allowed its own constant. Examinations of parameter estimates for these artificial data showed that the constants were almost invariably statistically significant, despite being genuinely absent in the model. The magnitude of the fitted constants was correlated with starting conditions y^*_{i0}, so that countries behind at $t=0$ were falsely predicted to be behind in equilibrium ($t=\infty$). Reflection reveals why this must occur. Our initial conditions y^*_{i0} are negative and, since $\hat{\beta}$ is biased up, the predicted path (with a zero constant) for a given country from $t=0$ to T must lie on average above the path in the data. It follows that the least-squares fit will be improved by choosing a negative constant. Thus bias to $\hat{\beta}$ creates bias to the fixed effects parameters.

This can also be seen heuristically by examination of (2.26). If $\hat{\rho}$ is derived with a fitted constant, α, then, since a regression line passes through the sample means, we must have

$$z_t = \hat{\rho}\,\bar{z}_{t-1} + \hat{\alpha} \tag{2.30}$$

Thus, with no constant present in the true model, we have

$$E(\hat{\alpha}) = E((\rho - \hat{\rho})\,\bar{z}_{t-1}) \tag{2.31}$$

Given that $\rho - \hat{\rho}$ is almost always positive, it follows that, for countries whose relative GDP/head is negative over the whole sample, we expect to find negative constants.

---

[66] See Nickell (1981).

2.15 Case Study: convergence in the OECD

As an example we have applied both methods of estimation to income per capita in 23 OECD countries (the whole set excluding Turkey and Yugoslavia)[67]. The sample thus consists of developed capitalist economies for whom the assumption of common tastes and technology is fairly supportable. The sample runs from 1950 to 1990. In 1950 these economies had been variously affected by the cataclysms of the first half of the century and thus are suitable for study of convergence in a homogeneous set of countries disturbed from equilibrium[68]. The United States was chosen as the comparator country.

Table 2.6 sets out estimates obtained by Shioji's skipping procedure. Equation (2.29) has been estimated using different values of m. The absence of any downward trend in the βs as m grows confirms the absence of measurement error bias in the estimates[69]. An OLS regression of $y^*_{iT} - y^*_{i0}$ on y^*_{i0} gave a parameter of -.39 with a standard error of .03 so the hypothesis of $\beta = 0$ in (2.2') is decisively rejected. The non-linear least squares estimate of β in (2.2') was $\hat{\beta} = .023$ (.002). The estimate of β from (2.25) was quite different, $\hat{\beta} = .028$ (.0019). Which do we believe? The Durbin's h test for the i equations in (2.25) was .86 on average suggesting that bias arising from serial correlation in the residuals is not a problem.[70]. Thus we can comfortably accept the null of absence of first order serial correlation.

---

[67] We use the Penn world tables (Version 5.6).

[68] One might seek to argue that Portugal and perhaps Greece and Ireland were not developed economies in 1950, by such measures as proportion of the workforce in agriculture, literacy, and female education. Our results are not overly sensitive to this assumption.

[69] The inclusion of fixed effects in (2.30) does not affect this result.

[70] The Durbin's result shows that, under the null of absence of first order serial correlation, with d corresponding to the Durbin Watson statistic (in our analysis, the average Durbin-Watson is 1.73) and s^2 to the estimated variance of the least square regression coefficient on the lagged dependent variable, the statistic:

$$h = \left(1 - \frac{d}{2}\right)\sqrt{\frac{T}{1 - Ts^2}}$$

is distributed as a standard normal. If $h > 1.645$ we reject the null at the 5% level.

In any case, this should bias the estimate towards zero. Similarly, variability across the βs will bias the estimates towards zero if the undeveloped regions are slow adjusters, as seems the most likely case. It would seem therefore that ML is fairly free of the mis-specification biases we have considered. The sample correlation of the v_{it} was about 0.4 on average so, according to Table 2.2, ML on (2.25) is more efficient and to be preferred.

When we include individual constants on the right of (2.25) we found $\hat{\beta} = .068$. The constants were always negative (the US always remains richer) and significant in all countries except Switzerland. The likelihood ratio test for the exclusion of all constants gave a reading of 77 which indicates a massive rejection ($\chi^2_{.01} = 40.3$). However, the discussion in section 3.2 leads us to expect bias and falsely significant constants in a regression such as this. To illustrate this problem for the OECD, we generated artificial data taking y^*_{i0} at its 1950 value, with shocks u_{it} drawn from a multivariate normal distribution with the covariance matrix of $u_{it} = y^*_{it} - 0.98y^*_{it-1}$ in the sample. The results are given in Table 2.7: the inclusion of constants, though genuinely absent in the true artificial data, introduces a substantial upward bias to $\hat{\beta}$, with an estimated convergence parameter of $\hat{\beta} = .079$.

Accordingly, we have constructed a critical level for the likelihood ratio by Monte Carlo. We first estimated β under the null of no constants and computed the residual variance-covariance matrix. We then simulated (2.25) using random v_{it} with the computed covariance matrix and the initial conditions y^*_{io} observed in our data. Equation (2.25) was then estimated with and without constants. Repeating the process 5000 times, we found for the likelihood ratio test a 1% critical level of about 70 and a 5% level of 61.3. Thus unconditional convergence is comfortably rejected at conventional levels though nowhere near as decisively as with the conventional χ^2. The problem countries are Greece, Ireland, Portugal and Spain: their growth has been too low, given their relative poverty over the sample. Without these countries, absolute convergence is accepted at the 1% level by a conventional χ^2 test and at the 5% level by Monte Carlo. It is noteworthy that, if we look at the data set, these four countries had the lowest secondary school enrolment in 1965[71].

[71] World Development Report (1991).

An alternative estimate of β in (2.25), robust to the presence of fixed effects, can be based on the Anderson-Hsiao estimator wherein the equation is differenced and estimated using appropriate lags of y^*_{it} as instruments. We compute a standard error for this estimate taking into account the cross-correlation between country shocks. Specifically, the asymptotic variance of the estimate is:

$$Var(\hat{\beta}) = (\Delta y^*_{-1}{}'\Delta y^*_{-1})^{-2} (\Delta y_{-1}{}^*{}'(\Sigma \otimes J)\, \Delta y^*_{-1}) \tag{2.32}$$

where J the usual Anderson-Hsiao moving average-matrix, and Σ is an estimate of the cross-sectional covariance matrix, given by the residual covariance matrix factored by 0.5. The vector Δy^*_{-1} is the stacked Δy^*_{-1}, instrumented by two lags of y^*_{-1}. We find $\hat{\beta} = .031\ (.08)$. The point estimate is very close to that obtained by ML, despite being free of the possible bias introduced by missing fixed effects. Table 2.8 sets out the values for β obtained by the four methods we have considered.

2.16 Summary of results

This Chapter has analysed the main features of some econometric techniques proposed for estimating the convergence parameter. We have seen that there is no consensus on which is the more appropriate methodology for estimating convergence. It is probably fair to say that "As yet, no technique is available that has shown uniform superiority in finite samples over a wide range of relevant situations as far as the true parameter values and the further properties of the DGP are concerned. Perhaps such a technique is just impossible."[72]

However, different methodologies may imply very different values of the convergence coefficient. These disparities in estimated coefficients imply significant differences in the predicted patterns of convergence and, possibly, even dissimilar interpretations of the convergence process. Despite these differences, the methodologies summarised in this Chapter share the common characteristic of placing no emphasis on the possibility that shocks are correlated across countries. In particular, all panel methods summarised so far have in fact assumed that shocks are uncorrelated across countries. While for more heterogeneous data set this assumption

[72] Kiviet (1995), page 72.

may be considered acceptable, it is surely unlikely when quite homogeneous data sets like OECD, European countries or regional samples are introduced. We have examined this point extensively and proposed an alternative panel estimation procedure. In fact, we have investigated a possibility so far ignored by all the empirical studies on convergence, namely, an annual panel estimator where shocks are allowed to be correlated across countries. In particular, we analyse by Monte Carlo the properties of the ML panel estimator with an unrestricted variance-covariance matrix in estimating the convergence parameter. We have found:

1. Both ML and the B-regression have various things in their favour. The B-regression is robust against some possible mis-specifications.
2. ML is a better estimator for cross-country correlation likely to be observed in most work.
3. The natural test for convergence in the ML approach of including country-specific constants has problems because bias to the lagged dependent variable, in conjunction with initial conditions, creates bias and false significance in the estimates of the constants.
4. Monte Carlo study of the likelihood ratio statistic suggests that the value obtained for the exclusion of the constants in the OECD data is statistically significant at conventional levels. In other words, unconditional β-convergence is rejected in these data – but only just.

The next Chapter introduces this alternative methodology for estimating the process of convergence among Italian regions. As we will see, the characteristics of this sample imply that this estimator should perform better than other conventional estimators introduced by the previous literature.

APPENDIX II-A

Table 2.1

Estimates of E(β) obtained from (2.2'), from (2.25) & the root mean square errors of the estimates of (2.25) as a proportion of (2.2').

	β=.04	β=.02	β=.00
λ=.5	.0415 (.0126)	.0212 (.0100)	.0009 (.0074)
	.1003 (.236)	.0252 (.0606)	.0007 (.0062)
	19.1	*6.02*	*.83*
λ=1	.0406 (.0074)	.0205 (.0058)	.0003 (.0042)
	.0407 (.0215)	.0200 (.0048)	.0002 (.0029)
	2.88	*.82*	*.70*
λ=2	.0401 (.0038)	.0201 (.0029)	.00010 (.0022)
	.0393 (.0040)	.0196 (.0023)	.00005 (.0014)
	1.06	*.79*	*.68*
λ=4	.0400 (.0019)	.0200 (.0015)	.00002 (.0010)
	.0391 (.0019)	.0195 (.0011)	.00003 (.0007)
	1.11	*.82*	*.67*

Notes:

1. For each λ and each β the cells contain, respectively, the estimate of E($\hat{\beta}$) from (2.25) (in the background), from (2.2') and the relative root mean square errors (*rmse*), (2.2')/(2.25) (in italics). Sample standard deviations are given in brackets. Equation (2.25) was estimated by maximum likelihood, with free covariance matrix of v_{it}. Equation (2.2') was estimated by non-linear least squares. Both equations were estimated using the LSQ option in TSP 4.2 (5000 replications).
2. Initial values of $(\Delta y_{1t},...,\Delta y_{20t}) = \lambda(1,2,...20)$.
3. Convergence tolerance for estimator convergence = .0001. All calculations performed in double precision.
4. The covariance matrix of the v_{it} was taken to be I_{20} to generate the data.

Table 2.2

Estimates of bias and RMSE for different methods of estimating the convergence parameter β with cross correlations of the v_{it}
(λ=2, β=.02)

	ψ=.00	ψ=.25	ψ=.5	ψ=.75
(1) ML	.0200 (.0029)	.0202 (.0043)	.0202 (.0040)	.0201 (.0030)
(2) B-regression	.0195 (.0022)	.0202 (.0043)	.0205 (.0074)	.0209 (.0157)
(3) Pooling	.0201 (.0020)	.0205 (.0051)	.0210 (.0060)	.0212 (.0072)
rmse(2)/rmse(1)	*.77*	*1.16*	*1.86*	*5.27*
rmse(3)/rmse(1)	*.68*	*1.01*	*1.52*	*2.46*

Notes:
(i) Convensions as for Table 1, (1)-(3).
(ii) *(ii)* ψ is the average cross-country correlation coefficient.
(iii) The Pooling estimator is OLS on the stacked data.

Table 2.3

Effect on E(β) of serial correlation in v_{it} (λ=2, β=.02)

	α=.25	α=.5
ML	.0196 (.0039)	.0183 (.0055)
B-regression	.0197 (.0030)	.0200 (.0046)
	.77	*.80*

Notes:

(i) Conventions as for Table 1, (1)-(3).

(i) *(ii)* α is the first order serial correlation coefficient of the vit process.

Table 2.4

Effect on *E(β)* of β-variability *(λ=2)*

high initial gap = slow adjusting	high initial gap = fast adjusting
.0155 (.0028)	.0249 (.0035)
.0150 (.0020)	.0245 (.0025)
.93	*.85*

Notes:

(i) Conventions as for Table 1, (1)-(3).

(ii) The first cell computes β when β_t ranges from .03 to .01 for starting values -2(1,2, ..., 20);

(ii) the second cell reverses this assignment.

Table 2.5

Properties of ML estimator as initial conditions vary (β=.02)

	mean	*Std. Dev.*	*skewness*	*Kurtosis (-3)*	*95% confidence intervals for β*
λ=.1	.0216	.0265	-.6280	1.1719	[-.0247, .0792]
λ=.5	.0221	.0160	-1.0061	3.2365	[-.0036, .0589]
λ=1	.0209	.0083	-.6893	2.1411	[.0065, .0392]
λ=2	.0202	.0042	-.4673	1.6036	[.0124, .0299]
λ=4	.0200	.0021	-.2378	.9502	[.0160, .0243]
λ=8	.0200	.0010	-.0695	.6628	[.0181, .0222]

Notes:

(i) Conventions as for Table 1, (1)-(3).

(ii) Standard Errors for the skewness and kurtosis statistics are .04 and .08 respectively.

Table 2.6

Estimated β-parameter: results from skipping estimation

m	*β-coefficient*	*St. Dev*
1	.0265	(.0030)
2	.0275	(.0064)
4	.0280	(.0121)
8	.0263	(.0223)
10	.0277	(.0283)

Notes:

(i) Method of estimation: OLS (Pooling Estimation).

(ii) *m* defines different samples (data are taken every *m* years).

Table 2.7

Estimates of β with and without fixed effects in OECD data

	Mean	*Standard Deviation*	*Bias*
β (fixed effects fitted)	.079	.0262	.059
β (no fixed effects)	.020	.0049	.005

Notes:

(i) The Table gives the results of Monte Carlo estimations of β in artificial data, taking as initial conditions those observed in the OECD and covariance matrix corresponding to β=.02. There are no fixed effects in the artificial data.

Table 2.8

Sample OECD (1950-90)

Estimates of the convergence coefficient by different methods

	β coefficient	*Std. Error*
B-regression	.023	(.030)
OLS pooling	.027	(.003)
ML procedure	.028	(.002)
Fixed Effects	.068	(.005)
Anderson-Hsiao	.031	(.080)

Notes:

(i) Number of countries 22, number of observations 41. The sample includes the OECD countries with the exception of Yugoslavia and Turkey. Data are in difference from US levels.

(ii) The estimated value of the average Durbin's h test (ML procedure) is .86.

CHAPTER 3

THE ROLE OF HUMAN CAPITAL IN THE DEVELOPMENT OF ITALIAN REGIONS

> "In reality, other factors could mean that the potential growth benefits of a highly qualified labour force could be wasted. We therefore think of a highly qualified labour force as a necessary but not a sufficient precondition for growth. Wasteful economic policies, wars and other political upheavals, natural disasters, and other events may delay progress in an otherwise promising economic environment." Azariadis and Drazen (1990).

3.1. Introduction

As seen in Chapter 1, differences in human capital endowments and their rates of investment have long been recognised as an important element in explaining observed GDP gaps. A number of growth models imply that public returns to education exceed private returns thus stressing the presence of positive externalities to education. For example, Lucas (1988) assumes that high average levels of human capital throughout the economy increase the productivity of any given worker. One could think of this as a positive peer-group effect. But there are a number of other possible mechanisms. A higher level of education could be associated with a reduction in crime, increased social cohesion, more informed political decisions, inter-generational benefits (assuming parents' education is transmitted to their children) and technological and organisational improvements not captured by private returns. In contrast, traditional signalling models of education may generate a socially sub-optimal outcome. In this case, education does not directly add to productivity. Rather it confers credentials used in the labour market to be selected as able workers: private returns to schooling can be high at the same time as social returns are nugatory. Signalling models are usually associated with higher levels of education.

Some authors have even argued that higher education tends to create rent-seekers who do not add to the genuine output of the economy.[1] But we may think of other mechanisms concerning lower levels of education. More prosaically, recent work suggests that conventional schooling may have harmful side effects by creating peer-groups with rival values to those of parents and adults generally. One could think of this as a negative peer-group effect. There is a vast amount of literature on the increase in adolescent psychological problems due to their separation from the influence of adults [2].

Note that individual-based micro analyses will be useless as a guide to public policy when there are important externalities, as such analyses will only measure private returns. Conversely, macroeconomic studies have a role to play in the analysis of returns to schooling[3], since these studies consider the data of direct interest, namely the returns at the level of the economy. Indeed, the existing empirical literature on macro growth and human capital shows substantial differences in the microeconometric evidence on returns to education[4]. In general, while Mincerian regressions[5] indicate the existence of positive private returns on educational attainments in both developed and developing countries, often of the order of 10% for each extra year, cross-country studies of aggregate returns to education (typically using the standard growth-regression approach) usually find that education is not strongly associated with per capita income growth.

In other words, empirical macro studies on aggregate returns to education show puzzling results. Too often education seems not to influence per capita income growth and, sometimes, it even seems to wield a negative influence on the development process of an economy. Different reasons have been put forward to explain this puzzle. Firstly, it has been claimed that the main problem causing the

---

1 See Wolff and Gittleman (1993). See also Lodde (1995) for a specific example on Italian regions.

2 Thus Hargreaves (1994): "If one wanted to create a separate teenage culture, if one wanted to make adolescents feel cut-off from adult responsibilities, the best way would be to do as we now do: segregate them for most of their lives outside the family with those who happen to have been born in the same year". See also Rutter and Smith (1995).

3 See Temple (1999a).

4 See Psacharopoulos (1985), Pritchett (1996) and Krueger and Lindhal (2001) among others.

5 See Section 3.3.

observed lack of empirical support is that most growth regressions, while using large international datasets, incorrectly impose a single coefficient and thus equal returns on schooling among different countries. This problem is likely to arise when the quality of education is influenced by differences in educational institutions making national statistics on education difficult to compare. To test for this problem different authors suggest to focus on "...the most coherent part of the data set rather than the whole sample"[6]. Moreover, it may well be that the quantity of education affects its quality: returns to education may be higher in more educated areas as usually predicted by growth models[7]. In both cases standard regressions would produce distorted estimates on education due to the presence of parameter heterogeneity and measurement error problems[8].

A second problem that may arise when we estimate returns to schooling is that in some cases the acquisition of educational skills is not necessarily linked with productivity. As noted by Shultz (1962), education may represent not only an investment for individuals, but can also be considered as a consumption good and, thus, be privately valued for its own sake[9]. But another interesting example is found in Pritchett (1996), who cites the case of Saudi Arabia where in 1988 fifty percent of university students were studying "Humanities, Religion and Theology". While this kind of degree probably provides good credentials in the Saudi Arabian job market, it does not guarantee an obvious acquisition of growth enhancing skills[10]. A related problem has been emphasised by Griliches (1997). He observes that in many

6 See Temple (1999). But see also Bond et al. (2001) "One potentially fruitful line of research would be to develop specifications that allow for some limited heterogeneity in slope coefficients, and to investigate the extent of such heterogeneity using sub-samples of countries where longer time series are available." pag.22, and Klenow and Rodriguez-Clare (1997b) as in Chapter 5, footnote 8.

7 Among them see Azariadis and Drazen (1990).

8 See Pritchett (1996), Temple (1999b), Krueger and Lindhal (2001) and Kyriacou (1991).

9 For example, some schooling may be acquired by persons who are not income earners and should not be included in the analysis of returns to schooling. This may be the case especially for women This is why we use variables on educational attainment of the regional labour force instead of using per capita schooling indicators as found in most macro studies.

10 In Saudi Arabia even in Western-oriented schools a large part of the new curriculum is devoted to religion. In particular, the memorization of the Quran, interpretation and understanding of the Quran and the application of Islamic tradition to everyday life are stressed. Religion is also studied at the university level alongside other subjects, and is compulsory for all students.

countries, and especially developing countries, the public sector employs most of the skilled labour force. This fact may create three sources of distortions when we estimate returns to schooling[11]. Firstly, the output of the Public Sector is certainly badly measured in National Accounts and, possibly, underestimated. Further, the literature on developing countries shows many examples where the growth of the Public Sector with the "absorption" of a skilled labour force in this sector has not been motivated by any efficiency criteria. Lastly, the Public Sector is not obviously an innovative sector while, as predicted by theoretical growth models *à la* Nelson and Phelps, educational capital is growth enhancing only when allocated to innovative sectors. These are all examples where the potential growth benefits of a highly qualified labour force could be wasted.

In this Chapter we investigate if, screening for the problems described above, a standard macro analysis of returns to education would produce significant results. To begin with, we deal with the first problem focusing on a more homogeneous data set rather than the whole international sample and ask what role human capital has had in Italian regional economic development. We claim that Italian data are most suitable for a macro study of returns to education. Unlike most regional data sets, the Italian regions are quite diverse in their endowments of human capital - among the European countries, Italy has one of the highest rates of dispersion in regional education attainment[12] - and, since the 60s, has experienced vast increases in the average duration of education at all three levels. Secondly, the Italian regions have common institutions[13] so that, in large part, the data represent a controlled experiment in ceteris paribus variation of labour force educational endowments in a developed economy. Further, there is a large amount of literature showing a clear divide in the Italian economy between the developed North/Centre areas and the less developed South, suggesting the presence of two convergence clubs. These two clubs are also characterised by the existence of homogeneous educational institutions in both areas, together with substantial differences in human capital endowments. In

11 "I would like to suggest another possible answer to this puzzle....much if not most of the growth in human capital was absorbed in the Public Sector of many of these economies". Griliches (1997).

12 See Lodde (1999). The sample includes Germany, France, UK, Belgium and Italy, 1981-1991.

13 Not to mention capital mobility.

fact, compared to the less developed South, the richer North/Centre can tap larger stocks of human capital. Therefore, this is an ideal sample to test the relationship between quantity and returns to education. Allowing for parameter heterogeneity in the two clubs, we analyse if returns to education have been different in these two areas of the country considered separately. Also, we suggest testing for the second problem by introducing a measure of the Public Sector into our empirical analysis and checking if this may possibly affect our estimates on returns to schooling.

Our investigation differs from previous studies on Italian convergence in that we use a measure of the stock of human capital rather than the flow. We have census data on average years of schooling and different levels of schooling distinguished by gender and use information on enrolment rates to construct a yearly dataset. Thus, we follow the standard development literature that predicts larger externalities for educated women than men and investigate if differences in male and female education have different impacts on the development of Italian regions. Further, we ask if different levels of education produce different impacts on growth. In fact, due to their emphasis on the role of technology, most of the theoretical growth models implicitly expect that higher levels of educational attainments act more powerfully on growth than, say, primary school. This prediction contradicts microeconometric evidence, where returns to investments in primary education are usually estimated as the largest[14].

This Chapter is organised into nine sections. The next section introduces a descriptive analysis of the Italian regional convergence process, while the third section stresses the distinction between private and social returns to education and briefly describes the results found by previous studies on private returns to education in Italy. Section four summarises the previous evidence on the effects of human capital on regional Italian convergence, while section five presents the main characteristics of our human capital data set. Section six explains the econometric methodology used, and the remaining sections discuss the major results of our empirical analysis. In particular, section eight proposes a new methodology for the analysis of convergence clubs and tests if different levels of educational attainment have different impacts on growth. The last section offers some conluding observations.

3.2 The distribution of Italian regional per capita GDP: stylised facts

A distinguishing feature of the study of convergence among Italian regions is the high inequality in the distribution of per capita income among regions. In 1950, Italy shows twice as much the dispersion calculated for other European countries. Even today, the degree of regional inequality in Italy is higher than in many EC countries[15]. Its high inequality in the distribution of income reflects the persisting gap (with an approximate but clear division) between the North and the South of the country. This is still true notwithstanding the fact that the Italian Government has always reported the development of the *Mezzogiorno* area as a key objective of its economic policy[16].

Among the most influential studies on regional convergence are the Barro and Sala-i-Martin papers (1991 and 1995). They examine convergence among US states and European regions and find a speed of convergence of 2 percent in all regional samples examined, including Italian regions[17]. Therefore, they conclude that ".... the south of Italy has not yet caught-up because it started far behind the north, and the rate of beta convergence is only 2 percent a year.". In other words, they see no evidence that poor regions, such as those in southern Italy, are being systematically left behind in the growth process: convergence for southern regions seems to be just a question of time. By now many other authors have disputed these somewhat optimistic conclusions[18]. In this section we stress the main stylised facts about Italian regional convergence and compare our descriptive evidence with that of previous

---

14See Psacharopoulos (1994), Pritchett (1996) and Krueger and Lindhal (2001).

15 See Barro and Sala-i-Martin (1991).

16 See Graziani (1978). He also includes the official view of the Italian Government from «Programma Economico, 1971-75», Ministero del Bilancio» and «Studi per il Programma Economico Nazionale, 1971-75», ISPE.

17 This conclusion is found also with international (or cross-countries) samples. For the Italian case they found an estimated convergence coefficient of 0.015, a lower speed of convergence with respect to the rest of Europe.

18 See Mauro and Podrecca (1994), Paci and Pigliaru (1995), Boltho Carlin and Scaramozzino (1996).

literature[19].

The first stylised fact on Italian convergence concerns the non-homogeneity of the process of regional convergence: decreasing dispersion in regional per capita GDP, while strong during the 60s, all but ceased after 1975[20].

This pattern is confirmed by the σ convergence analysis in Figure 3.1. As we have seen in Chapter 2, the *σ convergence* is an accepted descriptive measure of convergence. Two series are converging if their difference is decreasing on average and has a decreasing variance: that is, we test if the series tend to be equal in time and if this tendency towards equality is stable. The dispersion among Italian regions seems to have decreased until early 70s. Afterward, the dispersion is fairly stable, with some tendency to increase in the last few years.[21] It is impossible then, to conclude in favour of a strong and/or continuous process of sigma convergence. Explanations abound. There was a decrease in migration from the South to the North; there were efforts directed towards achieving a uniform wage between the northern and the possibly less productive southern labour force[22]; there was a change in policies directed to fostering the development of more backward regions. In particular, the Italian Government sought to boost industrial investment (especially in heavy industries like chemicals and steel) in the South during the 60s and part of the 70s[23]. After that period, there was a shift in policy from investment to income-maintenance in the form of direct transfers and an expansion of the public sector, also associated with an acceleration in the process of administrative decentralisation.

---

19 Our analysis is based on annual data on per capita GDP, covering the period 1963-1994, which has been collected and organised by Prometeia. See the appendices for more information about the data set.

20 See Mauro and Podrecca (1994), Di Liberto (1994), Boltho, Carlin and Scaramozzino (1997), Paci and Pigliaru (1995) among others.

21 The downward peaks in '75 can be explained by the strong negative effect that the oil shock had in the northern, more industrialised, regions.

22 This policy started officially in 1969.

23 See Graziani (1978).

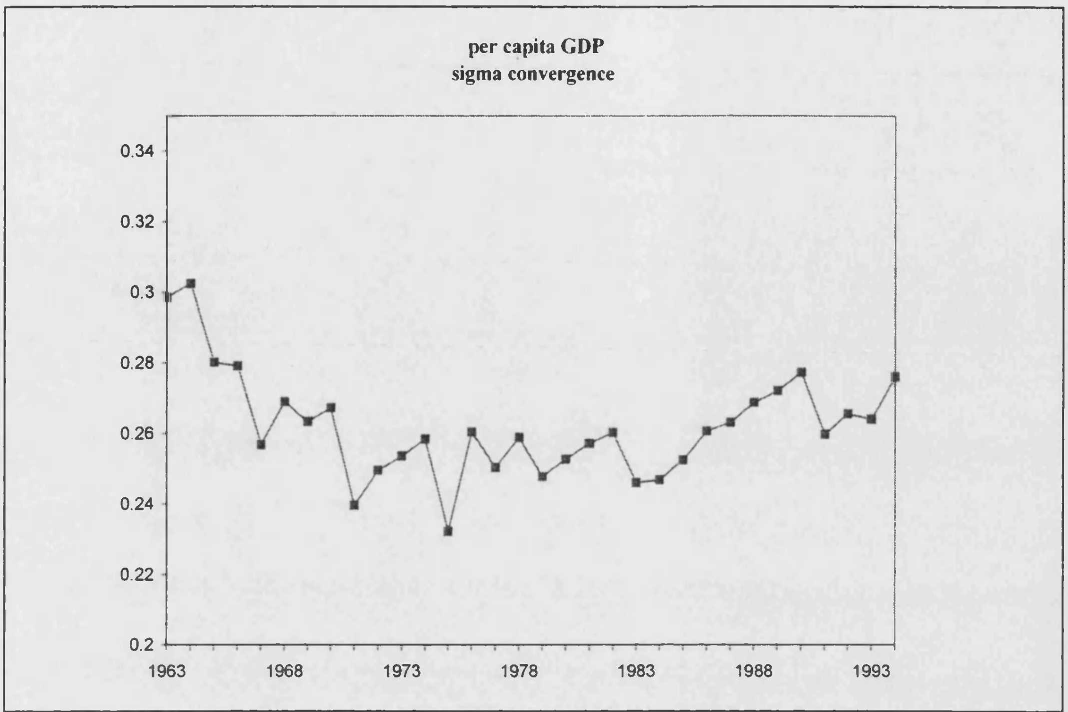

Fig. 3.1- Time path of the standard deviation of the logarithm of GDP across Italian regions 1963-94.

All this notwithstanding, this non-homogeneity of the convergence process has been found in studies of other countries. For example, the Spanish regions seem to have experienced a similar pattern[24], and many OECD economies experienced a stop in their process of regional convergence somewhere in the mid-1970s[25]. The rapid increase of oil prices in 1973-74 presumably influenced investments, technology and additional factors that most probably affect the convergence process internationally. In particular, the observed Italian sigma-convergence pattern may have been affected by a different sensitivity to oil shocks among regions due to the disparity in industrial development between north and south.

Table 3.1 compares (with respect to the Italian average) per capita income in each Italian region. During the 1960s, the richest regions, Valle d'Aosta and Lombardy, were respectively 42 and 34 percent wealthier than the average Italian region. The poorest regions of Calabria and Basilicata, registered 38 percent less

---

24 See Chapter 4.

25 See Sala-i-Martin (1996).

income per capita than the Italian average. This is a large gap for a relatively small industrialised country. This difference has lowered during the last three decades, but the decrease was not smooth throughout the period analysed[26].

Moreover, we have already seen that Italy underwent relative economic decline of the north-west regions (traditionally the most industrialised area of the country called "*industrial triangle*"), due to the success of a group of *newly industrialised regions* located in the north-east and central areas of the country. Therefore, even where there is evidence of sigma convergence in the first period, we have to be cautious in concluding in favour of a global catching up process. As we will see from the econometric results, a lot of the observed decrease in the dispersion is probably due to a process of convergence among northern regions while the traditionally poorest areas of the country have seemed to lag behind.

3.3 Private versus Social Returns to education in Italy: the Mincerian earning function

The literature on private returns to schooling investigate if educated workers receive a higher wage rate compared to uneducated workers, where the wage rate differential represents the direct benefit resulting from investment in education. Assuming that relative earnings effectively reflect labour force productivity, the wage rate differential should represent the increase in productivity resulting from improved levels of education. The micro labour literature usually estimates returns to education introducing the so-called Mincerian earning function. In his work Mincer (1974) showed how it is possible to estimate private returns to education using the following wage equation:

$$w_i = \gamma_0 + \gamma_1 S_i + \gamma_2 X_i + \gamma_3 X_i^2 + \varepsilon_i \qquad (3.1)$$

where w_i is the logarithm of the wage of individual i, S_i represents years of schooling,

26 For example, Campania and Liguria experienced a constant deterioration of their relative position. Three regions, Abruzzi, Molise and Basilicata had a tendency to narrow their differentials with respect to the national average, even during the last twenty years. We also observe changes in the relative positions among richest regions. Northwest (Piemonte, Valle d'Aosta, Lombardia, Liguria), the richest

X_i is experience and ε is the disturbance term. The quadratic term should measure returns to on-the-job training. That is, log of earnings are linearly related to an individual's years of schooling[27], where students choose the level of schooling that maximises their lifetime income. More precisely, in this model the time spent in school affects individual abilities, productivities and, consequently, earnings. Other factors may be included among regressors, such as family background, proxies for individual ability (such as IQ scores) and other observable individual characteristics that may help to determine earnings.

In recent years, a number of empirical studies have introduced the Mincerian earning function to investigate the (private) returns to education in Italy. Brunello, Comi and Lucifora (1999) offer an exaustive survey of this literature. In this survey they distinguish between a) early studies carried out in the late 1980s and early 1990s, based on OLS estimates and on unrepresentative data sets, and b) more recent studies that use nationally representative samples and employ more suitable econometric techniques such as Instrumental Variables (IV) and panel data methodologies.

In this Chapter we will focus only on the second most recent type of studies and briefly review the results found in terms of private returns to schooling. In general, these studies find that private returns to education are higher than previously suggested by early OLS studies. Nevertheless, estimates of Italian returns to education are still lower than those generally computed for other countries, especially the US. IV estimates of returns to years of schooling range from 5.7% to 7.6%, while studies that use longitudinal data find lower returns of approximately 4%. Morever, studies that investigate private returns for different levels of schooling suggest that that the expected returns from a year of tertiary education is 7.9%, higher than the expected returns from secondary education (4,3%) and in primary school (5%). However, as stressed by these authors, given that the expected duration of a college degree is much higher than the statutory duration, the computed number of years

---

area during the 60s, decreased its relative advantage. The opposite is true for the Northeast part of Italy (Veneto, Friuli Venezia Giulia, Trentino Alto Adige, and Emilia Romagna).

27 This specification is valid if the only cost of attending school one additional year was the opportunity cost of students' time and if the proportionate increase in earnings caused by this additional year is constant over time.

spent in tertiary education may carry an important measurement error affecting the estimated returns on tertiary education.

The earning function may also be introduced to estimate the social returns to education[28]. Empirical studies on international datasets show the presence of differences between estimated private and social returns to schooling. For example, Psacharopoulos (1985), using data from forty-four countries that include both developing and developed countries, compares private versus social rates of return to education distinguished by educational level and find that: a) returns to primary education (whether social or private) are highest among all educational levels, b) private returns are in excess of social returns, especially at university level, c) returns to education in developing countries are higher than the corresponding returns in more advanced countries. These results have been confirmed by more recent studies[29].

However, the use of the Mincerian earning function to estimate social returns to schooling has been criticised. Firstly, the use of the earning function for estimating social returns to schooling is justified only under the assumption that earnings represent a good proxy for productivity. In other words, we need to assume perfectly competitive markets and absence of externalities. Only in this case, would the extra earnings of educated workers represent their additional contribution to output. As we have already stressed before, growth models with human capital are often characterised by the presence of positive externalities. Thus, we claim that the standard convergence equation is more appropriate to estimate social returns to schooling.

3.4 Human capital and the development of Italian regions: previous empirical evidence

Most studies on growth and convergence that introduce international data sets find that human capital is insignificantly or even negatively correlated with the process of

---

28 Krueger and Lindhal (2001) show how to compute the "Macro-Mincer" wage equation.

29 See Pritchett (1996) and Krueger and Lindhal (2001).

development[30]. This fact has always been considered as an enigma since the predictions of theoretical models stress the important and positive role of human capital in the growth performance of an economy. One of the arguments for explaining the observed weak positive correlation between human capital and growth relies on the heterogeneity of international samples. In particular, Temple (1999b) argues that considering large samples of very heterogeneous countries may cause serious distortions during empirical analysis. The coefficient on human capital may, in fact, differ across different subsamples due to the presence of even a small number of influential outliers. Temple (1999b) replicates the Benhabib and Spiegel (1994) regressions. Using a robust estimator he excludes observations with the largest residuals, and the resulting homogeneous sample consists of 64 countries. Using this sub-subsample he finds a positive and significant coefficient on human capital. Thus, he stresses that researchers should focus on "...the most coherent part of the data set rather than the whole sample".

Note that focusing on a single country regional sample should help to control for this mis-specification. With respect to large international data sets, the quality of data is homogeneous, and even the quality of schooling itself should not differ significantly among the different regions. Nevertheless, similar puzzling evidence on human capital is also common in studies on Italian regions.

Most of these studies on Italian convergence use the secondary school enrolment ratio as a proxy for human capital. This flow indicator was firstly introduced by Mankiw et al. (1992) and its use is consistent with the convergence equation deduced from the augmented Solow growth model[31]. In particular, enrolment rates have been considered as a good proxy for the flow of investments in human capital. However, in Chapter 1 we distinguished two main approaches analysing the relationship between growth and education. The Mankiw et al. (1992) study is part of the first approach, where human capital is considered as an additional factor of production in a standard production function. Within this framework, the process of accumulation of human capital is congruent to that of physical capital: it is costly, it subtracts time available to production, but it represents a remunerative

30 See Islam (1995), Pritchett (1996) and Griliches (1997) among others.

investment. The second class of models has its roots in the work of Nelson and Phelps (1966). This literature de-emphasises the role of capital (both physical and human) accumulation and stresses the importance of technological change. As we have seen, these models allow "beta convergence" (catch-up among countries) but this is not caused by capital deepening in the presence of decreasing returns but by knowledge spillovers (or technology transfers). In this framework we expect that the higher the level of human capital and the larger the technology gap between the follower and the technology leader, the higher the resulting growth rate will be. More precisely, human capital stock is a proxy for technological advancements, which represent the ultimate source of growth. Thus, it is the level of human capital that affects the possibility of innovation and ultimately growth prospects. Hence, while these two approaches characterise the empirical analysis differently, with growth rates across countries explained by a) differences in human capital *stocks* in the Nelson Phelps approach and by b) human capital *rates of accumulation* in Lucas, most studies on Italian regions seem only to test the hypothesis of the first approach.

Other observations justify the use of stocks instead of flows. Apart from the theoretical reasons introduced above, Pritchett (1996) highlights that the use of enrolment rates as proxies for the rates of investments in human capital, as in Mankiw, Romer and Weil (1992) is justified only if the corresponding stock of human capital in each economy is (at least approximately) at its steady state[32]. This is obviously not true in the case of Italian regions where, as we will see in the following section, during the 1960s and 1970s, there was a massive expansion of schooling mainly in the South.

Secondly, it has been argued that the connection across time between growth and educational enrolment is likely to be very weak. Why should a change in regional school enrolment rates instantly produce an increase in the growth rate?[33] Moreover, even if the augmented Solow model theoretically justifies the use of enrolment rates,

---

31 See Chapter, equation (1.24).

32 In particular, Pritchett (1996), using international data sets, shows that enrolment rates are usually negatively correlated with the rates of growth of human capital, that is, with investments of human capital. As he says, a terrible proxy would be at least uncorrelated.

33 See Temple (1999a).

this characterisation of the growth process is nevertheless not obvious within a regional framework. The closed economy assumption in these models is particularly implausible given the mobility of capital, both human and physical. Indeed, labour mobility within the Italian regions is well documented, at least up to 1975[34]. The implication is that human capital accumulation in one area does not necessarily contribute to its growth. The regional stock of human capital represents the educational attainments of the labour force effectively present in an area and able to contribute to its productivity.

Table 3.2 summarises the main empirical results found by the previous Italian regional literature on this topic. In particular, we specify the type of human capital variables introduced in each study together with the sign and significance of the coefficients, as resulting from the regression analysis. None of these studies focuses specifically on the role of education in the process of regional development. In most cases the coefficient on the human capital variable is not significant or even shows the wrong sign. There are two exceptions: Cellini and Scorcu (1997), where human capital is positive and significant in a subperiod of the sample and Lodde (1995). However, Lodde's (1995) is a specific study on the allocation of talent between *rent-seeking* activities and entrepreneurial activities, and does not analyse general returns to schooling. He introduces two particular indicators for human capital: number of lawyers (negatively correlated with regional growth) and number of engineers (positively correlated with regional growth).

In the following sections we investigate whether or not the proxies introduced in these studies represent a bad choice when the relationship between human capital and growth is investigated. In other words, we follow the different arguments introduced above that suggest we use in empirical analysis measures of the stock of human capital such as the initial levels of educational attainments. We expect these indicators to be more strongly and positively correlated with regional growth than secondary school enrolment rates.

---

34 See Sestito (1991) and Attanasio and Padoa Schioppa (1989) for regional migration patterns and Goria and Ichino (1994) for a specific analysis of the relationships between migration and convergence among Italian regions.

3.5. Description of the data.

We begin with a brief description of the main regional differences in human capital endowments. We use data from the Italian census to construct four different indicators of the educational attainment of the regional labour force[35]: the illiterate proportion of the labour force and the percentages attaining primary school, secondary school and higher education as a maximum qualification. Data are available for the census years: 1961, 1971, 1981, and 1991. We define the total stock of human capital of the labour force[36] as:

$$\text{Total Stock of Human Capital} = \Sigma_j \; YR_j * HK_j$$

where j is the schooling level, YR_j is the number of years of schooling represented by level j, and HK_j is the fraction of the labour force for which the jth level of education represents the highest level attained. In the Italian education system, primary school lasts eight years[37], the secondary level is usually attained after five years, and university courses take four to six years. The total stock is thus the average years of schooling of the labour force. For descriptive purposes, we consider the usual partition of the Italian peninsula into three geographical areas, the North, the Centre and the less-developed South[38].

Table 3.4(a) gives average educational attainment by area. In 1961 the North had an average of 6.3 years of education versus 5.2 years in the South; by 1991 the two regions had increased to 9.8 and 9.4 years respectively, with the Centre now having the highest average educational attainment with approximately 10 years. Thus the South was still behind, but proportionately much less. The North and the Centre have always had quite similar average years of schooling. University attainment has been fairly similar across all three regions. Perhaps surprisingly, between 1971 and

---

35 The exact definition is not labour force but active population.

36 Characteristics of the dataset are described in Appendix I.

37 Compulsory schooling has been recently reformed.

38 The classification given by ISTAT, the National Institute of Statistics, is: North - Piemonte, Valle d'Aosta, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna; Centre - Toscana, Umbria, Marche, Lazio; South - Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna.

1991 the South had a greater stock of *laureati* (people with post-secondary school education) than the North. The Centre, which contains Rome, the seat of government, has always had the greatest proportion of highly educated labour force. During the 60s and into the 70s, a very high proportion of the Southern labour force had no formal education. For example, 20% of the Calabrian labour force had no schooling in 1961 as against 0.2% in Trentino Alto Adige. However, this gap narrowed quickly. By 1981 the proportion of illiterate labour force was almost zero everywhere[39]. This explains why differences in average schooling narrowed during the 60s and the 70s. The gap still present between the South and the North and Centre is caused primarily by the smaller fraction of the Southern labour force with secondary school attainment. Only 25.6% of this workforce completed secondary school, against 29.2% in the North and 30.8% of the centre. Thus a greater proportion of Southern workers leave school after the primary level. Table 3.4(b) shows a similar overall pattern for women, with rather stronger convergence. By 1991, Southern women had approximately the same average years of schooling as women in the North and, from 1961 to 1991, reversed a 5% disadvantage in years of schooling compared to Southern men to a 6% advantage.

In sum, we see large increases in schooling everywhere but some persistent differences. In particular, Southern males still lag behind. We analyse below if these differences and their patterns over time can help to explain the observed regional pattern of growth.

3.6 Regressions

We study the role of human capital by introducing lagged stocks into a standard beta-convergence growth regression: the role of the human capital endowment of an economy is then explicitly introduced into the catch-up process[40]. We estimate a system of 19 regional equations with an unrestricted variance-covariance matrix, thus allowing for cross-sectional correlation of the disturbances (Maximum Likelihood)[41].

---

39 Although the South still shows the highest proportion of labour force with no schooling, 1.1% in 1991.

40 A first version of this work may be found in Di Liberto (2001).

41 This is obtained by iterating a Feasible Generalised Least Squares procedure. ML enjoys no advantage over FGLS procedure in its asymptotic properties; however, it may be preferable in small

That is, we use the alternative estimator described in Chapter 2. In Chapter 2 we saw that, for samples where T>N, and with likely cross-sectional correlation of the disturbances, the described Maximum Likelihood estimator is more efficient than both the cross-section and panel estimator previously used. With N=19 and T=32 (we use annual data between 1963 and 1994) and likely cross-sectional correlation at regional level, our sample meets the criteria. The system of equations is described by:

$$\Delta y_{it} = \alpha + \beta y_{it-1} + \gamma h_{it-1} + \lambda_t + \varepsilon_{it} \tag{3.2}$$

where y_{it} is the logarithm of per capita GDP in period t for region i, h_{it} is the stock of human capital (or a vector of stocks) measured as regional average years of education, and λ_t is an index of technology, assumed constant across the Italian regions.

Equation 1 is transformed to:

$$\Delta y^*_{it} = \beta y^*_{it-1} + \gamma h^*_{i,t-1} + \varepsilon^*_{i,t} \tag{3.3}$$

where

$$y^*_{it} = y_{it} - \bar{y}_t \qquad\qquad h^*_{it} = h_{it} - \bar{h}_t \tag{3.4}$$

where $\bar{y}_t$ and $\bar{h}_t$ are the Italian average per capita GDP in period t[42].

The variable h will represent our four different school attainment indices: primary, secondary and tertiary education plus the total stock. All these indicators are estimates of the average years of schooling in the given category[43]. Following Krueger and Lindhal (2001) we adopt the macro-Mincerian specification of the

---

samples. The estimation procedure is fully described in Charter 2 and in Di Liberto and Symons (2003).

42 We excluded one region from the sample, Valle d'Aosta, in the estimation to avoid the multicollinearity arising from the use of data in differences from the mean.

43 See the Appendix for more details.

convergence equation where human capital variables do not enter the equation in logs[44].

3.7 Results.

We set the scene by first estimating the standard convergence equation: see model (1) in Table 3.5. The estimate of β implies absolute convergence among the Italian regions of approximately 2% a year, consistent with the stylised facts[45] of regional convergence. However, evidence of absolute beta-convergence may hide both the presence of a non-homogeneous process of convergence within the period covered by our sample or the existence of convergence clubs. In fact, as stated above, a standard result in the literature on Italian convergence is that decreasing dispersion in regional per capita GDP, while strong during the 60s, all but ceased after about 1975. As a provisional measure, we simply allow the β parameter to change after 1975 (see model 2). It will be seen that the convergence parameter falls from 3.3% per annum before 1975 to 0.7% after that date. Thus, while beta-convergence was strong in the 60s and early 70s, it is currently weak and only on the border of significance. In models 3 and 4 we include the aggregate human capital term: the parameter is small and insignificant in both models. Thus, in these experiments, allowing for different rates of convergence across time does not rescue human capital.

As noted above, one possible explanation of the observed shift in the convergence process after 1975 is a change in the nature of public intervention, from provision of physical capital to increases in local public administration. It has been argued that decentralisation gave rise to a new class of local bureaucrats with increasing control of local economies[46]. Mass recruitment of civil servants may have caused a distortion in the allocation of the labour force. For example, skilled workers may have found it more convenient to dedicate their efforts to rent-seeking rather than entrepreneurial activities.

Rent-seeking aside, it is possible that the expansion of public administration

---

44 Results do not change significantly when human capital variables enter the equation in logs.

45 See Barro and Sala-i-Martin (1995).

46 On this point see also Boltho, Carlin and Scaramozzino (1997).

in Italy has been distortionary. Recruitment of civil servants was one policy adopted to reduce the very high unemployment levels in the southern area of the country. This is a familiar problem in developing countries[47] and overstaffing may have created "disguised unemployment"[48] in Italy. A related problem is that the true output of the public sector is in any case almost certainly badly measured, as noted by Griliches (1997).

All of these considerations suggest introducing the relative size of the public sector as an explanator in the convergence regression[49]. This is done in Table 3.5, model 5. The size of the public sector is negatively signed and strongly significant. More importantly for our purposes, the human capital term becomes now more significant.

Finally we consider the level of education of the female labour force. Male and female education are often distinguished in both theoretical and empirical work. In Becker's (1976) framework, educated women have smaller families but devote more maternal time to each child. Experience in developing countries shows that female education is linked to a decrease in infant mortality and better health conditions. These may have macro effects. Moreover, empirical analysis of earnings differentials suggests that returns to education are higher for women[50]. Model 6 in Table 3.5 includes relative female human capital[51]. The variable is positively signed and significant, consistent with the two findings suggested above.

3.8 The analysis of Convergence Clubs

The shift in the beta parameter after 1975 is almost certainly due to the failure of the South to continue its former rapid growth. An attractive alternative to an *ad hoc*

---

47 Pritchett (1996) cites as an example the guarantee by the Egyptian government of a job to all educated people. The continual expansion of its Public Sector resulted in heavily overmanned bureaucracies and state enterprises. See also Griliches and Regev (1995) for evidence on the Israeli case and Funkhouser (1998) for Costa Rica.

48 In which workers work normal hours but their capacities are not fully utilised: see Blaug, Layard and Woodhall (1969).

49 The variable is defined as the ratio between the number of workers employed in the Public Sector over total employment.

50 See Psacharopoulos (1985) and Krueger and Lindhal (2001).

51 The difference between female and male average years of schooling.

parameter-shift is to allow the North-Centre and South to converge separately. Other considerations suggest a separate analysis of these two non-homogenous areas. For example, Krueger and Lindahl (2001) argue that a positive and significant coefficient on the level of human capital may result from incorrectly imposing a single coefficient and thus equal returns on schooling among different countries. Kyriacou (1991) explains the anomalous evidence on human capital and growth by arguing that human capital is more effective when its average (educational) level is higher [52]. These hypotheses can be tested by considering the North-Centre and the South separately, the latter having a lower average level of human capital with respect to the former over the sample period[53].

In Table 3.6 variables are expressed as deviations from the two regional averages (North-Centre, South). In preliminary experiments we found that the beta-shift variable was always insignificant and trivial in magnitude. Thus, allowing the two areas to converge to different levels removes the need for a shift in the convergence parameter. Models 1 and 2 in Table 3.6 differ from models 5 and 6 in Table 3.5 only in that the South and the North-Centre are allowed to converge to their own levels. Human capital is somewhat strengthened in these experiments. In models 3 and 4 in Table 3.6 we allow the parameters on the forcing variables to differ between the South and the North-Centre. One can see that the convergence parameters are of a similar order of magnitude in the two regions. Most striking however is that human capital is insignificant in the North-Centre while strongly significant in the South. Similar results hold for relative female human capital. In general, the implication appears to be that increased education in the South, but only in the South, has a positive effect on growth. As we have seen, increased education in the South took place from very low levels, particularly in the '60s.

In Table 3.7 (model 1), we decompose the total stock of human capital into components corresponding to the average years of schooling in primary, secondary

52 Remember also from Charter 1 the Azariadis and Drazen (1990) model in which the presence of threshold externalities to education implies that investments in human capital have significant effects on growth only when certain threshold levels of human capital are passed.

53 Thus the two areas can converge to different equilibria. The SURE estimation procedure does allow the shocks to be correlated among the two different clubs.

and tertiary education attained by the Italian regional labour force[54]. A number of growth models suggest that higher levels of educational attainments should act more powerfully on growth than primary levels[55] (despite the weight of microeconometric evidence that returns to primary education are usually estimated as higher than other levels[56]). Moreover, the analysis of the effects of the different levels of education may represent an indirect test of the hypothesis of the Nelson and Phelps approach. Models where human capital has a fundamental but indirect role in the growth and catch-up process of an economy, by increasing the capacity to adopt and implement innovations or new technologies implicitly suggest that higher levels of education should be more relevant for growth than lower levels.

We see that secondary education is good for growth but that tertiary education has a marginal negative effect. Failing to find an important positive effect of higher education on productivity is not new in this literature as similar results have been found with alternative international data sets[57]. There are a number of possible explanations for this negative sign. First, while the experience of university may be beneficial to some individuals in many respects, it need not, with the exception of some vocational studies, increase productivity in the market place[58]. Further, it also possible that, unlike lower levels of education, higher education performs mainly a signalling function in the job market. That is, it seems likely that, if the signalling model has anything to it at all, it should apply to higher education where children arrive with most of the numeracy and literacy needed as workers[59]. An alternative hypothesis is that university education, rather than encouraging productive activities,

54 For more details see Appendix.

55 In particular, models where human capital has a fundamental but indirect role in the growth and catch-up process of an economy, by increasing the capacity to adopt and implement innovations or new technologies. In these models the better educated are more involved in innovative activities. See Nelson and Phelps (1966), Romer (1990b) and Benhabib and Spiegel (1994) among others.

56 See Pritchett (1996) and Krueger and Lindhal (2001).

57 For example, Wolff and Gittelman find ambiguous evidence on the role of university education as a source of growth. See also Vandenbussche, Aghion and Meghir (2003). An exception may be found in Ayiar and Feiyer (2002).

58 And note that Italy (but also Spain) has low percentages of university students with a scientific-technical background compared to other OECD nations. See De la Fuente and Da Rocha (1996).

59 As shown by Psacharopoulos (1985), private returns are in excess of social returns, especially at university level.

simply stimulates rent-seeking activities, which inhibit growth[60]. Further, it is well documented that the Italian labour market is characterised by a "bureaucratic bias" among the highly educated. Sestito (1992) finds a bias towards bureaucratic skills, mainly in the southern area of the country[61]. Therefore, one explanation of the paradoxical result is that university educated workers have a greater tendency to be employed in the Public Sector, itself characterised by non-innovative and highly routine activities and/or, as we have previously said, whose contribution in terms of GDP is underestimated in national account statistics. However, this hypothesis is not confirmed by our data since we test for the Public Sector, and we do not observe any significant change in the tertiary education coefficient.

Finally, we have investigated another plausible explanation. Our negative sign on higher education could be a spurious result. Human capital models assume that the decision to invest in higher education is affected by the rate of return, the cost of this investment and by family background factors. In general, the opportunity cost of education may act countercyclically[62]. Moreover, there is evidence that in developing countries higher education is associated with a greater incidence of unemployment[63]. Our data on higher education for example show that, in some cases, northern regions invest less in higher education than southern regions. All this seems to suggest another solution for explaining our results: endogeneity. Regions are not performing badly because of their (high) stock of highly educated workers. The reverse could be true: people invest more in education since the economy and job opportunities are

60 Murphy, Shleifer and Vishny (1991) describe a model in which rent seeking is highly remunerative, prompting talented people to leave productive activities. Lodde (1995) tests this hypothesis for Italian regions and finds a positive relationship between engineers and growth but a negative one between lawyers and growth among Italian regions. See also Wolff and Gittleman (1993) and Pugno (1998).

61 We only have data on the percentage of the labour force employed in the public sector. See Table 3.3 in Appendix III-C.

62 For example, Sakellaris and Spilimbergo (1999) find that in the US, during recessions, when labour market opportunities are few, the university enrolment rate increases.

63 See Blaug, Leyard and Woodhall (1969). On this see also Padula and Pistaferri (2001). Blaug, Layard and Woodhall (1969) propose another explanation for this negative sign. "In most countries private rates of returns exceed social rates simply because (higher) education is subsidised by the State and subsidies are never recouped by subsequent income taxation of the earnings of educated people". In Italy, during the period covered by our sample, fees for higher education were almost completely subsidised.

low. This is a well known problem in this literature[64]. The use of the initial stocks instead of enrolment rates of education should help to mitigate this problem. But endogeneity may also be investigated by introducing an Instrumental Variable estimator. We have replicated our regressions by introducing lagged values of the level of regional GDP as instruments. However, using a different estimator did not change our results. Not surprisingly, all our coefficients lose significance (as IV studies tend to have relatively imprecise estimates) and our higher education indicator remains negative. Therefore, our hypothesis of endogeneity has not been confirmed by our analysis. Because of these disappointing results we do not explicitly include these regressions in our Tables.

In Table 3.7 (model 2), we allow the parameters to differ between the North-Centre and the South. In other words, we develop a specification that allows for some limited heterogeneity in slope coefficients[65]. Note that educational levels are positively significant at the 95% level only once: for primary education in the South, with a long-run GDP/capita return of nearly 100% for each extra year of primary education. Of course, all Italian children now attend school to age 14 and close to 95% of the workforce have completed primary school in the South. Between 1961 and 1991, the proportion of the workforce in the South with no schooling fell from almost 15% to 1%. Our point estimates thus indicate very high returns to this increase in basic education. It should be emphasised that these are long-run effects and thus include in principle the effects of more educated parents on the earnings of children. There is little evidence in these data that increases in secondary and tertiary education in the South have had any effect on GDP/capita. These increases have been substantial: between 1961 and 1991: the proportion of the workforce with a degree rose from 2.1% to 7.5%, while the proportion with a secondary school certificate rose from 5.0% to 25.6%.

The parameters on secondary education in model 2 both have positive point-estimates. However, secondary and tertiary education are positively correlated so these estimates may be an artefact of the negative parameter estimates on tertiary education. In fact, the likelihood-ratio test for the exclusion of *all* education

---

64 See Bils and Klenow (1995) and Caselli, Esquivel and Lefort (1996).

parameters in the North-Centre gives $\chi^2_{(3)} = 4.17$, insignificant at the 20% level[66], so the data are quite consistent with small values for all education parameters in the North-Centre. Similarly the likelihood-ratio test for the exclusion of *all* education variables except for primary in the South is insignificant at the 20% level. Thus, again, we fail to find an important positive effect of higher education on productivity.

On balance, how strong is the evidence that the returns to non-primary education are small? In Table (3.6), model 4, we find a 95% confidence interval of (-.07, .10) for the long-run return of human capital in the North-Centre. Thus, though small at the middle, the long-run return is quite reasonable towards the top of the confidence interval. It is fair to say that these results are suggestive rather than conclusive. They suggest that the principal gains from education, in terms of growth at least, flow from the elimination of illiteracy. This is a common result in micro analysis where estimated returns to schooling are higher for lower levels of educational attainments.

On the other hand, these results suggest another possible interpretation. As stressed in Chapter 1, catching up models imply that technological progress is the result of both the adoption of existing technologies from abroad (for backward countries) and also of pure innovation (for leader countries). These different tasks (imitation and innovation) may require different types of skills. In particular, innovation activities are certainly influenced by higher education while imitation may be performed by labour forces with lower levels of education. As stressed by Vandenbussche, Aghion and Meghir (2003), this implies that the growth enhancing impact of a highly educated labour force may increase with the proximity to the (technological) frontier, since only countries at the frontier are likely to innovate rather than to simply imitate. Using a panel of 19 countries they find evidence in favour of this hypothesis, showing that a highly educated labour force had a stronger growth enhancing effect in economies closer to the technological frontier. Moreover, for backward countries, they find that higher education may have a negative impact on growth. Italy has been estimated as being one of the countries more distant from

65 As suggested by Bond, Hoeffler and Temple (2001) among others.

66 The corresponding statistic for the South is 11.93, a P-level of about .007%.

the frontier[67]. Note that our finding on the absence of positive returns to tertiary education is thus consistent with these results.

3.9 Summary

The relationship between human capital and development has always been considered as a close one. Theoretical studies on growth claim that the level of education of the labour force should be positively correlated with growth. Likewise, development economists share the idea that, among different possible policy interventions in LDC's, investments in education may represent a "magic bullet" against poverty[68]. Despite the importance placed by both theoretical growth literature and development strategists, empirical evidence on aggregate returns to schooling is weak since econometric analysis that introduce international data sets usually find that human capital is insignificantly or even negatively correlated with the process of development.

This study investigates the regional Italian case introducing a new data set on human capital. We use a measure of the stock of regional human capital instead of its rate of accumulation as has been done so far and estimate a standard convergence equation using a new and, possibly, more efficient panel estimator. We have attempted to estimate the social returns to schooling by including measures of average primary, secondary and tertiary education. It is well known that convergence in the South slowed after about 1975. We deal with this problem using two different methods: first by allowing the convergence rate to slow after 1975; second by allowing the South to converge to its own, potentially different level. We find marginally significant returns to total education with both methods. When we allow the parameters to differ between regions, however, we find that increased education seems to contribute to growth only in the South. Decomposing total schooling into its three constituent parts, we find that primary education in the South seems to be important. The results thus suggest that Italian growth mainly benefited from the

67 Proximity to the technological frontier is calculated as the ratio of a country's TFP level to that of the US. Among 19 countries, only Ireland has been estimated to be more distant from the frontier than Italy.

68 Pritchett (1996).

elimination of illiteracy in the South, during the '60s, but not from the substantial increases in education at the other levels.

Thus, this study seems to confirm standard results on the effects of education on earnings in the microeconometric literature which, however, have hitherto been difficult to confirm in macroeconomic data. But these results may also indicate that growth rates in Italy have been mainly determined by low tech activities (imitation rather than innovation) where a high skilled labour force did not play a significant role. The next Chapter investigates if similar results are found using a sample of Spanish regions.

APPENDIX III-A

Interpolation of inter-censal observations.

We have data on the educational qualifications of the workforce (degree, secondary, primary, some primary, no school) for the census years, 1961, 1971, 1981, 1991. We have as well enrolments in school by type in each year. We assume certain of these enrolment rates are appropriate ot interpolate the qualification proportion in a given category. Specifically, let p denote the numbers of workers with a given qualification and let c be the enrolment rate to be used for interpolation. Then we assume:

$$dp/dt = -rp + \alpha c$$

where r is the retirement rate (assumed constant) and α is an unknown constant. If π = p/n where n is the labour force then

$$d\pi/dt = -(r+g)\pi + \alpha k$$

where k = c/n and g is the growth rate of n, assumed constant between the census years. The constant α can be obtained if the inter-censal average values of the variables in this equation are known. One then has:

$$d\pi/dt = (r+g)(Pk/K - \pi) + kD/K$$

where P, K and D are the inter-censal averages of π, k, and $d\pi/dt$, respectively. Thus we estimate

$$\Delta\pi = (r+g)(Pk/K - \pi) + kD/K$$

taking r = .02, and g, P, K and D as observed[69]. For the interpolations we take c as one minus the secondary school enrolment rate for the proportion of workers with primary school qualifications, while use the secondary school enrolment rate lagged three years for secondary qualifications, and the secondary school enrolment rate lagged ten years for degree qualifications. No school and some school are linearly interpolated.

Our primary, secondary and tertiary school variable are measured as average years of

69 P is not observed but can be approximated by the average of the two closest census years.

each level of education. That is:

$$primary = 8(p_1 + p_2 + p_3)$$

$$Secondary = 5(p_2 + p_3)$$

$$Tertiary = 4p_3$$

Where p_1, p_2 and p_3 measure the fraction of total population that has attained, respectively, a primary, secondary and tertiary schooling level. These fractions are multiplied for the number of years necessary to complete each level of education: 8 years of primary schooling, 5 years of secondary and 4 years of tertiary education. The definition of primary schooling sums up the two levels of Italian compulsory education: scuola elementare (5 years) and scuola media (3 years).

Given that the expected duration of a college degree is much higher than the statutory duration, average years of tertiary education have also been computed using 5 and 6 years of attendance without any change in econometric results.

APPENDIX III-B

Sources of Variables.

Gross Domestic Product (1963-1994): Dataset *Contabilità regionale* Prometeia, Bologna, Italy.

Population: CRENOS, Centro Ricerche Nord-Sud, Università di Cagliari.

Population 15-19 years: Ricostruzione della popolazione residente per sesso, età e regione, in A. Golini, L. Clucci, G. Caselli and ISTAT (eds.), (years 1952-72), CRENOS, Centro Ricerche Nord-Sud, Università di Cagliari (following years), and ISTAT, Popolazione residente per sesso, eta' e regione, Supplemento al Bollettino mensile di statistica anno 1978, n.11.

Secondary school enrolment rates: ISTAT, Annuario Statistico dell'Istruzione Italiana 1959 (years 1950-58), and ISTAT, Annuario Statistico dell'Istruzione Italiana, anni vari (years 1958-94).

Labour force with different educational attainments (1961, 1971, 1981, 1991): ISTAT, (XII-XV) Censimento della popolazione, fascicoli regionali, vol.II.

Workers employed in the Public Sector: Dataset *Contabilità regionale* Prometeia, Bologna, Italy.

Total employment: Dataset *Contabilità regionale* Prometeia, Bologna, Italy.

APPENDIX III-C

Table 3.1: Regional per capita GDP

	Italy	Piemonte	V.d'Aosta	Lombardia	Trentino A.A.	Veneto	Friuli V.G.
1963	100	126	154	139	114	107	109
average 60s	100	121	142	134	113	110	112
average 70s	100	116	147	128	121	111	115
average 80s	100	118	135	132	125	117	118
	Liguria	**Emilia R.**	**Toscana**	**Umbria**	**Marche**	**Lazio**	**Abruzzi**
1963	138	119	117	89	99	127	74
average 60s	134	121	116	90	104	122	81
average 70s	121	130	112	97	108	113	89
average 80s	117	129	111	98	106	115	90
	Molise	**Campania**	**Puglia**	**Basilicata**	**Calabria**	**Sicilia**	**Sardegna**
1963	65	80	74	58	60	69	81
average 60s	68	77	75	62	62	72	84
average 70s	73	72	73	66	62	70	80
average 80s	77	70	73	64	60	69	77

Table 3.2: The role of human capital in the literature on Italian convergence

Explanatory variables	Reference	Results
secondary school enrollment rate	Cellini -Scorcu (1997)	positive but ns. (* only 1970-80)
	Mauro-Podrecca (1994)	inconclusive results
	Paci-Pigliaru (1995)	negative and ns.
	Bianchi-Menegatti (1997)	positive but ns.
	Quadrella-Tullio (1998)	never significant
Proportion of the population with a degree or a diploma	Paci-Pigliaru (1995)	not directly included
students enrolled in secondary school over total population	Bianchi-Menegatti (1997)	negative and ns.
Proportion of the working population with a degree	Lodde (1995)	positive but ns.
Proportion of the working population with a diploma	Lodde (1995)	positive but ns.
ratio of the stock of lawyers to working population	Lodde (1995)	negative and significant
ratio of the stock of engineers to working population	Lodde (1995)	positive and significant

Notes

The third column introduce the results obtained on human capital variables by the empirical analysis (ns.= non significant).

Table 3.3: Percentage of the labour force employed in the Public Sector

	Piemonte	V.d'Aosta	Lombardia	Trentino A.A.	Veneto	Friuli V.G.	Liguria
average 60s	8%	13%	8%	18%	10%	20%	14%
average 70s	12%	16%	11%	20%	14%	24%	19%
average 80s	15%	16%	13%	21%	15%	24%	20%
	Emilia R.	**Toscana**	**Umbria**	**Marche**	**Lazio**	**Abruzzi**	**Molise**
average 60s	10%	11%	11%	10%	25%	12%	12%
average 70s	14%	15%	17%	14%	26%	16%	17%
average 80s	15%	17%	22%	16%	26%	18%	20%
	Campania	**Puglia**	**Basilicata**	**Calabria**	**Sicilia**	**Sardegna**	
average 60s	14%	15%	11%	11%	15%	18%	
average 70s	17%	18%	17%	18%	18%	22%	
average 80s	20%	21%	21%	21%	22%	24%	

Table 3.4a: Percentage of the total labour force with different educational attainments

	Total Stock of Human Capital		
	north	*centre*	*south**
61	6.1	6.0	5.1
71	6.8	6.9	6.2
81	8.1	8.3	7.8
91	9.5	9.7	9.1

	Higher Education (degree)				Primary School		
	north	*centre*	*south*		*north*	*centre*	*south*
61	2.2%	2.8%	2.1%	**61**	90.3%	86.2%	78.3%
71	3.2%	4.3%	3.5%	**71**	86.4%	83.2%	79.4%
81	4.8%	6.3%	5.6%	**81**	76.8%	73.1%	74.8%
91	7.3%	8.9%	7.5%	**91**	63.4%	60.1%	65.8%

	Secondary School				No school		
	north	*centre*	*south*		*north*	*centre*	*south*
61	6.3%	6.5%	5.0%	**61**	1.2%	4.4%	14.7%
71	9.9%	11.0%	9.5%	**71**	0.5%	1.5%	7.6%
81	18.2%	20.2%	17.4%	**81**	0.2%	0.4%	2.2%
91	29.2%	30.8%	25.6%	**91**	0.2%	0.2%	1.1%

Notes:

i) According to the ISTAT (1961) classification of regions

ii) Total stock of human capital is the average years of education in the labour force

iii) The percentages in the table represent the percentage of people within the labour force with the corresponding maximum qualification

Table 3.4b: Percentage of the female labour force with different educational attainments

	Total Stock of Human Capital		
	north	***centre***	***south***
61	6.3	6.2	5.0
71	7.1	7.4	6.5
81	8.5	8.8	8.5
91	10.0	10.2	9.9

	Higher Education (degree)				Primary school		
	north	***centre***	***south***		*north*	*centre*	*south*
61	1.6%	2.5%	2.0%	**61**	89.1%	81.8%	67.9%
71	3.0%	4.8%	4.3%	**71**	84.4%	78.0%	70.8%
81	4.8%	7.0%	7.2%	**81**	73.2%	67.5%	65.6%
91	8.5%	11.1%	10.6%	**91**	57.4%	53.2%	56.2%

	Secondary School				No school		
	north	*centre*	*south*		*north*	*centre*	*south*
61	8.3%	10.3%	9.1%	**61**	0.9%	5.4%	20.9%
71	12.1%	15.5%	14.5%	**71**	0.4%	1.7%	10.4%
81	21.8%	25.2%	24.5%	**81**	0.2%	0.4%	2.8%
91	34.0%	35.5%	32.2%	**91**	0.1%	0.2%	1.0%

Notes:

i) According to the ISTAT (1961) classification of regions

ii) Total stock of human capital is the average years of education in the labour force

iii) The percentages in the table represent the percentage of people within the labour force with the corresponding maximum qualification

Table 3.5: Human Capital in Convergence Regressions
Sample: 1963-1994 (Italy, 19 regions)

Dependent variable: regional growth rates
yit - yit-1

	1	2	3	4	5	6
Beta-Convergence: yit-1	-0.019	-0.007	-0.021	-0.007	-0.007	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Beta-Shift (before 1975)		-0.026		-0.026	-0.025	-0.029
		(0.005)		(0.005)	(0.005)	(0.005)
Total stock of human capital			0.001	0.0001	0.002	0.002
			(0.002)	(0.001)	(0.002)	(0.002)
Proportion of the Public Sector					-0.007	-0.007
					(0.002)	(0.002)
Relative total stock of female human capital						0.005
						(0.001)
Log of Likelihood Function	1761.2	1767.1	1761.3	1767.1	1768.7	1770.6
Obs.	589	589	589	589	589	589
Average Durbin's h	-.43	-.56	-.41	-.56	-.67	-.70

Notes:
(1)
i) standard errors in brackets
ii) yit is the logarithm of per capita GDP in region i in period t
iii) Beta-convergence is the beta parameter in equation 2.
iv) Proportion of the Public Sector means public sector employment as a proportion of the total employment.
v) relative stock of female human capital means the average years of education of females calculated as the difference from the corresponding male value
(2)
i) Variables are expressed as deviations from the Italian average
ii) Total stock of human capital means the average years of schooling in the labour force (eight years for primary schooling, five years for secondary and five years for tertiary education)

Table 3.6: North-Centre and South as Convergence Clubs

Sample: 1963-94 (North-Centre and South as Convergence Clubs)

Dependent variable: regional growth rates yit - yit-1	**Restricted* Estimates**		**Unrestricted Estimates**	
	1	2	3	4
Beta-Convergence: yit-1 (North-Centre)	-0.046 (0.005)	-0.041 (0.005)	-0.048 (0.007)	-0.045 (0.007)
Total stock of human capital (North-Centre)	0.003 (0.002)	0.003 (0.002)	-0.001 (0.002)	0.0008 (0.002)
Proportion of the Public Sector (North-Centre)	-0.012 (0.002)	-0.012 (0.002)	-0.006 (0.002)	-0.006 (0.002)
Relative total stock of female human capital (North-Centre)		0.005 (0.001)		-0.003 (0.004)
Beta-Convergence: yit-1 (South)			-0.039 (0.009)	-0.028 (0.010)
Total stock of human capital (South)			0.022 (0.005)	0.015 (0.006)
Proportion of the Public Sector (South)			-0.024 (0.008)	-0.039 (0.009)
Relative total stock of female human capital (South)				0.007 (0.002)
Log of Likelihood Function	1709.1	1710.5	1715.4	1717.4
Average Durbin's h	.22	.18	.13	.11

Notes:

*In model 1 and 2 the parameters are restricted to be the same in the two areas

i) See notes section (1) Table 2

ii) Variables are expressed as deviations from the regional (North-Centre or South) average

iii) The beta-shift has never been introduced in the included results

iv) Total stock of human capital means the average years of schooling in the labour force (eight years for primary schooling, five years for secondary and five years for tertiary education)

Table 3.7: Different levels of schooling

Sample: 1963-94 (North-Centre and South as Convergence Clubs)

Dependent variable: regional growth rates yit - yit-1	Constrained* Estimates	Unrestricted Estimates
	1	2
Beta-Convergence: yit-1 (North-Centre)	-0.034 (0.005)	-0.036 (0.008)
Average years of tertiary studies (North-Centre)	-0.097 (0.022)	-0.07 (0.032)
Average years of secondary studies (North-Centre)	0.031 (0.008)	0.019 (0.011)
Average years of primary studies (North-Centre)	0.0008 (0.001)	-0.0008 (0.001)
Proportion of the Public Sector (North-Centre)	-0.011 (0.002)	-0.006 (0.002)
Relative total stock of female human capital (North-Centre)	0.005 (0.002)	-0.001 (0.004)
Beta-Convergence: yit-1 (South)		-0.045 (0.014)
Average years of tertiary studies (South)		-0.104 (0.050)
Average years of secondary studies (South)		0.035 (0.022)
Average years of primary studies (South)		0.046 (0.02)
Proportion of the Public Sector (South)		-0.041 (0.012)
Relative total stock of female human capital (South)		0.004 (0.002)
Log of Likelihood Function	1713.8	1723.7
Average Durbin's h	-0.01	-0.001

Notes:

*In model 1 and 2 the parameters are restricted to be the same in the two areas

i) See notes section (1) Table 2

ii) Variables are expressed as deviations from the regional (North-Centre or South) average

iii) The beta-shift has never been introduced in the included results

iv) Total stock of human capital means the average years of schooling in the labour force

v) Average years means the average years of each level of schooling in the labour force

CHAPTER 4

THE ROLE OF HUMAN CAPITAL IN THE DEVELOPMENT OF SPANISH REGIONS

"...we think the insights gleaned from cross-country regressions have run into sharply diminishing returns. We would like to see more detailed country analysis a la Young (1995)...."
Klenow and Rodriguez-Clare (1997b)

4.1 Human capital and Spanish regional convergence: an introduction[1]

In the previous Chapter we investigated the returns to education among Italian regions using a measure of the stock of regional human capital. Results have shown that elementary levels of education had the strongest positive impact on growth, thus confirming standard results on the effects of education on earnings in microeconometric literature. Moreover, we found some evidence stressing the importance of the allocation of human capital when returns to schooling are estimated.

In this Chapter we perform the same analysis using Spanish regional data as in the one carried out on Italian regions. In terms of regional GDP patterns and educational institutions, Spain and Italy share some characteristics. For example, both countries traditionally have high levels of regional economic disparities and have seen these disparities decrease, mainly during the 1960s and 1970s. Moreover, in comparison with the other OECD economies, both countries show low levels of educational attainment together with significant regional disparities. Finally, as for the Italian case, previous empirical evidence on returns to education in Spain reveal puzzling, non-homogeneous results.

However, even though there are a number of similarities, the comparison between the two countries also highlights numerous differences. This implies that the results we obtain with the Spanish sample cannot be exactly compared with those found for Italian regions. In particular, we have identified two different types of problems. First of all, since the Spanish educational system is different and more complex than the Italian one, the organisation of the Spanish educational datasets reflects this complexity. For example, Spanish data on primary schooling represents a very basic level of schooling and does not encompass compulsory education as is the case in Italy. Further, Spanish data on secondary schooling includes dissimilar possibilities in terms of educational attainments, with time periods considered ranging from 3 to 8 years of schooling, including compulsory schooling, while in Italy the term secondary schooling embraces only upper secondary education. In terms of our empirical investigation, these data sets characteristics imply that our analysis of Spanish returns to schooling on different levels of educational attainment produces results that differ somewhat to those found in the Italian study. Secondly, data on regional GDP in Spain are only computed every two years. As we will see in the following sections, this factor will limit our econometric analysis, since the estimator used for Italian regions does not perform well for samples with T close to N.

Apart from problems of comparability, as stressed by De la Fuente (2002), the Spanish regional data set is highly informative, and it enables us to investigate the effects of education on growth and convergence in considerable detail. In particular, unlike the Italian data set, Spanish human capital datasets include data at sectoral level. In Chapter 3 we noted how in many countries the public sector is the chief employer of most of the skilled labour force, and that this may be a factor that produces distorted results when we estimate returns to schooling. Examining the different levels of educational attainment in the labour force, disaggregated by sector, enables us to test directly the hypothesis of what possible effects the public sector

[1] I am in debt with Ester Vaya and Rosina Moreno who have been a valuable source of information on the Spanish educational system and with Angel De la Fuente for providing me with the data on GDP, employment and population at Spanish regional level.

will have on the analysis of returns to schooling. In other words, we may estimate whether or not excluding the public sector from the analysis significantly changes our results on returns to schooling.

The Chapter is organized as follows. The next section presents a descriptive analysis of the Spanish regional convergence process and briefly describes differences and similarities with the Italian case. Section three compares the Italian and the Spanish educational systems, and describes the main characteristics of the Spanish educational regional data set. Section four presents the previous empirical evidence on returns to education in Spain, while section five presents the econometric methodology and illustrates the results obtained with the whole sample of Spanish regions. Section six discusses the results obtained introducing the possibility of Spanish convergence clubs. The last section contains some concluding observations.

4.2 The distribution of Spanish regional per capita GDP: stylised facts

Stylised facts on Spanish regional convergence are similar to those observed in Italy. As in Chapter 3, we use the σ-convergence analysis to describe the pattern of the standard deviation of regional per capita GDP during the period 1963-1997. In Spain we identify seventeen regions defined at NUTS2 level[2]. Figure 4.1 shows the results. The process of σ-convergence in Spain has been very similar to that observed in Figure 3.1 in Chapter 3. We identify a significant decrease in the dispersion of regional per capita GDP during the sixties and mid-seventies, but this process ended after that period. Thus, as in Italy, this process was not homogeneous throughout the period analysed.

As we observed in Chapter 3, the oil shock may have influenced regional economic development and thus the pattern of regional inequalities. However, note that regional GDP had a different immediate reaction to the '74 oil shock in the two countries. While in Italy there was a sudden decrease in inequalities, the opposite seems to have happened in Spain. This fact may be due to the different regional economic structure in the two countries, with rich Spanish regions less industrialized in 1974 (and therefore less immediately affected by the oil shock) than Italian

---

[2] We are excluding Ceuta y Melilla for which data were not available.

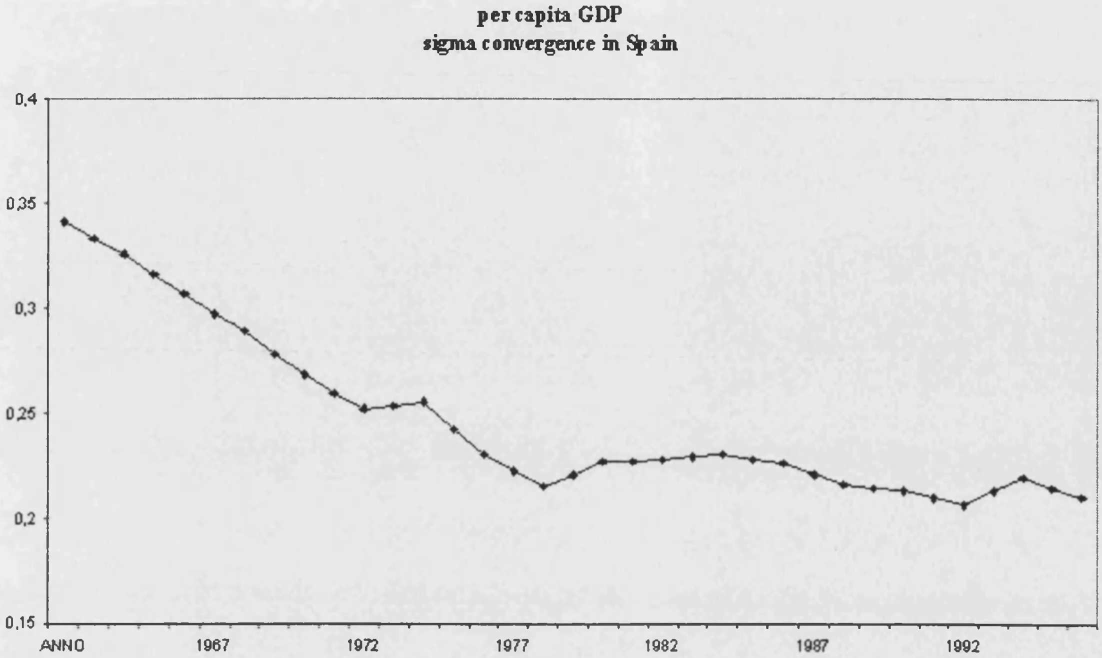

Fig. 4.1- Time path of the standard deviation of the logarithm of GDP across Spanish regions 1963-97.

regions. Nevertheless, this effect of the oil shock was fairly easily absorbed in both countries. Together with the oil shock, there are other reasons for the decline of the Spanish regional convergence process, which are very similar to the Italian case. In particular, to explain this phenomenon, De la Fuente (2001) emphasizes the influence of a decrease in internal, regional migration rates, together with a specific structural change pattern. Indeed, like many other countries in the same period, Spain went through a process of job destruction in the agricultural sector with the subsequent expansion of other sectors, in particular the service sector.

Serrano (1999) investigates this process of structural change focusing on the proportion of workers as a percentage of total labour force and finds significant changes in all sectors. Between 1964 and 1995 the proportion of workers fell both in Agriculture and Industrial (Manufacturing) sectors[3], decreasing respectively from 37% in 1964 to 9.2% in 1995 in the former, and from 23.3% in 1964 to 19.5% in 1995 in the latter sector. Conversely, he notes a sharp increase mainly in public administration and services. The proportion of workers in the public sector increased

[3] Minor changes are observed in constructions (from 7.7% to 9.4) and Energy (from1.6% to 1.2%).

from 6.4% to 14.3%, while that in other services from 24.7% to 46.4%.[4] As stressed by De la Fuente (2001), until the mid seventies the surplus of agricultural labour had migrated from poor to richer regions characterised by a more dynamic labour market, and where the expansion of the service sector has been more significant. After that period, Spain went through a relatively long period of economic crises with a simultaneous halt in internal migration due to a sharp decrease in employment opportunities even in the richer areas. Thus, "...job destruction in agriculture translated directly into rising unemployment rates in the poorer regions and falling convergence rates. Somewhat surprisingly, the situation has not changed much in spite of the recovery of the last decade[5]".

Table 4.1 shows the logarithm of per capita GDP for each region (or Comunidades Autonomas). Years included are 1964, 1974, 1984, 1994 and 1997. We do not analyse this data in terms of groups of regions as in Chapter 3. In fact, unlike in the Italian case, the existence of regional clubs is less obvious in Spain as are even geographical clusters of poor and rich regions[6]. To facilitate the reading, regions are ordered starting from the poorest region in 1963 (Extremadura). This Table shows seven regions in 1964 with (the logarithm of) per capita GDP lower than the national average: Extremadura, Castilla y la Mancha, Galicia, Andalucia, Castilla y Leon, Murcia and Canarias. Among these regions there is only one group that may well form a geographical cluster of southern regions: Extremadura, Andalucia, Murcia and Castilla-y-la Mancha. In other words, in terms of per capita GDP, the group of relatively poor regions is partly formed by southern regions together with the inclusion of Galicia and Castilla y Leon (both North-West), and the Canaries. Moreover, Table 4.1 shows that, even if Spain has experienced a decrease in regional inequalities as emphasised by the σ-convergence analysis, the regional per capita GDP distribution is characterised by persistency or low regional mobility.

---

[4] A similar sectoral dynamic may be observed in Italy. See *XI Rapporto Crenos*(2004), Università di Cagliari e Sassari.

[5] De la Fuente (2001), page 11.

[6] One of the first attempts to distinguish different groups of regions or clubs is found in Dolado et al. (1994). They use data at provincial level (not regions) and identify three clubs (poor, average, rich) using thresholds defined by the estimated (by LSDV) values of the regional constants. At regional level they identify three groups of regions: rich (Aragon, Baleares, Cataluna, Madrid, Navarra, Rioja and Valencia), average (Asturias, Canarias, Cantabria, Castilla-yla-Mancha, Castilla-y-Leon, Murcia y Pais Vasco), and poor (Andalucia, Extremadura).

Indeed, if we focus on the first and last year of our sample, we see that the poor regions in 1964 are still the lagging ones in 1997.

4.3 Human capital stocks: a comparison of the Spanish and the Italian educational systems

As for per capita GDP, when we compare Spanish and Italian educational institutions we find many similar features[7]. For example, in both countries the educational system is mostly public, with approximately only 5% of students going to private education for primary or secondary education, and both have low percentages of students with a scientific-technical background[8]. Moreover, as in the Italian regional case for Lazio, the most educated region in Spain is the Madrid region, the administrative capital. The difference compared to the rest of the country is significant: Madrid has approximately 15% more educational capital than the Spanish regional average. Finally, among OECD countries, together with Italy, Spain has one of the lowest levels of educational capital. Table 4.2 presents recent OECD data which highlights that both countries have a very low percentage of people with a secondary school qualification.

However, unlike Italy, Spain has a significantly higher percentage of people completing tertiary education and, if we focus on recent evidence, we find that enrolment rates in Spain, mainly in tertiary education, are among the highest in Europe. Thus, Spain is currently investing more than Italy in educational capital.

In our empirical analysis we use the dataset developed by the Ivie (Instituto Valenciano de Investigaciones Economicas). The Spanish dataset includes variables at regional (NUTS2) level for the different levels of educational attainment of the labour force[9]. These different levels of education include: illiterate, primary school, secondary, lower tertiary and tertiary education. At first glance, this dataset seems

---

[7] Apparently, compared to the rest of the EU, they even share the characteristic of having very crowded universities. See Palafox, Mora and Perez (1995).

[8] On average, 37% of all university students in OECD countries graduate in scientific-technical discipline while this percentage decreases to approximately 20% in both Italy and Spain See De la Fuente and Da Rocha (1996).

[9] More precisely, the exact definition is not labour force but active population (*poblacion activa*). See also footnote 21 in Chapter 3.

perfectly comparable with that used in Chapter 3 for Italian regions. Yet, in the following analysis we will see that this is not exactly the case.

Tables from 4.3 to 4.5 include a brief descriptive analysis of Spanish regional human capital endowments. As for per capita GDP, we take five observation years (1964, 1974, 1984, 1994, and 1997) and disaggregate them by region, listed in alphabetical order. More on the dataset together with a detailed analysis of the Spanish education system can be found in the Appendix to this Chapter. Table 4.3 [section (a)] shows data on illiteracy rates. This Table stresses that, as in Italy, and despite there being a law on compulsory schooling dating back to 1945, the proportion of illiterate people in Spanish regions has been high until relatively recently. Moreover, the computed percentages of illiterates in poor Spanish areas are similar to those found in poor Italian regions. With 15% of illiterates in 1964, the Canaries used to be the "least educated" region.

On the other hand, in Spain during the 1960s and 1970s regional percentages of illiterate labour force were far from zero even in more developed areas, while in the same period, in Italy developed regions already had minimal percentages of illiterate labour force. This phenomenon has currently disappeared almost everywhere[10].

Data on primary school attainments are given in Table 4.4 [section (a)]. As in the Italian case, Spanish data on primary school attainment includes individuals that have not completed primary education. In other words, it is not possible to distinguish between the active population that has finished primary school from primary education dropouts. This may cause an upward bias for poorer (in terms of human capital) regions and so reduce the observed regional inequalities, since it is usually the case that the proportion of active population that did not complete primary school is higher in "less educated" regions[11]. Unlike in Italy then, in the

[10] We observe that in 1993 (in absolute terms) more than 6 million people had no school qualifications (no completed studies), but, as expected, more than half of these were people over 64 years of age, and 25.7% were in the 55-64 age group.

[11] And sometimes the difference is significant. For a specific year, 1993, we have highly disaggregated data and observe this characteristic. For example, the percentage of the population that completed primary studies in Andalucia in 1993 is only 29%. In our dataset on primary studies (which includes both the percentage of people that completed primary studies plus people that only have some schooling) shows a percentage of 50.6% in the same region, same year. That is, 20% of individuals only have some schooling.

Spanish data set the definition of primary school covers only five years of education and does not correspond to the definition of compulsory schooling. As a matter of fact, Spanish compulsory schooling embraced 5 years only from the years 1945 to 1964[12]. Thus, only during this period (not included in our sample) did the definition 'primary schooling' coincide with compulsory schooling. After 1964, compulsory schooling was increased by 2 years and, again, by a further two years in 1990 [13]. Thus, it is no surprise to observe that the proportion of people completing primary education decreased from an average of 86% in 1964 to approximately 33% in 1997.

Conversely, there was a significant expansion in numbers completing secondary school [Table 4.4, section (b)], where the proportion of people with this level of education dramatically increased from 4% to 51%. Again, this is not surprising, since this variable includes compulsory schooling and, as seen before, the length of compulsory studies in Spain increased during the period analysed.

Finally, Table 4.5 shows data on tertiary education. Note that in Spain the highest level of education is divided into two different levels: universidad de ciclo corto, which involves a total of at least 15 years of attendance, and universidad de ciclo largo, which on average must cover 17 years of studies. In general, we observe that while in the 1960s and 1970s tertiary education was attained by a very low percentage of persons in all regions, by 1997 the proportion of people with a university degree had increased significantly. However, at the same time there was also an increase in regional dispersion. For example, if we sum up the above two university education variables (ciclo corto and ciclo largo) we observe that the proportion of people with tertiary education varied in 1997, from 12% in Castilla y la Mancha to 24% in Madrid. A significant difference indeed.

In general, our analysis on regional educational levels seems to indicate that, Spain differs from Italy in that the process of increase in regional educational levels did not bring about a commensurate decrease in regional inequalities. To investigate this possibility we examine the pattern of regional inequalities in educational levels in Italy and Spain computing the σ-convergence process of the average years of schooling over time.

---

[12] Pupils from 6 to eleven years of age.

[13] See Serrano (1997).

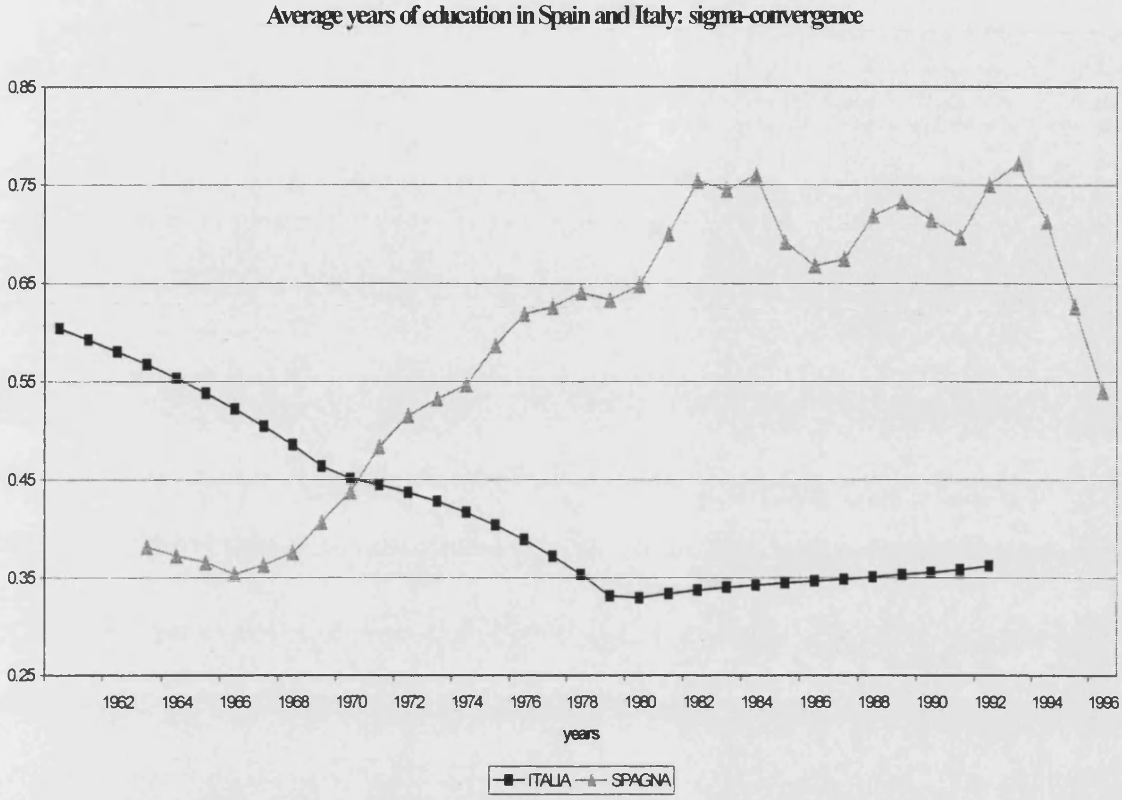

Fig. 4.2- Time path of the standard deviation of average years of schooling across Italian regions (1961-1993) and Spanish regions (1964-97)

This variable is estimated using the standard procedure (see Chapter 3, section 3.5). As in Serrano[14] (1996), to compute the average years of education we assume (for each level of schooling) the following average years of attendance:

1. Illiterate (analfabeta): zero years
2. primary school and some school (sin estudios y primarios): 3,5 years
3. average schooling (medios): 11 years
4. lower tertiary (anterior al superior): 16 years
5. tertiary and more (superior): 17 years

Table 4.3 [section (b)] presents data on this synthetic measure of educational capital. In general, data on the attainment of different levels of education show that

---

[14] This author has directly contributed to the construction of the dataset. On this see also Serrano (1996) and Lopez-Baso and Moreno (2003).

human capital in Spain has rapidly increased in the last 30 years, in particular during the eighties.

Moreover, Figure 4.2 shows the σ-convergence analysis for both Spain and Italy. While regional inequalities in Italy have decreased steadily over time, in Spain differences among regions increased for almost 30 years and seem to decrease significantly only very recently[15]. This result is surprising, since policies directed at promoting education will usually also promote equality in educational standards. Apparently, this has not been the case in Spain for very long.

Overall, this comparison of the Spanish and Italian education systems has brought to light several problems that may affect the interpretation of our empirical results. First of all, note that when computing the standard three levels of schooling (primary, secondary and tertiary education) usually analysed in this literature, we obtain significantly different levels of education in the two countries. In particular, Spanish primary school education represents a very basic level of schooling, since it consists of only five years of attendance and also incorporates people that did not even complete this level of education. Thus, Spanish primary education is not equated with compulsory schooling and is not in accordance with the definition of primary schooling as defined for Italy[16]. Our data on Italian primary education refers to eight years of compulsory education and is in line with the OECD definition of primary school.

Moreover, as stated above, Spanish data on secondary schooling covers a variety of school curricula, embracing the range from compulsory schooling to upper secondary education. In reality, the length of these curricula may vary significantly. As indicated in Table 4.11 (see the Appendix), secondary studies curricula end after just 3 years of further studies (bachiller elemental, EGB...) while others last 8 years[17]. In general, this non-homogeneity of curricula certainly implies that the Spanish secondary school indicator attracts the same criticism as the average years of

---

[15] De la Fuente and Vives (1995) find the opposite result. However, they use a different dataset and concentrate their analysis on the 80s only.

[16] For more details see the Appendix.

[17] A detailed analysis of these curricula can be found in the Appendix.

schooling indicator[18]. That is, this indicator implicitly assumes that workers with very diverse levels of education (such as compulsory schooling only and upper secondary education) are perfectly substitutable and does not enable us to distinguish returns to secondary schooling (as defined by OECD) from returns to lower levels of education. Further, even if Spanish data distinguish two different levels of tertiary education, the sum of these two indicators approximately corresponds to the Italian tertiary education level. Thus, for this level of education Spanish and Italian data are comparable. To sum up, we cannot assume that the three levels of education (primary, secondary and tertiary education) identified in Chapter 3 for Italy equate with the corresponding Spanish levels. These problems may certainly cause difficulties when we try to compare the regression results obtained for Spain and Italy.

4.4 Human capital and the development of Spanish regions: previous empirical evidence

As for Italy, the previous literature on regional Spanish convergence highlights different and puzzling empirical results concerning the effect of human capital on growth. A number of studies have found that education has not positively influenced Spanish regional development processes. Among them we include one of the first papers on this subject, the Dolado, Gonzalez and Roldan (1994) study. This work represents one of the few attempts to form groups of regions and identify clubs. They use the values of the constants obtained by a LSDV estimator and identify three "supra-regiones" but they did not perform any formal analysis on separate convergence clubs[19]. They use data for 1955 to 1989 at provincial level, a finer level of geographical disaggregation than regions, and perform the standard unconditional and conditional β-convergence analysis. In their conditional convergence analysis they introduce two different human capital indicators: the first is a measure of the stock of human capital in 1981 computed as the proportion of population that

[18] Mulligan and Sala-I-Martin criticise the use of the average years of schooling indicator since it implicitly assumes that workers with different educational levels are perfectly substitutable and that the human capital endowment is proportional to years of schooling. On this see also Serrano (1997) and Lopez-Bazo and Moreno (2003).

[19] See also footnote 6.

attained tertiary education in 1981[20], while the second is a flow indicator, the level of public expenditure in education in 1964. Neither of these human capital indicators seems to positively affect Spanish provincial growth.

The standard convergence equation approach may also be found in Gorostiaga (1999). She firstly introduces the Mankiw Romer and Weil approach and performs a convergence analysis at Spanish regional level, 1969-1991. In this specification, human capital enters the equation in terms of investment rates. More precisely, she introduces a measure of the investments in education financed by the public administrations as a percentage of GDP. She uses a panel IV estimator, with fixed effects[21] and finds paradoxical results on human capital variables, where the coefficients on this indicator are almost invariably negative. Secondly, she investigates whether following the Nelson and Phelps approach and using a measure of the stock of human capital changes the results. In other words, using a specification *à la* Benhabib and Spiegel (1994), she introduces as a proxy the stock of human capital in the labour force with at least lower tertiary education. However, the use of this alternative specification does not significantly change the results.

Serrano (1997) and (1999) represent one of the few examples of studies that investigates whether or not returns to education will be different when the educated labour force is employed in different sectors and stresses the role of the public sector as an "absorber" of educated labour force. In his first study Serrano examines aggregate returns to education in Spain during 1964-1991. His focus is not primarily on regions. In fact, he performs an econometric analysis using series at national level, while introducing a regional panel only to control for the robustness of results. In his analysis at national level he removes data on the public sector. In other words, he investigates if the human capital endowments of the workforce employed in the private sector had any growth effect on private sector output. This distinction is not present when regional data are introduced, since in this case data includes both the private and the public sector. Moreover, he was the first to compute average years of schooling by different levels of education, and in his empirical analysis he introduces measures of the average years of tertiary, lower tertiary and secondary education,

[20] The definition of this variable is not clear as it is defined as the proportion of population with primary, secondary and tertiary studies.

[21] As found in Arellano (1998).

together with the standard measure of average years of schooling. Thus, he purposely excludes primary school as a possible explanatory variable[22]. He finds that only secondary school seems robustly positively correlated with growth, while the coefficients on tertiary and lower tertiary education are negative and non significant in all specifications. Finally, the results on average years of schooling are not robust given that this variable is positive and significant only in the regional panel specification.

In a second paper Serrano (1999) examines Spanish regional growth dynamics focusing on the role of human capital at sectoral levels. He remarks that, as we have seen in the previous section, Spain has experienced a significant sectoral transformation during the last 30 years (1964-95) and that this process may influence the analysis of returns to schooling since in terms of human capital endowments there are consistent sectoral differences. In particular, he emphasises how there are very high levels of human capital in the Spanish public sector where the percentage of employees with at least lower tertiary education has increased from 30% in 1964 to 47% in 1995. Conversely, data on the remaining sectors show a different picture, with only 1.6% of employees with a degree in 1964 and 10% in 1995. Thus, even if during the period analysed we observe a sixfold increase in the proportion of highly qualified workers in the private sector, the gap existing with the public sector is still significant. His results show that human capital affects different sectors of the economy in different ways. In particular he does not find any positive influence of human capital in Primary Sectors such as (Agriculture and Energy) and he interprets this result as evidence of an overqualified labour force. Conversely, in secondary and tertiary sectors such as industry, constructions and services (excluding the public sector) he finds a positive effect of human capital on (sectoral) growth. However, as found in other studies included in this survey, he does not find any evidence of a positive role of tertiary (lower and upper) education on growth.

Finally, unlike in previous works, we identify one study where the role of human capital on growth is unambiguously positive. Using a different approach with respect to the standard convergence literature, de la Fuente and Vives (1995)

[22] Human capital indicators are included separately in each regression. The estimated equation is specified in first differences to control for stationarity. He also uses IV to control for the possibility of endogeneity of educational variables.

investigate whether traditional policy instruments such as infrastructures and training schemes had an impact in decreasing regional Spanish inequalities. They use a smaller sample, from 1981 to 1990, and find that the coefficient of their human capital proxy, estimated as average years of schooling of the employed labour force, is positive and strongly significant, appearing thus as an important determinant of regional productivity. Interestingly, they also estimate how much regional income inequalities would be reduced if differences in human capital were equalized. They firstly compute the coefficient of variation of the log of regional income per capita and then estimate the same index under the assumption of complete equality in regional human capital endowments: this index drops from 19.5 to 14.5. They stress how this exercise seems to suggest the importance of education as a potential effective instrument for regional cohesion policies[23].

4.5 Regression analysis: returns to education at Spanish regional level

Using the IVIE dataset we replicate the regression analysis carried out for Italy in Chapter 3 with our sample of seventeen Spanish regions. However, we are not able to exactly replicate the previous analysis since the characteristics of the Spanish data set do not allow us to do so. Remember that in Chapter 2 we saw that for samples where T>N, and with likely cross-sectional correlation of the disturbances, the described Maximum Likelihood estimator is more efficient than both the cross-section and panel estimator previously used. With N=19 and T=32 and likely cross-sectional correlation at regional level, our Italian sample perfectly met the criteria. Conversely, regional Spanish data on GDP cover the period 1963-1997 but are only biannual. This implies that, with annual data on education starting from 1964 and excluding one region from the sample (as for Italy) we cannot use our estimator since T=N=16. Ultimately, this problem may be overcome by identifying clubs and estimating each of them individually. In this case we are able to estimate the usual system of regional equations, defined by:

$$\Delta y^{*}_{it} = \beta y^{*}_{it-\tau} + \gamma H^{*}_{i,t-\tau} + \varepsilon^{*}_{i,t} \qquad (4.1)$$

[23] However, the estimated effect of the contribution of actual public investments on income convergence is estimated as being very small (approximately 1% of the observed reduction in income inequalities during the 80s).

allowing for cross-sectional correlation of the disturbances as previously done for the Italian sample. As before, y_{it} is the logarithm of per capita GDP and h_{it} is the stock of human capital in period t for region i, and:

$$y^{*}_{it} = y_{it} - \bar{y}_{t}, \qquad H^{*}_{it} = H_{it} - \bar{H}_{t} \qquad (4.1')$$

where $\bar{y}_t$ and $\bar{H}_t$ are the Spanish average in period t. Again, the variable H represents our four different educational attainment indices: primary, secondary and tertiary education plus the total stock, where these indicators are estimates of the average years of schooling in the given category. The only difference with the Italian case is that here data are biannual, that is, $\tau = 2$. We will investigate the returns to education on clubs in the following section.

However, there are two possible options to choose from to perform this type of analysis for the whole sample. The first is to transform our biannual sample into an annual sample. This may be done by interpolating our GDP series in order to obtain an annual sample, starting from 1964 to 1997[24], that is, with T=33. However, not surprisingly, when using this approach our results show the presence of serial correlation. The second option is to reduce N, that is, to reduce the number of regions in the sample. To this end, it is possible to identify seven Spanish macro-regions at NUTS1 level. These are: Noroeste (Galicia, Asturias, Cantabria), Noreste (Pais Vasco, Navarra, La Rioja, Aragon), Madrid, Centro (Castilla y Leon, Castilla y la Mancha, Extremadura), Este (Cataluna, Comunidad Valenciana, Baleares), Sur (Andalucia, Murcia), Canarias. Note that, these macro-regions are determined only by their geographical proximity, but in most cases each group is formed by heterogeneous regions. Thus, it is not possible to simply perform the econometric analysis using the NUTS1 definition of macro-regions since in order to reduce the sample we have to group regions that are similar. A possible choice is to identify within each macro-region groups of regions that had similar human capital endowments at the start of the period. In order to do this, we have identified three candidates: Navarra and Rioja (Noreste), Castilla y la Mancha and Extermadura

[24] GDP data start from 1963 but we have to reduce the sample since human capital data are available from 1964.

(Centro), Andalucia and Murcia (Sur). Secondly, we eliminate the Canaries and Balearic islands from the sample since they clearly represent outliers[25]. In this case, we are left with a sample where T=16 and N=12[26] and we are able to perform our analysis.

Table 4.6 sets out the results obtained for the Spanish sample. In this case, when we check for the possible presence of (second order) autocorrelation, our standard Durbin tests largely accept the null hypothesis of absence of serial correlation[27]. In Model 1 we estimate the standard (absolute) β-convergence equation. The coefficient is negative and significant but, as observed in Chapter 3, this result may hide the presence of a non-homogenous process of convergence or the existence of convergence clubs. As expected, when we introduce the β-shift in Model 2, thus allowing the convergence parameter to change after 1977, we observe that this process of convergence disappeared after the mid seventies[28].

Models from 3 to 8 introduce our human capital indicators and estimate the returns to schooling at Spanish aggregate level. Remember that in Chapter 3 we presented various considerations suggesting a possible role of the public sector when we investigate returns to schooling. Among them, we stressed that this sector may be linked to rent-seeking activities, and that it may not always be governed by efficiency criteria since the recruitment of civil servants is one of the policies adopted to reduce high unemployment levels in the poorest areas of a country. This policy may have also slowed down regional migration for tertiary educated thus affecting the convergence process, since it is usually the case that there is a national scale for civil servants. Moreover, since we do not have good measures of the real output of the public sector, if the proportion of educated labour force employed in the

[25] In particular, differently from other regions their economies are highly dependent on the tourism sector.

[26] Note that as stressed by Evans and Karras (1996) it is likely that the performance of this estimator improves the larger the difference between T and N. Beck and Katz (1995) show that this is the case for the Parks FGLS estimator. However, to answer this question it would be necessary to perform a specific Monte Carlo analysis.

[27] We do not use Durbin's h test here, since we have to test for second order serial correlation but apply Durbin's (1970) standard alternative test. See Wooldridge (2003).

[28] We follow the result obtained by our σ-convergence analysis in section 4.2 and allow the β parameter to shift after 1977. Note that results do not change if we allow the β parameter to shift after 1975, as for the Italian case.

public sector is significant, this may result in serious problems when we try to estimate aggregate returns to education.

In comparison with the Italian case, the Spanish sample has a distinct advantage when we test for the effects of the allocation of human capital in the public sector. The Spanish regional human capital data set is in fact very detailed and includes sectoral disaggregation. This means we may identify the number of workers[29] employed in the public sector and their levels of education. Table 4.7 shows how the proportion of highly educated labour employed in the public sector in Spain is significant in all regions. On average, in Spain 53% of people with tertiary education are employed in the public sector. In the poorest regions this percentage is very high, and reaches 70% in Extremadura, while we observe significantly lower percentages in the more developed areas, especially Pais Vasco (35%) and Cataluna (38%). The Madrid area which, as indicated in Table 4.3 section (b), represents the region with the highest proportion of highly educated labour force, absorbs 46% of its graduates in the public sector. With regard to other levels of education, we observe that the public sector absorbs relatively low percentage of people with secondary schooling (the Spanish average is 15%), and marginal percentages of people with very basic levels of education (only 5%). These observations confirm our idea that when we investigate returns to schooling we have to probe the public sector, especially with regard to tertiary education.

Thus, in order to test if returns to education are affected by the sectoral allocation of the labour force, we adopt two strategies. Firstly, we use the methodology implemented in Chapter 3 and introduce a measure of the proportion of the public sector in our regression[30] and replicate the analysis performed for Italian regions. Secondly, we compute a new set of human capital indicators (total stock of human capital plus primary, secondary and tertiary schooling) excluding the individuals employed in the public sector: that is, we effectively compute measures of average years of schooling for the private sector.

In Model 3a, we include our standard measure of average years of schooling, or total stock of human capital, while in Model 3b we use the same variable

[29] In this case the definition is not *poblacion activa* but *poblacion ocupada* in the various sectors.

[30] As in Chapter 3, this variable is defined as the ratio between the number of workers employed in the public sector over total employment.

computed for the private sector. In the first case, our human capital variable has a positive but non significant parameter, while in the second case the coefficient is significant at the 10% level and the value of the parameter is larger. Thus, results stress a possible influence of the public sector in the analysis of returns to schooling. Model 4 confirms this result. In this case, we replicate the analysis of Chapter 3, that is, we use the standard measure of human capital as in Model 3a, also including a measure of the proportion of the public sector. In this case, the coefficient on human capital becomes positive and significant at 1% level.

In Model 5a, 5b and 6 we decompose our human capital indicator into components corresponding to the three different levels of education. In both models 5a and 6, these variables represent the economy-wide average years of schooling in primary, secondary and tertiary education, while in Model 5b we have computed the same variables excluding the public sector. Among the three levels of schooling, only primary education seems to have an unambiguous positive role for growth. Secondary schooling is never significant, while the tertiary education coefficient is positive and significant at 9% level only in Model 5b, where we include our private sector's human capital indicators. Thus, not surprisingly, the exclusion of the public sector from our human capital indicators mainly affects the results on tertiary education, since, as stressed in Table 4.7, the vast majority of Spanish regions show high proportions of individuals with this level of education employed in this sector. Again, these results seem to stress the importance of the allocation of human capital in the public sector in the analysis of returns to education.

4.6 Identifying convergence clubs

In this section, we investigate how far returns to education in Spain have differed in the various regions. In other words, we define the Spanish convergence clubs and allow for some heterogeneity in the slope coefficients. As seen in Chapter 3, a variety of considerations suggest a separate analysis of returns to schooling in non-homogenous areas. First, Krueger and Lindahl (2000) argue that a positive and significant coefficient on the initial level of human capital may result by incorrectly imposing a single coefficient and thus equal returns to schooling among different economies. Secondly, we saw in chapter 1 that Azariadis and Drazen (1990) and Benhabib and Spiegel (2004) describe models in which the presence of threshold externalities to education cause the investments in human capital to have different returns depending on the existing level of human capital[31]. In particular, their model introduces the presence of threshold effects on returns to education that depend on human capital endowments. Further, quantity and quality of education may be positively correlated, and we may expect to control for measurement error problems and find lower returns to education in the South and higher returns in the North-Centre. Finally, as stressed by Vandenbussche, Aghion and Meghir (2003) we may expect that the different levels of education will have varying impacts on growth depending on the level of development of an economy. All these hypothesis may be tested by allowing the different Spanish clubs to converge separately.

Our previous descriptive analysis shows that, unlike in Italy, for Spain it is more difficult to formulate an *a priori* hypothesis on convergence clubs and, in general, there is less consensus on how to identify groups of homogeneous regions. This may be due to the fact that, as previously emphasised, groups of regions sharing the same characteristics in terms of either per capita GDP or human capital levels do not form a geographical cluster as observed for the Italian case. Note that, to investigate the hypothesis on returns to education listed above, human capital levels are fundamental elements in identifying clubs. This is important, since in Spain there is no similar correspondence (as there is in Italy) between poor (in terms of per capita GDP) regions and uneducated regions. The main exception to the rule poor region-uneducated region is the Balearic Islands that show a very high level of per capita GDP but a relatively low level (less than the Spanish average) of human capital throughout the period analysed. Although not as extreme as the Balearic islands Cataluna is a comparable case. Nevertheless, it is possible to identify two clubs of poor and rich (in terms of both per capita GDP and human capital endowment) Spanish regions. In Table 4.1 we have seen that seven regions show a level of per capita GDP below the national average both in 1963 and 1997. Moreover, these regions also share another characteristic, since they all have low human capital levels, lower than the national average (See Table 4.3). Thus, in our empirical analysis we will consider two different clubs. The first group is the poor regions group and includes Extremadura, Castilla y la Mancha, Andalucia, Galicia, Canarias,

[31] Empirical evidence on this may also be found in Kyriacou (1991). Using an international data set, he finds that the growth of human capital is more effective the higher its average level is.

Murcia and Castilla y Leon. Accordingly, Comunidad Valenciana, Asturias, Argon, Baleares, Rioja, Cantabria, Navarra, Cataluna, Pais Vasco and Madrid form the second group of rich regions. Even though this definition may certainly be disputed, from now on we will define these groups in terms of their geographical location: that is, we shall call the group of relatively poor regions *Southeast*, while the remaining regions will form the rich club called *Northwest*.

In the previous section, we stressed that, given the characteristics of our Spanish sample we were not able to use the alternative estimator described in Chapter 2 with the whole regional sample, since this may only be applied to samples with more time periods than countries *(T>N)*. However, this estimator may be confidently applied when we investigate if returns to education are different in our two convergence clubs although we are not able to control for the possibility that shocks may be correlated across regions belonging to different groups. That is, in the following analysis we estimate two systems of equations separately, as shown in eq. (4.1), one formed by the Southeast group and the other by Northwest regions.

Table 4.8 shows the results for the Southeast club. As for Italian clubs, the β-convergence parameter is negative and significant in all specifications, while the β-shift has never been found significantly different from zero, thus implying that within this subgroup of regions β-convergence has been a homogeneous process. In Model 2 we introduce the total stock of human capital as a regressor and find a negative but non significant coefficient. Introducing the proportion of the public sector in Model 3 does change the sign of our human capital indicator but does not enable the coefficient to become significant. The public sector indicator is itself negative and significant.

Model 4 and 5 includes the different levels of education estimated as average years of primary, secondary and tertiary education. In this case, only primary schooling seems to have been beneficial for growth. Both the coefficients on secondary and tertiary education are never significant, with the latter even showing a negative sign although considerably smaller and less significant once we control for the share of the public sector. Thus, as for the Italian case, our estimates indicate high returns to basic education in the poorest areas of the country.

In Table 4.9 we have replicated the same analysis using the Northwest club. In this case, the β-shift parameter, even if not robust, was sometimes negative and significant in some specifications. We do not include these results here. We interpret this evidence as stressing that this group of regions is less homogeneous than the previous one. In other words, they do not necessarily form a convergence club. Nevertheless, in terms of our human capital analysis, we are still able to test if returns to education are different and possibly higher in highly endowed areas. In Model 1 the β-convergence coefficient is significant at 9% level, but its value and significance increases when we introduce our human capital indicators. In particular, Models 2 and 3 show that, unlike in the poor regions club, the average years of education coefficient is now positive and significant[32]. The public sector coefficient is never significant and the introduction of this indicator never affects other results. Comparing this result with that obtained for the Southeast club, we are thus induced to interpret our negative coefficient in poor areas as a spurious result. In other words, the estimate of this coefficient may be plagued by reverse causality, since it is possible that the expansion of public administration has been one of the policies adopted to reduce the very high unemployment levels in the poorest areas of the country.

When we distinguish among the different levels of education (Model 4 and 5) only secondary school seems to positively affect growth, while we may explain the non significant result on primary education observing that, among developed regions, there is a very low variance in terms of primary school endowments, and this may imply that this coefficient is more difficult to estimate precisely. Moreover, as found by both the previous literature on Spanish regions and in the Italian case, the coefficient on tertiary education is negative in both clubs. Remember that this result of the negative sign on tertiary education is not new in this literature and, as shown in section 4.4, it seems to represent a standard outcome even in the specific literature on Spanish regions. Possible explanations of this result have been already discussed in Chapter 3. Here, we will briefly summarise them. First, we have already seen as university educated workers have a greater tendency to be employed in the Public Sector and as this fact may influence our empirical analysis on returns to education. Secondly, we have argued that if the screening model has anything to it at all, it

[32] To report all details, the results of models 2 and 3 in Table 4.9 on human capital are not robust to the inclusion of the beta-shift, while that obtained in models 4 and 5 on primary, secondary and tertiary education are robust to the use of different possible specifications.

should apply to higher education. Further, note that Spain and Italy have low percentages of students with scientific and technical background and it may be claimed that with the exception of these technical, vocational studies, the experience of university not necessarily increase productivity in the market place. Finally, even if the use of the initial stocks instead of enrolment rates of education should help to mitigate problems of endogeneity, remember that the opportunity cost of education, especially for tertiary education may act countercyclically.

Finally, as in the previous section, we introduce our alternative human capital indicators and exclude the labour force employed in the public sector. Table 4.10 shows the results. In contrast to previous results at national level, when we analyse the clubs, results do not change significantly. The average years of schooling coefficient remain positive and significant only in the Northwest area and primary school is positive and significant only in the Southeast club. The only minor exception is represented by secondary school, whose coefficient is positive and significant at 6% level even in poorer regions. Therefore, our results do not indicate that the public sector plays a significant role in the analysis of returns to schooling.

Overall, these results seem to suggest that the level of development of an economy influences the estimation of returns of schooling in growth regressions. In fact, our evidence is consistent with the idea that there exist complementarities between skills and proximity to the frontier. Remember from Chapter 1 that in the Nelson and Phelps approach technological progress represents the engine of growth but that technology is a dual phenomenon including both innovation and imitation activities, and that the latter activities do not necessarily involve the use of the highly educated. In particular, as stressed by Vandenbussche et al. (2003) when a country is far from the frontier, growth may be mainly caused by imitation activities that do not require a highly skilled labour force. Conversely, growth in economies that are close to the frontier is mainly driven by innovation activities that rely more on the most educated. On the whole, our results seem to be consistent with this hypothesis since they suggest that skilled human capital has a stronger growth-enhancing effect in more developed economies[33].

[33] In Vandenbussche et al. (2003) Italy has been estimated as being significantly distant from the frontier, while Spain has been estimated to be closer. Thus, we may explain the absence of significance in our higher levels of education in the most developed Italian regions by arguing that they are still too far from the frontier.

4.7 Summary

This Chapter estimates the social returns to education at Spanish regional level and compares these results with those obtained for the sample of Italian regions in Chapter 3. Although differences in the characteristics of the two data sets do not enable us to exactly replicate for Spain the analysis conducted in Chapter 3, we are nonetheless still able to find comparable results.

Overall, Spanish regional evidence is similar to that found for Italian regions. In particular, as for Italy, when we introduce the human capital term in our convergence regressions, its coefficient becomes significant only when we introduce the relative size of the public sector as an explanator. Moreover, when we introduce in our analysis a measures of average years of schooling of the private sector, excluding therefore, the human capital allocated in the public sector, we again obtain a positive and significant coefficient. When we separate the total stock of human capital into components corresponding to primary secondary and tertiary education, we find that only primary school seems to have an unambiguous positive role for growth. The tertiary education coefficient becomes positive and marginally significant only when we exclude the public sector from our human capital variables. Therefore, these results seem to stress the importance of the allocation of human capital in the public sector in the analysis of returns to education.

However, this result is not confirmed by our analysis on clubs. When we allow for some parameter heterogeneity and analyse separately the effect of education in the two clubs of poor and rich Spanish regions, we find that the coefficients on human capital variables do not change significantly when we take the public sector into account. Thus, this relationship needs to be further investigated. Moreover, we find that returns to education are different in the two areas. In particular, human capital computed as average years of education is positive and significant only in the more developed regions club. Further, when we divide human capital into the three different levels of education we find significant differences in the two clubs. Among poor regions, only primary schooling seems to positively affect growth rates: as for the Italian case, our estimates indicate high returns to basic education in the poorest areas of the country. Conversely, for rich regions we find a positive result only for secondary schooling. Again, these results are similar to those obtained in Chapter 3 even if the positive coefficient on secondary schooling in Italy is only marginally significant. Thus, overall our results on Spanish regions together with those found in Chapter three stress the importance of the relationship existing between the level of development of an economy and returns to different levels of education. In particular, the Spanish evidence suggests that, while primary schooling seems to contribute to growth in poorly developed areas, more skilled human capital has a stronger growth-enhancing effect in more developed economies. In other words, our evidence emphasizes that there is likely to be heterogeneity in rates of returns to education across economies since the effect of schooling in growth regressions is influenced by the level of development of an economy. Failing to take this heterogeneity into account in empirical analysis may produce misleading results.

APPENDIX IV-A

A close look to the Spanish educational system.

The Spanish educational system is quite complex and there exist a variety of options beyond primary level. The Table below can be found in Palafox, Mora and Perez (1995), and shows the five levels of education identified by our Spanish regional dataset with the corresponding curricula. Moreover, for each possible curriculum we identify the years necessary to complete these educational phases.

Dataset Classification	*Different educational attainments in each category*	*Years of schooling*
1) ANALFABETA		0
2) SIN ESTUDIO O CON ESTUDIOS PRIMARIOS	Primarios	5
3) ESTUDIOS MEDIOS	Bachiller elemental, EGB ciclo superior o segunda etapa y ESO Certificado de escolaridad	8
	Formacion profesional (FP) de 1er grado o equivalente Otras ensenanza tecnico-profesionales de 1er grado Modulo 2 de formacion profesional	10
	Bach. Superior, BUP i bachillerato Ensenanzas regladas equivalentes laboralmente o similares a FP2	12
	FP2 y FP3	13
4) ESTUDIOS ANTERIORES AL SUPERIOR	Universitad de ciclo corto	15
5) ESTUDIOS SUPERIORES	Universitad de ciclo largo y doctorados	17

This Table stresses that the Spanish primary level education is lower than the equivalent Italian level. In fact, in Italy primary school involves a period of eight years of education, but only five in Spain. Also, secondary school in Italy involves from between 11 to 13 years of formal education, while the rather complex Spanish system ranges from compulsory schooling (hasta bachiller elemental) to upper secondary education (bachiller superior, FP2), thus covering from 8 to 13 years of studies. The abundance of post primary school choices (with their corresponding different time periods according to level of attainment) certainly poses a problem when we try to measure average years of schooling. Finally, the Spanish dataset distinguishes lower tertiary (15 years of education) from tertiary education (17 years), while Italian data includes only one level of tertiary education (17 years). Average years of education are computed as described in the Appendix to Chapter 3.

APPENDIX IV-B

Table 4.1: Logarithm of per capita GDP

	1964	1974	1984	1994	1997
EXTREMADURA	5.57	6.07	6.26	6.63	6.77
CASTILLA Y LA MANCHA	5.72	6.34	6.46	6.78	6.87
GALICIA	5.84	6.36	6.53	6.82	6.91
ANDALUCIA	5.86	6.34	6.41	6.67	6.78
CASTILLA Y LEON	5.96	6.44	6.57	6.91	7.01
MURCIA	5.99	6.49	6.56	6.85	6.93
CANARIAS	6.02	6.54	6.70	6.94	7.03
ASTURIAS	6.24	6.65	6.72	6.88	6.95
ARAGON	6.24	6.64	6.79	7.09	7.20
RIOJA	6.28	6.66	6.83	7.19	7.29
COM. VALENCIANA	6.28	6.66	6.77	7.03	7.11
CANTABRIA	6.29	6.65	6.74	6.96	7.05
NAVARRA	6.32	6.73	6.86	7.19	7.30
BALEARES	6.56	7.02	7.17	7.37	7.46
CATALUNA	6.58	6.89	6.95	7.24	7.34
PAIS VASCO	6.62	6.90	6.85	7.15	7.26
MADRID	6.75	6.98	6.98	7.24	7.32
ESPANA	6.18	6.61	6.72	7.00	7.09

Table 4.2: Levels of education in industrialised countries

Secondary education attainment rates (% Population 25-64 years old)		Tertiary education attainment rates (% Population 25-64 years old)	
Portugal	20	Portugal	9
Spain	*41*	*Italy*	*10*
Italy	*43.5*	Czech Rep.	11.5
Poland	45.5	Poland	12
Greece	51.5	Austria	14
Ireland	57.5	Hungary	14.5
Belgium	58.5	Greece	18
Holland	62	France	23
UK	63	Germany	23
France	64	Holland	23.5
Hungary	70.5	*Spain*	*23.5*
Finland	74	UK	26
Austria	75.5	Denmark	26.5
Denmark	80.5	Belgium	27.5
Germany	82.5	Finland	32.5
Japan	83	Japan	34
Czech Rep.	86.5	Ireland	35.5
USA	87.5	USA	37

Data OECD "Education at a Glance" (2003)

Table 4.3: Illiterates and Average years of schooling

a) Percentage of total labour force with no education

	1964	1974	1984	1994	1997
ANDALUCIA	14.7	10.1	5.4	2.1	1.5
ARAGON	3.4	2.1	0.9	0.5	0.3
ASTURIAS	2.1	1.6	0.5	0.2	0.0
BALEARES	8.2	6.3	1.8	0.9	0.8
CANARIAS	15.0	10.0	4.2	1.5	1.3
CANTABRIA	1.7	1.0	0.3	0.2	0.0
CASTILLA Y LA MANCHA	10.9	8.4	3.9	1.9	1.3
CASTILLA Y LEON	2.5	2.2	1.0	0.4	0.2
CATALUNA	4.0	2.8	1.1	0.4	0.4
COM. VALENCIANA	6.3	4.0	2.0	0.6	0.6
EXTREMADURA	13.9	9.9	5.6	2.4	2.0
GALICIA	7.8	6.4	3.0	1.0	0.5
MADRID	3.5	2.5	1.2	0.3	0.2
MURCIA	11.8	8.7	3.3	2.3	1.2
NAVARRA	2.5	1.8	0.6	0.3	0.2
PAIS VASCO	1.9	1.4	0.7	0.2	0.2
RIOJA	2.1	1.4	0.4	0.1	0.1
AVERAGE SPAIN	6.6	4.7	2.1	0.9	0.6

b) Average years of schooling

	1964	1974	1984	1994	1997
ANDALUCIA	3.52	4.26	5.89	8.03	8.77
ARAGON	4.12	4.93	6.80	8.81	9.56
ASTURIAS	4.12	4.88	6.47	8.91	9.23
BALEARES	3.91	4.76	6.30	8.48	9.32
CANARIAS	3.70	4.66	6.33	8.53	9.01
CANTABRIA	4.26	5.01	6.71	9.20	9.66
CASTILLA Y LA MANCHA	3.51	4.15	5.68	7.84	8.73
CASTILLA Y LEON	4.11	4.77	6.42	8.53	9.32
CATALUNA	4.20	5.17	7.19	9.02	9.62
COM. VALENCIANA	3.95	4.72	6.42	8.52	9.33
EXTREMADURA	3.42	4.06	5.58	7.51	8.68
GALICIA	3.68	4.14	5.50	7.52	8.37
MADRID	4.96	6.15	8.33	10.13	10.49
MURCIA	3.79	4.57	6.00	8.05	9.22
NAVARRA	4.23	5.44	7.38	9.78	9.72
PAIS VASCO	4.33	5.36	7.47	9.82	10.19
RIOJA	4.23	4.78	6.50	9.04	9.16
AVERAGE SPAIN	4.00	4.81	6.53	8.69	9.32

Notes:
i) Numbers in the Tables represent the percentage of people in each Comunidad Autonoma with the corresponding maximum educational qualification
Source: Mas, Pérez and Uriel (various years).

Table 4.4: Percentage of total labour force with different educational attainments

a) Primary school

	1964	1974	1984	1994	1997
ANDALUCIA	80.1	78.0	65.4	44.5	37.1
ARAGON	89.4	81.4	61.9	38.7	30.8
ASTURIAS	91.0	82.5	65.3	37.8	34.0
BALEARES	84.8	77.4	64.8	39.0	29.1
CANARIAS	77.7	73.2	61.9	39.9	34.6
CANTABRIA	90.0	81.9	63.6	33.5	28.5
CASTILLA Y LA MANCHA	85.4	81.8	69.5	46.4	37.5
CASTILLA Y LEON	90.8	83.4	66.2	42.1	34.7
CATALUNA	87.3	77.2	55.7	35.1	28.7
EXTREMADURA	82.2	80.7	68.6	50.0	37.9
GALICIA	87.7	84.4	72.9	51.6	43.4
RIOJA	89.9	84.4	65.7	37.8	37.1
MADRID	80.2	67.4	45.2	26.9	24.5
MURCIA	81.2	76.8	66.8	42.4	33.0
NAVARRA	89.4	76.1	55.1	28.7	30.4
PAIS VASCO	89.0	77.1	53.7	28.6	25.5
COM. VALENCIANA	86.9	81.2	63.5	40.2	31.3
AVERAGE SPAIN	86.1	79.1	62.7	39.0	32.8

b) Lower secondary (or secondary)

	1964	1974	1984	1994	1997
ANDALUCIA	2.6	7.8	21.9	42.5	48.2
ARAGON	3.7	11.5	27.3	46.7	52.2
ASTURIAS	3.7	11.4	26.2	48.1	51.6
BALEARES	3.8	11.8	26.9	50.9	59.3
CANARIAS	3.9	12.2	25.7	45.9	50.3
CANTABRIA	4.8	12.1	26.9	52.8	56.8
CASTILLA Y LA MANCHA	1.6	5.9	20.7	42.1	48.7
CASTILLA Y LEON	3.3	9.5	23.6	44.1	47.7
CATALUNA	5.2	15.0	34.2	51.7	56.0
EXTREMADURA	1.7	5.5	19.6	37.9	46.5
GALICIA	2.2	6.0	18.6	38.3	43.8
RIOJA	4.2	9.4	25.4	46.1	45.5
MADRID	9.7	21.5	38.4	51.8	51.2
MURCIA	3.9	9.3	22.9	46.6	50.9
NAVARRA	4.2	15.7	33.6	53.6	50.6
PAIS VASCO	5.3	16.0	35.1	53.7	53.9
COM. VALENCIANA	3.8	10.4	27.1	48.1	54.3
AVERAGE SPAIN	4.0	11.2	26.7	47.1	51.0

Notes:
i) Numbers in the Tables represent the percentage of people in each Comunidad Autonoma with the corresponding maximum educational qualification
Source: Mas, Pérez and Uriel (various years).

Table 4.5: Percentage of total labour force with different educational attainments

a) Upper secondary school (lower tertiary)

	1964	1974	1984	1994	1997
ANDALUCIA	1.6	2.7	4.5	6.0	7.4
ARAGON	2.0	3.0	4.8	7.6	8.6
ASTURIAS	2.0	2.8	4.6	7.1	7.7
BALEARES	2.0	2.5	3.5	5.0	5.5
CANARIAS	2.1	3.0	5.0	6.9	8.0
CANTABRIA	2.4	3.2	5.1	7.4	7.9
CASTILLA Y LA MANCHA	1.4	2.6	3.6	5.5	6.6
CASTILLA Y LEON	2.0	2.9	5.1	7.0	9.4
CATALUNA	2.1	2.7	4.6	6.0	6.9
EXTREMADURA	1.4	2.8	4.1	5.7	8.1
GALICIA	1.4	2.1	3.3	5.1	6.1
RIOJA	2.1	2.7	4.6	8.0	9.1
MADRID	3.0	3.4	5.9	7.6	9.1
MURCIA	1.9	3.2	3.7	4.4	7.6
NAVARRA	2.0	3.7	5.6	9.2	9.6
PAIS VASCO	2.2	3.2	5.6	7.7	8.7
COM. VALENCIANA	1.8	2.7	4.4	5.9	7.1
AVERAGE SPAIN	2.0	2.9	4.6	6.6	7.8

b) Degree (tertiary)

	1964	1974	1984	1994	1997
ANDALUCIA	1.0	1.5	2.8	5.0	5.9
ARAGON	1.6	2.0	5.0	6.5	8.0
ASTURIAS	1.2	1.7	3.3	6.9	6.6
BALEARES	1.3	2.1	3.0	4.2	5.2
CANARIAS	1.2	1.6	3.2	5.8	5.8
CANTABRIA	1.2	1.8	4.1	6.1	6.8
CASTILLA Y LA MANCHA	0.8	1.3	2.3	4.1	5.8
CASTILLA Y LEON	1.5	2.0	4.0	6.4	7.9
CATALUNA	1.4	2.2	4.4	6.7	8.0
EXTREMADURA	0.8	1.1	2.1	4.0	5.6
GALICIA	0.9	1.1	2.2	4.1	6.3
RIOJA	1.7	2.0	4.0	8.1	8.3
MADRID	3.6	5.3	9.2	13.4	15.0
MURCIA	1.3	2.0	3.2	4.4	7.4
NAVARRA	1.8	2.7	5.0	8.3	9.1
PAIS VASCO	1.6	2.3	5.0	9.9	11.6
COM. VALENCIANA	1.2	1.8	3.0	5.2	6.7
AVERAGE SPAIN	1.4	2.0	3.9	6.4	7.7

Notes:
i) Numbers in the Tables represent the percentage of people in each Comunidad Autonoma with the corresponding maximum educational qualification
Source: *Mas, Pérez and Uriel (various years).*

Table 4.6: Spanish regional sample

Sample: 1963-97 (Spain, 17 regions)

Dependent variable: average regional growth rates
yit - yit-2

	1	2	3a	3b	4	5a	5b	6
Beta-Convergence: yit-2	-0.084	0.021	0.008	0.001	-0.005	0.005	0.006	0.0007
	(0.008)	(0.006)	(0.10)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)
Beta-shift		-0.079	-0.071	-0.065	-0.057	-0.079	-0.079	-0.073
		(0.008)	(0.009)	(0.011)	(0.011)	(0.009)	(-0.010)	(0.012)
Total stock of human capital			0.003	0.004	0.009			
			(0.002)	(0.003)	(0.003)			
Average years of tertiary studies						0.014	0.035	0.018
						(0.018)	(0.021)	(0.021)
Average years of secondary studies						0.0007	-0.001	0.003
						(0.003)	(0.003)	(0.004)
Average years of primary studies						0.058	0.054	0.053
						(0.015)	(0.014)	(0.016)
Proportion of the Public Sector					-0.007			-0.003
					(0.003)			(0.003)
Log likelihood	585.2	594.5	558.7	559.1	560.1	561.5	561.7	561.7
Obs	187	187	176	176	176	176	176	176

Notes:
i) Standard errors in brackets
ii) yit is the logarithm of per capita GDP in region i in period t
iii) Proportion of the Public Sector means public sector employment as a proportion of the total employment
iv) Variables are expressed as deviations from the Spanish average
v) Total stock of human capital means the average years of schooling in the labour force
vi) Average years means the average years of each level of schooling in the labour force
vii) region excluded: Asturias

Table 4.7: Percentage of the labour force with different educational attainments employed in the Public Sector

	tertiary education	secondary education	primary education
ANDALUCIA	60%	18%	6%
ARAGON	53%	15%	5%
ASTURIAS	48%	12%	3%
BALEARES	44%	11%	4%
CANARIAS	60%	17%	6%
CANTABRIA	50%	14%	4%
CASTILLA Y LA MANCHA	69%	15%	5%
CASTILLA Y LEON	60%	16%	4%
CATALUNA	38%	9%	3%
COM. VALENCIANA	53%	11%	4%
EXTREMADURA	70%	21%	6%
GALICIA	55%	14%	3%
MADRID	46%	19%	10%
MURCIA	62%	18%	5%
NAVARRA	49%	11%	5%
PAIS VASCO	35%	10%	3%
RIOJA	50%	15%	4%
AVERAGE SPAIN	53%	15%	5%

Notes:
i) Numbers in the Tables represent the percentage of people employed in the Public Sector within each educational category in each region.
That is, 60% of tertiary education in Andalucia, means that the 60% of the Andalusian labour force with a degree is employed in the Public Sector.
Each percentage is an average 1964-1997.
Source: Mas, Pérez and Uriel (various years).

Table 4.8: Southeast as Convergence Club

Sample: 1963-97

Dependent variable: average regional growth rates
yit - yit-2

	1	2	3	4	5
Beta-Convergence: yit-2	-0.027	-0.027	-0.042	-0.048	-0.052
	(0.009)	(0.014)	(0.014)	(0.015)	(0.015)
Total stock of human capital		-0.001	0.006		
		(0.004)	(0.005)		
Average years of tertiary studies				-0.086	-0.070
				(0.055)	(0.060)
Average years of secondary studies				0.006	0.010
				(0.008)	(0.008)
Average years of primary studies				0.069	0.054
				(0.017)	(0.018)
Proportion of the Public Sector			-0.021		-0.010
			(0.005)		(0.007)
Log likelihood	299.4	279.9	282.5	284.0	284.5
Obs	102	96	96	96	96

Notes:

i) Standard errors in brackets
ii) yit is the logarithm of per capita GDP in region i in period t
iii) Proportion of the Public Sector means public sector employment as a proportion of the total employment
iv) Variables are expressed as deviations from the Southwest average
v) Total stock of human capital means the average years of schooling in the labour force
vi) Average years means the average years of each level of schooling in the labour force
vii) region excluded: Canaries

Table 4.9: Northwest as Convergence Club
Sample: 1963-97

Dependent variable: average regional growth rates
yit - yit-2

	1	2	3	4	5
Beta-Convergence: yit-2	-0.014	-0.086	-0.085	-0.079	-0.077
	(0.008)	(0.011)	(0.011)	(0.009)	(0.010)
Total stock of human capital		.022	.023		
		(0.002)	(0.003)		
Average years of tertiary studies				-0.055	-0.058
				(0.020)	(0.022)
Average years of secondary studies				0.031	0.030
				(0.003)	(0.003)
Average years of primary studies				-0.067	-0.078
				(0.038)	(0.039)
Proportion of the Public Sector			-0.001		0.004
			(0.003)		(0.003)
Log likelihood	442.5	425.4	425.4	425.1	425.3
Obs	153	144	144	144	144

Notes:

i) Standard errors in brackets
ii) yit is the logarithm of per capita GDP in region i in period t
iii) Proportion of the Public Sector means public sector employment as a proportion of the total employment
iv) Variables are expressed as deviations from the Northeast average
v) Total stock of human capital means the average years of schooling in the labour force
vi) Average years means the average years of each level of schooling in the labour force
vii) region excluded: Baleares

Table 4.10: Exclusion of the Public Sector
Northwest and Southeast as Convergence Clubs
Sample: 1963-97

Dependent variable: average regional growth rates
yit - yit-2

	Northeast	*Northeast*	*Southwest*	*Southwest*
	1a	2a	1b	2b
Beta-Convergence: yit-2	-0.072 (0.012)	-0.07 (0.011)	-0.030 (0.014)	-0.046 (0.013)
Total stock of human capital	0.020 (0.003)		-0.0005 (0.004)	
Average years of tertiary studies		-0.131 (0.027)		-0.220 (0.078)
Average years of secondary studies		0.033 (0.003)		0.015 (0.008)
Average years of primary studies		-0.015 (0.032)		0.071 (0.015)
Log likelihood	422.3	424.7	279.8	285.4
Obs	144	144	96	96

Notes:

i) See notes on Table 4.7 (Model 1a and 2a) and Table 4.8 (Model 1b and 2b)
ii) Total stock of human capital means the average years of schooling in the labour force excluding the Public Sector
iii) Average years means the average years of each level of schooling in the labour force

CHAPTER 5

A PANEL TECHNIQUE FOR THE ANALYSIS OF TFP CONVERGENCE

"Why do countries have different levels of technology? How do technology change over time? How do we measure technology – is it sufficient to consider a labour-augmenting technology factor or are other differences in the production function important? How much of the convergence that we observe is due to convergence in technology versus convergence in capital-labour ratios?" Bernard and Jones (1996).

5.1. Introduction

The survey on the theoretical literature on growth and convergence in Chapter 1 shows how the role of technology has evolved within the growth literature in the last decades. We have seen that early contributions to this literature introduce technology as a pure public good, freely available to all countries. This explains why early empirical analyses of growth and convergence have been mostly based on models that rule out technology heterogeneity by assumption[1]. Nowadays, differences in productivity levels are considered as a major component of the observed large cross-country differences in per capita income[2]. Most empirical studies on this subject analyse large international datasets and find significant differences in productivity levels across countries [see Islam (1995) Coe and Helpman (1995), Caselli Esquivel and Lefort (1996), Coe, Helpman and Hoffmaister (1997)], stressing that the great part of per capita income differences are explained by these productivity differences

[1] See Mankiw Romer and Weil (1992).

[2] See Bernard and Jones (1996) p. 1043. See also Parente and Prescott (2000), Easterly and Levine (2001), Lucas (2000), on problems concerning technology adoption and various diffusion mechanisms.

and not by differences in physical or human capital[3] [see Klenow and Rodriguez-Clare (1997a) and Hall and Jones (1999)]. Moreover, remarkable differences in TFP levels have even been found in highly integrated areas [as the EU regions in Boldrin and Canova (2001)] and across regions of a single country [see De la Fuente (2002) for the Spanish regions].

Although few economists would currently dispute the finding that differences in productivity reflect – among other things – differences in technology levels[4], more controversial is the question of whether such differences in technology are stationary or temporary, that is, whether technology convergence is taking place, at what speed, under what conditions. In fact, as stressed in Chapter 1, observed convergence may be due to three different mechanisms: convergence due to capital accumulation, convergence due to technology transfer (catch up), and convergence due to both. Indeed, as Bernard and Jones (1996) put it, we often do not know "how much of the convergence that we observe is due to convergence in technology versus convergence in capital-labour ratios". Both theoretically and empirically, the problem is therefore to find a methodology able to discriminate among these three hypotheses. Recently, things have improved on both the analytical and the empirical side.

On the analytical side, simple models in which technology convergence and capital deepening can be studied within a common framework are now available. In these models the transitional dynamics is simple enough to be useful for empirical analysis[5]. On the empirical side, one of the main obstacles when testing the hypothesis of catching up has always been how to measure TFP at different points in time. Given the current availability of data in most of the existing cross-country and cross-region datasets, this is a difficult task. Previous studies often use per capita (or per worker) GDP levels as a proxy for technology and interpret the estimated coefficient on this variable as a technological convergence coefficient. This methodology has been used by two pioneering works on this subject, Dowrick and

---

[3] For example, Klenow and Rodriguez-Clare (1997a) find that over 60% of per capita income differences are explained by differences in productivity.

[4] Among them see Baier, Dwyer and Tamura (2002).Using growth accounting techniques in a sample of 145 countries they find that TFP growth is an unimportant part of average output growth (about 8%).

Nguyen (1989) and Benhabib and Spiegel (1994). A second approach computes technology levels as a residual once the contribution of factors of production to per capita GDP has been taken into account [See Klenow and Rodriguez-Clare (1997), Hall and Jones (1999) and Aiyar and Feyrer (2002)]. Here technology is measured indirectly, as the residual component of GDP growth that cannot be explained by the growth of the assumed inputs of production. Finally, a third approach tests for the presence of technology heterogeneity in cross-country convergence analysis by using an appropriate fixed-effects panel estimator but does not test directly the presence of catching-up among countries. [See, Islam (1995) and Caselli et al. (1996) among others].

The contribution of the present study is on the empirical side.[6] In this study we propose a new methodology based on Islam (2000) designed to test whether part of the observed economic convergence is due to technology convergence. In his study Islam (2000) compares the distribution of the estimated fixed effects over two points in time, but the possibility that technology convergence lies behind the observed changes in the distribution is neither discussed nor tested. The aim of this study is to do just this. We firstly estimate the standard convergence equation on regional GDP per worker data with a fixed effects estimator over two sub-periods. Second, we use the values of the individual intercepts to compute our regional TFP levels. The robustness of our results is assessed comparing the resulting estimates obtained using different estimators, in particular, a Least Square with Dummy Variable (LSDV) estimator, a corrected LSDV estimator and a difference-GMM (or Arellano and Bond) estimator. Third, we analyse the two TFP series to test whether the observed pattern over time is consistent either with the catching-up hypothesis or with the hypothesis that the current degree of technology heterogeneity is at its stationary value.

In this Chapter we follow the Klenow and Rodriguez-Clare (1997b) suggestion of using within country data bearing on the process of technology

---

[5] See for instance, De la Fuente [(1997) and (2002)] and Pigliaru (2003).

[6] Companion studies of the present one are Paci and Pigliaru (2002), in which convergence across EU regions is analysed, and Pigliaru (2003).

diffusion[7] and use a panel dataset of Italian regions, 1963-93.[8] There are three main reasons for this choice. We list them from general to specific. First, we use a regional dataset because it deals with areas where various unobservable components are supposed to be far more homogeneous than across countries. In our case, this feature of regional data (as opposed to international ones) represents a distinctive advantage. The reason is that fixed effects in panel regressions reflect all the unobservable components (institutions, geography...), and the more homogeneous are those not directly linked to technology, the closer the fixed effects get to yield a satisfactory measure of technology levels. Second, data comparability is easier. Consider human capital, a crucial variable for convergence analysis. One of the main criticisms with cross-country datasets is the limited comparability of the different schooling institutions. The use of a regional dataset enables us to limit this type of problem. Third, we study the Italian case because it is notoriously characterized by a remarkable degree of regional heterogeneity in variables such as per capita income levels and human capital stocks,[9] and because the available time-series are rather long, starting from 1963. In fact, the Italian case is one of the best known cases of a regional divide and papers close to ours do exist, in that they obtain measures of the cross-region distribution of TFP [Aiello and Scoppa (2000), Marrocu, Paci and Pala (2001)]. However, these papers do not apply the fixed-effect methodology to measure TFP and, more importantly, they do not examine how this distribution evolves over time. In other words, our study yields the first explicit analysis of technology convergence across Italian regions.

5.2 Is convergence due to technology catch-up or capital accumulation? Previous empirical literature

As shown in Chapter 1, the theoretical literature has identified two main

---

[7] "...we think the insights gleaned from cross-country regressions have run into sharply diminishing returns. We would like to see more detailed country analysis a la Young (1995)...." Klenow and Rodriguez-Clare (1997b) pag.614. See also Chapter 3 and Temple (1999b) He argues that the use of samples of very heterogeneous countries may cause serious distortions during the empirical analysis. researchers should focus on "...the most coherent part of the data set rather than the whole sample".

[8] The length of the dataset is constrained by the human capital variable: we use census data and 2001 observations are not available yet.

[9] Paci and Pigliaru (1995), Di Liberto (2000), Boltho, Carlin and Scaramozzino (1999), among several others.

determinants for convergence in levels across countries: factor accumulation and technology transfers. Early empirical evidence on convergence corroborates the hypothesis of a process of convergence fuelled by capital accumulation[10]. In particular, the detailed studies on the East Asian miracles[11] by Young [(1994) and (1995)] have contributed to the debate stressing the importance of neoclassical transition dynamics in explaining one of the most significant episodes of convergence observed in the recent years. Nevertheless, the reaction in favour of catching up has been fast as different studies "...call for returning productivity differences to the centre of theorizing about international differences in output per worker"[12].

As stressed above, this literature has always had to face a major empirical problem: that is, how to estimate something like TFP that is not directly observable. We identify three methodologies that try to estimate differences in technology and catch-up. Firstly, we have seen in Chapter 2 (section 2.3) that, one of the proposed approaches to control for possible cross-country differences in technology has simply been to assume that TFP is in fact unobservable and, moreover, possibly correlated with other explanatory variables in standard growth-convergence regressions[13]. In this case, suitable panel econometric techniques are adopted to control for this problem. This approach will be examined in detail in the following sections.

A second approach introduces standard growth accounting techniques to measure the contribution of TFP to per capita (or per worker) GDP, where this is computed separately from the contribution of capital (usually identified in its augmented form) and labour accumulation. In general, growth accounting is an empirical methodology that measures productivity indirectly, as the residual component of GDP growth that cannot be explained by the growth of the assumed inputs of production. In other words, given a standard production function $Y = F(A, K, L)$, if we take logarithms and derivatives with respect to time we obtain:

[10] Including all early empirical studies on convergence. For a review see the (new edition) Barro and Sala-i-Martin (2004).

[11] South Korea, Taiwan, Singapore and Hong Kong.

[12] Klenow and Rodroguez-Clare (1997a), page 99.

[13] See Islam (1995) and Caselli, Esquivel and Lefort (1996).

$$\frac{\dot{Y}}{Y} = g + \left(\frac{F_K K}{Y}\right) \cdot \left(\frac{\dot{K}}{K}\right) + \left(\frac{F_L L}{Y}\right) \cdot \left(\frac{\dot{L}}{L}\right) \tag{5.1}$$

where F_K and F_L are the factors (social) marginal products and g is equal to growth due to technological change. Assuming the absence of externalities and that factors are paid their private marginal product, thus, $\left(\frac{F_K K}{Y}\right)$ and $\left(\frac{F_L L}{Y}\right)$ represent, respectively, the fraction of GDP used to rent capital (or capital share) and to pay wages (or labour share). Thus, with data on growth rates of Y, K and L and data on capital and labour shares, equation (5.1) implies that g, the growth due to technological change, can be estimated as a residual[14].

A similar procedure has been applied by the level accounting approach that computes TFP levels, rather than TFP growth rates, directly from the production function. Klenow and Rodriguez-Clare (1997a), and Hall and Jones (1999)[15] propose a model based on a production function of the form $Y = K^{\alpha}(AH)^{1-\alpha}$, where human capital is defined by $H = e^{\mu(E)}L$, and E denotes average years of schooling attained by the workforce. In other words, labour L is assumed to be homogeneous with each unit of labour trained for E years. The derivative $\mu'(E)$ is the return to education estimated in a Mincerian wage regression. They rewrite the production function in terms of output per worker and obtain:

$$y = A\left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} h \tag{5.2}$$

with $y = \frac{Y}{L}$ and $h = \frac{H}{L}$. Hall and Jones (1999) collect data on GDP per worker, human capital per worker, the capital-output ratio for a sample of 127 countries for the year 1988. They assume that α =1/3 as is standard in this literature, while for μ'

---

[14] A recent application of the growth accounting approach may be found in Baier, Dwyer and Tamura (2002). For more on growth accounting see Barro and Sala-i-Martin (2004)

[15] See also Coe and Helpman (1995), and Coe, Hoffmaister, and Helpman (1997).

they use Psacharopoulos (1994) assuming that $\mu(E)$ is piecewise linear, with a coefficient of 13.4 for the first four years of schooling, 10.1 for the second four years of schooling, and 6.8 for schooling beyond the 8th year for all 86 countries of their sample. In this way, they are able to estimate A, the TFP level, from equation (5.2), as a residual. Their results show that only a small part of the observed variation in output per worker across countries is explained by differences in physical and human capital, while a significant part, over 60%, is explained by residual or TFP, differences. Both Klenow and Rodriguez-Clare (1997a) and Hall and Jones (1999) conclude that as long as technology levels differ across economies, technological diffusion is likely to play a significant role in economic convergence.

However, this is only a conjecture, since they do not test for the possibility of catch-up directly. In other words, the studies surveyed above do not offer any answer to the open question of the convergence literature, that is, how to distinguish between convergence due to capital accumulation and convergence due to technology transfers. In fact, while these studies stress the importance of TFP rather than physical and human capital in determining per capita GDP differences, they do not investigate the dynamics of TFP levels across time. In other words, since they limit the analysis to a single year, they do not offer any direct empirical evidence of the existence of cross border technology transfers.

Aiyar and Feyrer (2002) develop further this level accounting approach and devise an empirical methodology able to incorporate simultaneously the main determinants of convergence identified by the theoretical literature. While earlier studies propose a level accounting exercise for one particular year, Aiyar and Feyrer (2002) introduce the same methodology to compute TFP levels for different points in time and examine their evolution across time. In particular, they estimate TFP levels for a sample of 86 countries over the period 1960-1990 using a five-year time span, thus obtaining 7 observations of TFP. With these, they may analyse the evolution of TFP levels over time and, to this end, they estimate what they call a model of "...conditional convergence in TFP, where the long run level of TFP relative to the frontier is determined by the level of human capital"[16]. In particular, they follow the standard catching up literature *a la* Abramovitz assuming that the rate of growth of a

[16] Aiyar and Feyrer (2002), page 3

country's TFP is a positive function of the gap between its actual TFP level at a point in time and its potential TFP level, where the latter is a function of three things: the stock of human capital per worker, the level of TFP at the world technological frontier, and country's specific factors such as institutions or geography. In this way they obtain a regression specification of the form:

$$a_{i,t} = f_i + \rho a_{i,t-1} + \xi x_{i,t-1} + \eta_t + u_{i,t} \tag{5.3}$$

with $a_{i,t}$ equal to the logarithm of TFP and $x_{i,t}$ equal to the logarithm of human capital per worker. This is the usual dynamic panel specification of the convergence regression[17] and they use the Arellano-Bond (1991) estimator and find evidence of conditional convergence in TFP levels, with human capital positively affecting the steady state growth path of TFP. These results are interpreted as supporting the Nelson and Phelps approach. A similar approach, and similar results have been found by De la Fuente (2002) for Spanish regions. De la Fuente (2002) deals with technology diffusion by means of a fixed effect model, where technology levels are computed independently and then used as regressors in a convergence equation. As a consequence, the estimated individual intercepts yield a measure of unobservable characteristics other than technology, with evidence of conditional (to human capital level) TFP convergence.

The growth accounting approach has been strongly criticised[18]. Firstly, this methodology assumes the absence of spillovers between factor accumulation and productivity. As stressed in Chapter 1 and three, given the role played by externalities and, mainly, by human capital externalities, in the recent theoretical literature on growth, this assumption is certainly debatable. In particular, when social returns to capital are higher than private returns, the accounting framework implies that too much of the observed income variation is ascribed to differences in productivity. Moreover, as shown by Barro and Sala-i-Martin (2004), accounting decompositions may easily attribute to capital accumulation something that conversely should be attributed to technological progress and *vice versa*. This is

---

[17] See Chapter 2, section 2.3.

[18] See also Islam (2000) for a direct comparison between growth accounting and panel methodologies.

certainly true if capital is endogenous and responds to technological progress or if improvements in educational attainment have indirect effects on output through changes in labour force participation or R&D and growth of TFP[19]. In general, as stressed by Temple (2001), the growth accounting methodology "...does not capture these indirect effects, and so gives only a partial picture of the overall importance to growth of (different) variables....". A second criticism arises from the assumption that income shares should be identical across heterogeneous countries, with α (the capital share) usually assumed equal to 1/3. Gollin (2002) shows using comparable UN data on employee compensation as a proportion of GDP, a variable used to calculate the labour share in these studies, that there is an enormous across-countries variance[20].

A third approach introduced to control for possible cross-country differences in technology and catching-up uses the initial level of per capita/worker GDP, or a combination of GDP and other variables, as a proxy for TFP. The use of this methodology dates back to one of the first empirical study on growth and catching up, the Dowrick and Nguyen (1989) study. Here the whole observed convergence is assigned to the catch-up mechanism, while capital deepening is neglected on a priori grounds rather than tested[21]. Moreover, as shown in Chapter 1, the use of per capita GDP as a proxy for technology can also be found in Benhabib and Spiegel (1994) and (2002).

This approach may be criticised for the use of the lagged level of GDP per worker as a proxy for technology gap. As stressed by de la Fuente (1995), the coefficient on this variable may also capture the effect of diminishing returns rather than technological diffusion. More recently, Dowrick and Rogers (2002) develop further this methodology for estimating technological convergence in a panel of 57 countries[22] controlling for possible observational equivalence problems. They firstly use two different model specifications for the growth of output per worker

[19] See Barro and Sala-I-Martin (2004) pp.457-60, and Temple (2001).

[20] But in his paper Gollin (2002) justifies the use of a common $\alpha = 1/3$.

[21] This is the approach usually introduced by separate, non neoclassical line of research, where technology diffusion is regarded as the crucial source of convergence. See Fagerberg and Verspagen (1996).

[22] They use a panel 1965-1990 of 57 countries (Penn World Tables) for which data on capital per worker were available.

regression: the standard Mankiw, Romer and Weil (1992) structural specification (henceforth MRW) as described in both Chapter 1 and 2, and an alternative one given by:

$$\left[\frac{\dot{y}}{y}\right]_{it} = g_{Ai}(1-\alpha)+\alpha\left[\frac{\dot{k}}{k}\right]_{it} + \varepsilon_{it} \qquad (5.4)$$

This model is obtained differentiating with respect to time a standard Cobb-Douglas production function $Y = K^{\alpha}(AL)^{1-\alpha}$, where y and k in equation (5.4) are output and capital per worker respectively, and g is the rate of technological progress. They firstly test for TFP heterogeneity as in Islam (1995) and Caselli Esquivel and Lefort (1996), that is, using country-specific effects in a growth regression, and find that country-specific effects are strongly significant in both specifications, thus, rejecting the assumption of homogeneous technology among countries.

Secondly, to estimate the presence of convergence due to technology transfers, they model the rate of growth of technology in country i as:

$$g_{AiT} = \ln\left(\frac{A_{i,T}}{A_{i,T-\tau}}\right) = g_{Ai} + g_{AT} + \phi\ln\left(\frac{A^{*}_{T-\tau}}{A_{i,T-\tau}}\right) \qquad (5.5)$$

where τ is the time-span considered, A^{*} represents the technology level in the leader country, g_{Ai} is the constant country specific component and g_{AT} is the period specific component. They show that, under standard assumptions on the production function, and introducing labour productivity as a proxy for the unobservable technology, the growth rate of output per worker may be described by:

$$g_{yi,T} = \left\{g_{AT} + \phi\ln y_{*,T-\tau}\right\} + g_{Ai} - \phi\ln y_{i,T-\tau} + \alpha_k\left[\frac{\dot{k}}{k}\right]_{i,T} + \alpha_h\left[\frac{\dot{h}}{h}\right]_{i,T} + \varepsilon_{i,T} \qquad (5.6)$$

where the dependent variable $g_{yiT} = \left(\frac{\ln y_{i,T} - \ln y_{i,T-\tau}}{\tau}\right)$, the first set of brackets identifies the period specific term (comprising both common technology slowdowns/speed ups and the level of productivity of the leader), α_k provides an estimate of the output-physical capital elasticity, and α_h provides an estimate of the output-human capital elasticity. Given this specification they assume that the coefficient on the lagged dependent variable should now capture convergence due to technology transfers while it should not capture the usual solovian convergence effect. Conversely, the solovian β-convergence parameter is recovered as in MRW by the formula $\beta = (1-\alpha_k-\alpha_h)(\delta+g+n)$[23], using $\hat{\alpha}_k$ and $\hat{\alpha}_h$. Equation (5.6) is estimated with a GMM-Arellano and Bond estimator. Their results show the presence of both technology and solovian convergence.

Finally, De la Fuente (1995) examines another possibility of including in a single theoretical framework both solovian convergence and catching up, with the use of alternative proxies for technology. He develops a model where per capita output growth can be written as $g_y = g_A + \alpha g_Z$, that is, the sum of the rate of technical progress g_A and the accumulation of productive factors g_Z, where α measures the degree of returns to scale in capital and $Z = \frac{K}{AL}$. Moreover:

$$g_Z = g_K - g_A - n \tag{5.7}$$

$$g_A = \gamma\theta + \varepsilon(\ln A_{\max} - \ln A) \tag{5.8}$$

where θ represents the fraction of GDP invested in R&D, γ measures R&D productivity, and, ε measures the speed of diffusion of new technologies across countries. Given these assumptions and following the MRW approach[24], he develops a convergence equation where the growth rate of income per worker is a function of the initial level of income per worker (which should capture the standard solovian convergence process), investment rates in both physical and human capital, investment in R&D, and the initial technological gap, which should capture the catching up effect. In his empirical analysis, θ is measured by total R&D

[23] See Chapter 1, section (1.1.1).

[24] See Chapter 1.

expenditure as a fraction of GDP, while to construct a proxy for technological backwardness he uses a combination of three variables based on an average of three indices, which should be able to capture the initial position of each country relative to the US: the fraction of the population holding a university degree in 1960, the number of scientists employed in R&D activities as a fraction of the labour force, and the average product per worker at the beginning of the sample period. The equation is estimated using a dataset of 21 OECD countries during the period 1963-1988 and the results point to both convergence mechanisms (solovian and catch-up) as characterising the cross-country paths of GDP per worker.

5.3. A Panel Data approach to estimate technology convergence

As noted in the previous section, standard growth accounting techniques have been criticised as they require the imposition of too many assumptions on cross-country parameter homogeneity and the absence of externalities. Secondly, studies that introduce the initial level of per capita GDP as a proxy for technology into the empirical analysis have been accused of capturing the effect of diminishing returns rather than only technological diffusion. Another approach to control for possible cross-country differences in technology is to test for the presence of technology heterogeneity in cross-country convergence analysis by using an appropriate fixed-effect panel estimator[25]. Islam (1995) has been among the first to suggest this econometric solution to the problem of estimating TFP levels. In details, in Islam (1995) the standard Mankiw Romer and Weil (1992) structural approach (hereafter MRW) is extended by allowing TFP levels to vary across individual economies, together with saving rates and population growth rates[26]. The convergence equation is given by:

$$\ln Y_{it2} = (1-\beta)\frac{\alpha}{1-\alpha}\ln(s_{it1}) - (1-\beta)\frac{\alpha}{1-\alpha}\ln(n_{it1} + g + \delta) + \beta \ln Y_{it1} + (1-\beta)\ln A_{i0} + g(t_2 - \beta t_1) \tag{5.9}$$

where Y_{it_1} is per capita GDP in economy i at time t_1 (initial period, while t_2 is the

[25] See Islam (1995) and (2000) and Caselli Esquivel and Lefort (1996) among others.

final one), and s , n, δ and g are, respectively the saving rate, the population growth rate, the depreciation rate, and exogenous technological change, the latter assumed to be invariant across individual economies. Moreover, α is the usual capital share of a standard Cobb-Douglas production function. Finally, $\beta \equiv e^{-\lambda\tau}$, where $\lambda = (1-\alpha)(n+g+\delta)$ represents the convergence parameter and $\tau \equiv t_2 - t_1$, is the time span considered.

Differently from MRW, Islam introduces the possibility that the unobservable differences in TFP are correlated with other regressors[27], and uses suitable panel techniques to estimate:

$$y_{it} = \beta y_{it-1} + \sum_{j=1}^{2} \gamma_j x_{j,it} + \eta_t + \mu_i + v_{it}, \qquad j=1,2 \qquad (5.10)$$

where the dependent variable is the logarithm of per capita GDP (measured in terms of population working age), v_{it} is the transitory term that varies across countries, and the remaining terms are:

$$x_{it}^1 = \ln(s_{it}) \qquad (5.11)$$

$$x_{it}^2 = \ln(n_{it} + g + \delta) \qquad (5.12)$$

$$\gamma = (1-\beta)\frac{\alpha}{1-\alpha} \qquad (5.13)$$

$$\mu_i = (1-\beta)\ln A(0)_i \qquad (5.14)$$

$$\eta_t = g(t_2 - \beta t_1) \qquad (5.15)$$

In this specification, technology is summarized by two terms. The first is the time trend component that captures the growth rate of the technology frontier assumed constant across individuals. The second term, μ_i, a time-invariant

---

[26] For more on this see Chapter 2, Section 2.3.

[27] In their study MRW's assume $\ln A_{i0} = \ln A_0 + \varepsilon_i$, with $\ln A_0$ constant across individuals, and ε_i representing a random shock, uncorrelated with the other explanatory variables. Notice that, if

component that varies across economies, should control for various unobservable factors like institutions or climate, and – crucially for our aim – technology. Since technology is likely to be correlated with other regressors, a fixed effect estimator is appropriate.[28] Once we have the estimated individual intercepts, we can easily compute a proxy of TFP by:

$$A(0)_i = \exp\left(\frac{\mu_i}{1-\beta}\right) \tag{5.16}$$

In other words, this methodology can be used to obtain a measure of the degree of cross-country technology heterogeneity.[29]

From our point of view, the main problem with this methodology is that, while it was designed to control for the presence of cross-country TFP heterogeneity, it rules out technology convergence by assumption and completely ignores possible problems of observational equivalence between technological catch up and capital deepening. More precisely, as shown by equations (5.14) and (5.15), equation (5.10) is obtained by log-linearizing the Solow model around the steady-state under the assumption of a *stationary* degree of TFP heterogeneity. In other words, all economies are assumed to growth at the same technological rate according to the process $\ln A_{it} = \ln A_{i0} + gt$, whatever their level of technological knowledge.

This is clearly in sharp contrast with the technological catching-up hypothesis. The latter may be described by a process where the growth rate of technology is proportional to the current gap between the world technology frontier and the technology level currently adopted in an economy. Typically, during the transition towards the steady-state in which all economies share the common long-run technological growth g, the presence of technological catch-up enables the

instead technology is correlated with the explanatory variables, MRW's OLS results are not consistent.

[28] For more on this see Baltagi (2003) and Chapter 2.

[29] One of the main criticisms of this approach is that the estimated individual intercepts do not simply control for technology but include also the effect of other possible unobservable factors such as institutions or geography. As explained in the following section, one way to control for this problem is to apply this methodology to samples that are relatively homogeneous with respect to other factors such as institutions.

technology levels in the lagging economies to growth faster than g. As a consequence, during the transition, the technology gap between the leader and a follower should decrease. On the contrary, if no systematic process of technology diffusion is at work, this gap should stay constant over time, since all economies grow at a common rate of technology growth. Note that, since productivity is certainly correlated with technology, equation (5.10) is plagued by problems of observational equivalence, as the β coefficient may still capture the effect of both, neoclassical (or solovian) convergence and catch-up.

Hence, how can we use equation (5.10) to test for the presence/absence of technological convergence? First, notice that, the longer the time dimension of the panel, the higher the risk that differences in TFP levels are not stationary within the sample period, since technological diffusion is more likely to be at work. As a consequence, in the presence of technological convergence equation (5.10) should be regarded as an approximation of the real process – an approximation that worsens as the length of the period under analysis increases.

Second, and consequently, the presence of technological convergence should be detected by comparing the TFP values obtained by estimating (5.16) over different periods. This type of comparison should reveal whether the observed pattern of TFP values is consistent either with the catching-up hypothesis or with the alternative hypothesis that the current degree of technology heterogeneity is at its stationary value. Indeed, in this case we are estimating the initial level of TFP in two different points in time. By doing this, we are able to detect if the pattern over time of these TFP levels is consistent with the presence/absence of catch up. This enables us to control for observational equivalence problems.

The technique we use follows several, simple steps. First, we estimate equation (5.10) over different sub-periods, in order to obtain a sequence of estimated values of individual intercepts. Second, the latter values are used to compute the individual values of $\ln A_i$.[30] Third, we analyse the evolution over time of the distribution of $\ln A_i$ in order to test for the presence of technological convergence.

[30] A similar approach has been previously introduced by Islam (2000)., where the author compares the distribution of the estimated fixed effects over two points in time. However, in his paper the possibility that technology convergence lies behind the observed changes in the distribution is neither discussed nor tested.

Indeed, while technology convergence implies a variance of $\ln A_i$ that decreases over time while approaching its stationary value, the alternative hypothesis implies that the variance of $\ln A_i$ is at its stationary value, and thus no significant trend in its value should be detected.

5.4. Comparing the available estimation procedures

We use Italian data on regional GDP per worker[31] to estimate the following equation:

$$\tilde{y}_{it} = \beta \tilde{y}_{it-\tau} + \sum_{j=1}^{3} \gamma_j \tilde{x}_{jit-\tau} + \mu_i + u_{it} \tag{5.17}$$

$$\tilde{y}_{it} = y_{it} - \overline{y}_t, \qquad \tilde{x}_{it} = x_{it} - \overline{x}_t \tag{5.18}$$

where $\overline{y}_t$, and $\overline{x}_t$ are the Italian average in period t: data are taken in difference from the Italian mean, in order to control for the presence of a time trend component η_t and of a likely common stochastic trend (the common component of technology) across regions[32]. We use a time span $\tau = 5$ in order to control for business cycle fluctuations and serial correlation, which are likely to affect the data in the short run. Moreover, $x_{1i,t}$ is the lagged saving rate proxied by the ratio of regional investment to GDP, and x_{3it} represents a measure of human capital stock, namely average years of schooling. Both these variables are taken at their $t-\tau$ level, while $x_{2i,t}$ represents the sum of *n*, population growth, δ the depreciation rate and *g* the exogenous technology growth rate and is taken as an average over the five years preceding *t*.[33] As standard in this literature, $(g+\delta)$ is assumed equal to 0.05. Note that equation (5.17) simply augments equation (5.10) to include a measure of the stock of human capital: indeed, in order to identify TFP differences it is essential to control for one

---

[31] Our aim is to obtain TFP estimates from a standard Cobb-Douglas technology. Given that unemployment rates differ greatly across Italian regions, GDP per worker is a more adequate variable than per capita income for our purposes.

[32] On this see also Chapter 2.

[33] In fact, regional series may be characterised by high volatility and this was the case for $x_{i,t}^2$.

of its most likely determinants.[34] Finally, as shown in the previous section, the coefficient on the lagged dependent variable yields a measure of the speed of the solovian conditional convergence (or *within* convergence), while individual effects reflect the degree of TFP heterogeneity.

The first problem we face when we estimate a dynamic panel data model such as the one represented by equation (5.17) is which estimator suits our case better. The answer is not simple. It is still true today what Kiviet wrote a few years ago: "As yet, no technique is available that has shown uniform superiority in finite samples over a wide range of relevant situations as far as the true parameter values and the further properties of the DGP are concerned."[35] Indeed, the LSDV estimator, while consistent for large T,[36] is characterised by small sample problems and, in particular, it is well known to produce downward biased estimates in small samples. Conversely, the Arellano and Bond (1991) estimator (GMM-AB from now on) is becoming increasingly popular since it has both the advantage of producing consistent estimates in a dynamic panel regression with both (i) endogenous right hand side variables, and (ii) presence of measurement error. Moreover, it is more efficient than other standard IV estimators such as the Anderson-Hsiao estimator. However, it has been recently shown[37] that, when T is small, and either the autoregressive parameter is close to one (highly persistent series), or the variance of the individual effect is high relative to the variance of the transient shock, then even the GMM-AB estimator is biased[38] and, in particular, downward biased. Note that the presence of a relatively small number of time periods and persistent time series are typical features of macro-growth datasets like ours.

To control for this problem, Kiviet (1995) put forward a more direct approach to the problem of the LSDV finite sample bias by estimating a small sample

---

[34] For details on how this variable is computed see Chapter 3.

[35] See Kiviet (1995) page 72.

[36] See Amemyia (1967) and Chapter 2.

[37] See Blundell and Bond (1998) and Bond-Hoeffler-Temple (2001).

[38] It may be that the inclusion of additional explanatory variables among regressors and the inclusion of additional lags of these regressors among instruments will improve the performance of this estimator. See Bond-Hoeffler-Temple (2001).

correction to the LSDV estimator. Monte Carlo analysis[39] finds that for small T (such as the one we find in the convergence literature) LSDV estimates corrected for the bias (KIVIET from now on) seem more attractive than GMM. In particular, these Monte Carlo studies explicitly analyse typical macro dynamic panels and find that for $T \leq 20$ and $N \leq 50$, as in our case, the KIVIET and Anderson-Hsiao estimators consistently outperform GMM-AB. Moreover, despite having a higher average bias, KIVIET turns out to be more efficient than Anderson-Hsiao. Overall, these Monte Carlo analyses suggest that a reasonable strategy would be to use the KIVIET estimator for smaller panels ($T \leq 10$), while Anderson-Hsiao should be preferred for larger panels, as the efficiency of the latter improves with T (Anderson-Hsiao has the additional advantage of being computationally simpler than the former).

Let us now turn to our specific case. Our Italian regional panel includes the period 1963-93 for 19 regions.[40] Using the five-year time span implies that we are left with T=7 observations for each of the N=19 regions, corresponding to 1963, 1968, 1973, 1978, 1983, 1988, and 1993. Since, as we noticed above, no technique shows a clear superiority in finite samples, in the following we will use several estimators and will compare their results in order to assess their robustness. In doing this, given the dimension of our panel and the above discussion, the Kiviet-corrected LSDV estimator will be used as our benchmark.[41]

Since all these estimators perform poorly in small samples, to evaluate how each of them performs in our case we start our empirical analysis by using the whole sample 1963-93. Table 5.1 shows our results for this case. For each regression we include the estimates obtained and the implied $\hat{\lambda}$, i.e. the speed of solovian convergence parameter.[42]

Let us start by comparing the results obtained by using the pooling-OLS estimator and the (uncorrected) LSDV estimator. As expected, when we introduce the pooling-OLS estimator (Model 1), the coefficient on the lagged dependent

---

[39] See Kiviet (1995) and Judson and Owen (1996).

[40] The Italian regions are 20. We have excluded Valle d'Aosta because it represents an outlier. Nevertheless, results do not change if we include this region.

[41] To implement the Kiviet's small-sample correction we use the STATA routine proposed by Adam (1998).

[42] From $\beta = e^{-\lambda t}$

variable is high compared with other individual effects estimators, with a corresponding speed of solovian convergence of 3%. Among the regressors, only the coefficients on the lagged dependent variable and on population growth are significant, while both the coefficient on the investment share and on human capital are not significant[43]. These results are robust as they remain stable when other estimation procedure are introduced. When equation (5.17) is estimated with LSDV (Model 5) we find a lower AR(1) coefficient and a correspondingly higher speed of solovian convergence of 9%.

Let us now extend our comparison to the other available estimators. Both the GMM-AB and the Kiviet correction require us to drop one initial observation.[44] Consequently, in order to compare the results of all the different estimators we perform again the regressions discussed in the previous paragraph excluding the first observation. With this reduced sample, the estimated AR(1) OLS parameter (Model 2) is lower than before and equal to 0.80, while the estimated AR(1) LSDV parameter (Model 6) declines to 0.51. The use of the Kiviet correction procedure increases the LSDV parameter from 0.51 to 0.67, with a decline in the corresponding speed of convergence coefficient from 13% to 8%. Note that KIVIET only corrects the bias in the LSDV estimated parameters but does not produce alternative or corrected standard errors. This is why they are not shown among results.

The GMM-AB estimates are shown together with the p-value of the AB-2 statistic and the Sargan test as in Arellano and Bond (1991). The first statistic tests for the presence of serial correlation. In particular, since the final regression equation is in first differences, it tests for second order serial correlation in the error term. The latter must be absent for the assumption of no serial correlation in the model in levels to be accepted. The presence of second-order serial correlation would imply that the estimates are inconsistent. The second statistics tests the validity of overidentifying restrictions. The consistency of this estimation procedure crucially depends on the

[43] Note that, contrary to the model assumptions, the sign of the savings rate coefficient is even almost invariable negative (the only exception is represented by model 5) but never significant. This result is not new in the literature on regional Italian convergence; see for example Cellini and Scorcu (1997) and Paci and Pigliaru (1995). The latter study justify the negative and non significant sign on investments arguing that in Italy a large part of private investments have been in fact influenced by public policies where these have not been necessarily governed by efficiency criteria.

[44] To compute the estimated bias the methodology requires the use of a consistent estimator, such as Anderson-Hsiao or GMM, and the routine used to calculate KIVIET cannot handle missing observation. See Adam (1998).

identifying assumption that lagged values of both income and other explanatory variables are valid instruments in these growth regressions. The GMM-AB estimator may be performed under very different assumptions on the endogeneity of included regressors[45]. In this study we specify two different hypothesis on the $x's$. First, Model 3 (or model GMM-AB1) in Table 1 assumes that all regressors are weakly exogenous, that is $E\left[x_{it}u_{is}\right]\neq 0$ for $s<t$, and $E\left[x_{it}u_{is}\right]=0$ for $s\geq t$. Second, Model 4 (or model GMM-AB2) assumes instead that all $x's$ are strictly exogenous, that is, $E\left[x_{it}u_{is}\right]=0$ for all t and s.

The results in Table 5.1 show that both specifications are valid: the p-values of the AB-2 and Sargan tests say that it is not possible to reject the null hypothesis of absence of second-order autocorrelation and that the over-identifying restrictions are valid. Then, the choice between these two specification is not obvious, even if the increase of the p-value of the Sargan test in GMM-AB1 indicates that treating the included regressors as predetermined makes it more difficult to reject the null and, thus, that Model 3 should be preferred to Model 4.

However, these estimates may be biased. To detect a possible bias in our GMM-AB models we follow the procedure suggested by Bond, Hoeffler and Temple (2001). Given that it is well known that OLS is biased upwards in dynamic panels while LSDV is biased downwards, these authors suggest that a consistent estimate should therefore lie between the two. Since we expect that the true parameter values lie somewhere between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$, in our case we expect its value to be between 0.80 and 0.51. The estimated AR(1) coefficient on GMM-AB2 is higher than that obtained with OLS, where the latter should be characterized by upward bias. Consequently, we exclude GMM-AB2 from the following analysis. Conversely, the estimated AR(1) coefficient on GMM-AB1, 0.696, is very similar to that obtained in KIVIET, 0.669. With a value included between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$[46], this estimate does not suggest any obvious presence of bias.

Thus, to sum up, in this section we have seen that previous Monte Carlo

[45] We always use all available lags in the estimation.

[46] The AR(1) coefficient in GMM-AB1 is lower than that in GMM-AB2 also because treating included regressors as predetermined instead of strictly exogenous increases the size of the instrument matrix and, while additional instruments increase efficiency of the GMM procedure, they may also increase the downward bias in a small panel. See also Ayiar and Feyrer (2002).

analysis suggest KIVIET as the best estimation procedure to estimate model (5.17) with samples with similar characteristics as ours. Nevertheless, since LSDV and GMM-AB are both employed estimators in this literature, in the following section we will use LSDV, KIVIET and GMM-AB1 to compute our regional TFP levels and compare the results obtained.

5.5. Testing for TFP heterogeneity

With these estimates in hand we now move on to compute our regional TFP measures. In our LSDV estimates the regional dummy coefficients, $\hat{\mu}_i$, are almost invariably statistically significant. As for the GMM-AB (1 and 2) estimator, note that the latter controls for fixed effects by transforming data in first difference and, thus, the individual effects are not directly estimated. Following Caselli, Esquivel and Lefort (1996), we obtain estimates of μ_i by:

$$(\hat{\mu}_i + \hat{u}_{it}) = \tilde{y}_{it} - \hat{b}\tilde{y}_{it-1} - \sum_{j=1}^{2} \hat{\gamma}_j \tilde{x}_{jit-1} - \hat{\xi}\tilde{h}_{it-1} \tag{5.19}$$

$$\hat{\hat{\mu}}_i = \frac{1}{T} \sum (\hat{\mu}_i + \hat{u}_{it}) \tag{5.20}$$

The same procedure has been used to obtain $\hat{\mu}_i$ and, through equation (5.16) $\hat{A}(0)_i$, using KIVIET. In all cases, the TFP estimates are then used to compute the ratio $\hat{A}(0)_i / \hat{A}(0)_{Lom}$, with $\hat{A}(0)_{Lom}$ being the estimated TFP value for Lombardia, currently the richest, most industrialised and arguably the most technologically advanced Italian region.

Table 5.2a includes the estimates of the relative (to Lombardia) levels of regional TFP obtained by applying each different estimator. Moreover, to make the interpretation of results easier, Table 5.2b shows the ranking that each region obtain with the different methodologies.

Overall, these results suggest that different econometric methodologies produce similar TFP estimates. This conclusion is confirmed by the analysis of the Spearman rank order coefficient in Table 5.3.

Table 5.3: Spearman rank order correlation coefficient			
	LSDV	GMM-AB1	KIVIET
LSDV	1		
GMM-AB1	0.94	1	
KIVIET	0.98	0.96	1

As expected, the estimates of the regional relative TFP levels obtained by LSDV and KIVIET are very similar, with a correlation coefficient equal to 0.98. Eight regions out of nineteen hold the same ranking, three regions (Abruzzo, Liguria and Sardegna) change their rank by two positions, while for the remaining regions the rank changes by only one position. A lower but still very high ranking correspondence if found between the LSDV, KIVIET and GMM-AB1 estimates.[47]

To sum up, the close correspondence found in this section among the TFP estimates obtained with different estimation procedures support the conclusion that our results can be easily regarded as robust.

More generally, the overall picture emerging from our estimates is an interesting one. In particular, it strongly confirms that TFP differences can be significantly large even across regions, and that an important part of the Italian economic divide seems to be due to such differences. For instance, in 1968 the GDP per worker in Basilicata (the poorest region) was 53% of Lombardia value; in our estimates, the corresponding relative TFP value is even higher (an average of 67,7%: see Table 2a). Moreover, we find confirmation that the northern and richer regions are also the most technologically advanced areas in the country, and that at the bottom end are the southern, less developed areas.

The pattern and the magnitude of TFP heterogeneity as measured by our estimates suggest that a potential for technological catch-up does exist for the lagging regions. In turn, this implies that any analysis of aggregate convergence

[47] For GMM-AB2 the Spearman rank correlation coefficient was lower, ranging from 0.94 (with GMM-AB1) and 0.92 (with LSDV). We have also checked the rank correlation between the initial level of income and the different TFP measures obtained. In this case, the Spearman rank correlation coefficient is 0,87 (with LSDV), 0,82 (with KIVIET), and 0,76 (with GMM-AB1).

across Italian regions should take this potential source of convergence into account. This is what we will do in the next section.

5.6. Detecting technological convergence: Empirical results

In the previous section we have shown that a high degree of TFP heterogeneity does exist across the Italian regions. In this section we investigate whether this degree of hereogeneity is either stationary or is the source of a process of TFP convergence. As suggested by Islam (2003) and Pigliaru (2003), to test for the presence of TFP convergence we need to generate TFP-level indices for several consecutive time periods, so that the TFP dynamics can be directly analysed. The indices produced by panel methods may be used to this end as "...they contain ordinal as well as cardinal information, which can both be helpful in answering questions regarding TFP-convergence".[48] The main difficulty with this procedure is that, in order to generate different TFP-level indices for consecutive time periods we need to further reduce the time dimension of the estimated samples, thus worsening the problems associated with small sample bias discussed above. Note that using a time span equal to 5 implies that we are left with T=7 observations, which in turn implies T=6 in LSDV because of the presence of the lagged dependent variable among regressors, and T=5 with Kiviet since it uses the Anderson-Hsiao estimates to calculate the bias.[49]

With such a dataset it is possible to obtain two sub-samples and to apply LSDV to estimate regional TFP levels, but the implementation of the KIVIET correction procedure to these short sub-samples becomes infeasible. A possible alternative is to gain degrees of freedom by using a shorter time span. For example, a time span equal to three ($\tau = 3$) yields T=11 (i.e., T=10 with LSDV and T=9 with KIVIET). Clearly, using a shorter time span has the obvious disadvantage that it increases the problems related to short term disturbances and serial correlation of the error term.[50]

Given these problems, firstly we estimate TFP levels using LSDV with a

---

[48] See Islam (2003), page 349.

[49] In this case data are taken in first difference and levels of the dependent variable (lagged twice and further) are introduced as instruments. For more details see Baltagi (2003).

standard time span equal to five (see Table 5.4, columns 1 and 2). Secondly, we apply KIVIET to a sample with (non-standard) $\tau = 3$ (Table 4, columns 3 and 4) and compare the results.

Let us start with analysing the results with the standard time span of five years in Table 5.4. Our LSDV estimates in columns 1 and 2 are based on two sub-samples of 4 observations each, with one overlapping year: the first sub-sample includes 1963, 1968, 1973 1978, and the second 1978, 1983, 1988, 1993. As before, we estimate equation (5.17) and save the two different series of $\hat{\mu}_i$.

The solovian (conditional) convergence coefficient is significant only in the first subsample, 1963-78: we do not observe evidence of solovian convergence during 1978-93. Other explanatory variables are never significant while the regional dummies coefficients, $\hat{\mu}_i$, are almost invariably significant. Again, we use equation (5.14) to obtain $\hat{A}(0)_i$, and transform the data as $\frac{\hat{A}(0)_i}{\hat{A}(0)_{Lom}}$, with $\hat{A}(0)_{Lom}$ being the estimated fixed effect of Lombardia. This procedure yields two different estimates of regional effects, the first corresponding mainly to the 1970s and the second mainly to the 1980s. Table 5.5 presents the results and shows the TFP relative values for the two sub-periods. A well-defined dynamic pattern emerges. First, relative TFP values increase for most southern laggard regions in the second period, while they decrease for most northern regions. Second, regional TFP dispersion decreases: the variance of (relative) TFP's is higher in the first period (with a value of 0.027) than in the second (0.010).

These results are strongly consistent with the hypothesis that a process of *technological convergence* does exist and represent an important component of the aggregate convergence observed across these two sub-periods. This conclusion finds a clear confirmation in Figure 5.1, where the relationship existing between the TFP estimated for the 1963-79 interval and the subsequent one is shown.

The dotted 45 degree line shows the locus where the relative TFP level in each region would be unchanged between the two periods. Most southern regions are

---

[50] In this case we need to assume that measurement error is not three-order serially correlated. Moreover, it has been argued that short time spans may not be appropriate for studying growth convergence. See Islam (1995) p. 1140 and Caselli Esquivel and Lefort (1996) among others.

clearly above the 45 degree line[51] as they performed consistently better in term of relative TFP growth, while six (northern) regions are below the 45 degree line. This pattern is consistent with the hypothesis of TFP convergence.

The same data may be rearranged to analyse this result in terms of a typical *growth-initial level* convergence relationship. In Figure 5.2 the Y-axis represents the rate of growth of relative TFP, while the X-axis represents the initial relative TFP level. Convergence implies a negative correlation between the initial level of TFP and its subsequent growth rate. This is exactly what our data reveal. Nevertheless, in spite of this clear convergence pattern the distance between northern and southern regions in terms of relative TFP was still significant in the second sub-period, as shown by Table 5.5.

Let us now go back to Table 5.4, columns 3 and 4, in order to assess the robustness of our LSDV result by applying the Kiviet-corrected LSDV estimator. When we use the latter, the two sub-samples each include 5 observations, with one overlapping year. The first sub-sample includes 1969, 1972, 1975 1978, 1981, while the second 1981, 1984, 1987, 1990, 1993.[52]

Models 3 and 4 in Table 5.4 suggest that, in contrast with LSDV, the solovian (conditional) convergence coefficient is significant in both sub-periods. In the first subsample analysed, the other variables included are never significant, while in the second both $\ln(s)$ and $\ln(n+\delta+g)$ are negative and significant. Human capital is never significant.

With respect to the TFP estimates, our previous result based on the LSDV estimator does not change significantly. Again, the estimated variance of relative TFP's is higher in the first period (with a value of 0.020), than in the second (0.011). Figure 5.3 illustrates the relationship existing between the relative TFP levels estimated for the 1969-81 interval and the following ones. Similarities with Figure 5.1 are remarkable. As a consequence, our previous result pointing to the presence of a clear pattern of TFP convergence appears to be robust to the use of the Kiviet

---

[51] These are Molise, Basilicata, Calabria, Puglia, Abruzzo, Umbria Sicilia and Campania.

[52] Note that there is not a perfect correspondence between the samples used in LSDV and KIVIET and, thus, the evidence obtained in the two cases is not perfectly comparable.

correction. In particular, eleven regions out of eighteen[53] confirm the pattern revealed in Figure 5.1. The most substantial difference is observed for a group of three regions (Abruzzo, Umbria, Sardegna) that were among the (relative) winners in Figure 1 and now are among the (relative) losers.

5.7. Technology convergence and the role of human capital

Finally, our measures of regional levels of TFP may also be used to test one of the main hypothesis of the catching-up literature and, in particular, of the Nelson and Phelps (1966) approach. In Chapter 1 we have seen that in these models TFP growth is determined by the technological distance from the leader and by the level of human capital, where the latter influences the capacity for both discovering new technologies and adopting innovations from abroad. In other words, human capital levels determine the capacity of adopting new technologies from abroad and, thus, the possibility of a catch up process among countries. As a consequence, we should expect TFP levels to depend on human capital stocks. This is exactly what our data reveal. The correlation coefficient between the regional human capital level in 1963 and TFP levels estimated using LSDV ($\tau = 5$) is equal to 0.94, while that calculated between the level of human capital in 1978 and the subsequent TFP levels is 0.87. When we use KIVIET, the results are almost identical. The correlation coefficient between the level of human capital in 1969 and the estimated TFP levels (KIVIET, $\tau = 3$) is 0.93, while that calculated for the level of human capital in 1981 and subsequent TFP levels is lower and equal to 0.89. The same relationship may be observed in Figures from 5.4 to 5.7, where we include regional relative TFP estimates in the Y-axis and the initial level of human capital in the X-axis. Figure 5.4 and 5.5 introduce respectively the TFP levels estimated with LSDV ($\tau = 5$) and KIVIET ($\tau = 3$) in the first sub-period of the analysis, while Figure 5.6 and 5.7 introduce the same analysis for the second sub-period. In general, this evidence, together with the absence of significance of the human capital variable in our regressions, corroborate the hypothesis of a relationship between human capital and TFP as described by the Nelson and Phelps approach.

[53] Being the benchmark region, we exclude Lombardia from this analysis.

5.8. Summary

The aim of this study was to assess the existence of technology convergence across the Italian regions between 1963 and 1993. Different methodologies have been proposed to measure TFP heterogeneity across countries, but only a few of them try to capture the presence of technology convergence as a separate component from the standard solovian (capital-deepening) source of convergence. To distinguish between these two component of convergence, we have proposed and applied a fixed-effect panel methodology.

First of all, our results identify the presence of a TFP heterogeneity across Italian regions. This result is robust to the use of different estimation procedure such as simple LSDV, Kiviet-corrected LSDV, and GMM *a la* Arellano and Bond (1991). Second, we find strong support to the hypothesis that a significant process of TFP convergence has been a key factor in the observed aggregate regional convergence that took place in Italy up to the mid-seventies. To the best of our knowledge, this is the first time that evidence on TFP convergence across Italian regions has been produced in a context in which the traditional Solovian-type of convergence is simultaneously taken into account.

Moreover, our results show that a period of significant convergence in TFP has not generated a significant, persistent decrease in the degree of cross-region inequality in per capita income. The solution to this puzzle may be a simple one. Our evidence shows that technology convergence took place *between* the two sub-periods of our analysis (1963-78 and 1978-93), while nothing can be inferred on what has happened, in terms of technology diffusion, *within* the second sub-period. So, one possibility is that the halt of aggregate convergence in this sub-period is due to a halt of technology diffusion. More data and research are needed to test this additional hypothesis.

Finally, our human capital measures has been found to be highly positively correlated with TFP levels. This result confirms one of the hypothesis of the Nelson and Phelps approach, namely that human capital is the main determinant of technological catch-up. This latter result suggests an explanation for the existence of persistent differences in regional GDP per worker: this might be due to the fact that the backward regions never caught-up with the northern and richest ones in terms of their human capital endowments.

APPENDIX V-A

Table 5.1: Estimation of the augmented Solow model

Sample: Italian regions (1963-93)

Dependent Variable $ln(y_{i,t})$

	1 OLS	2 OLS	3 GMM-AB1	4 GMM-AB2	5 LSDV	6 LSDV	7 KIVIET
Observations	*114*	*95*	*95*	*95*	*114*	*95*	*95*
$ln(y_{i,t-1})$	.852	.800	.696	.834	.630	.514	.669
	(.045)	(.051)	(.097)	(.135)	(.078)	(.090)	
$ln(s_{i,t-1})$	-.024	-.063	-.047	-.044	.027	-.019	-.022
	(.018)	(.020)	(.043)	(.037)	(.026)	(.030)	
$ln(n_{i,t-1}+g+d)$	-.085	-.108	-.125	-.108	-.073	-.074	-.089
	(.022)	(.025)	(.031)	(.028)	(.025)	(.028)	
human capital	.015	.024	.001	-.028	-.022	-.010	0.00
	(.010)	(.011)	(.021)	(.022)	(.017)	(.019)	
λ	0.03	0.04	0.07	0.04	0.09	0.13	0.08
Sargan test (p-value)			0.79	0.35			
AB-2 test (p-value)			0.31	0.20			

Notes:

19 Italian regions included (Val d'Aosta excluded)
Standard errors in parentheses.
LSDV is the Least Squares with Dummy variables estimator.
GMM-AB1 is the Arellano-Bond estimator under the assumption that x's are predetermined
GMM-AB2 is the Arellano-Bond estimator under the assumption x's strictly exogenous
KIVIET is the LSDV estimator with the Kiviet (1995) correction. KIVIET only corrects the bias in the LSDV estimated parameters, but does not produce alternative or corrected standard errors. This is why they are not shown among results.
The figures reported for the Sargan test are the p-values for the null hypothesis, valid specification.
The figures reported for the AB-2 test are the p-values of the Arellano-Bond test that average aucovariance in residuals of order 2 is 0.
Lambda is the corresponding (conditional) convergence coefficient

Table 5.2a: Regional relative TFP levels by different estimation procedures

ln(y) 1968		LSDV		GMM-AB1		KIVIET	
Lazio	3.69	*Lombardia*	1.00	*Lombardia*	1.00	*Lombardia*	1.00
Liguria	3.67	*Lazio*	0.97	*Lazio*	0.99	*Lazio*	0.98
Lombardia	3.61	*Liguria*	0.95	*Friuli*	0.94	*Emilia Romagna*	0.95
Toscana	3.55	*Emilia Romagna*	0.94	*Emilia Romagna*	0.94	*Friuli*	0.95
Trentino	3.54	*Friuli*	0.92	*Veneto*	0.94	*Liguria*	0.95
Emilia Romagna	3.51	*Veneto*	0.90	*Liguria*	0.93	*Veneto*	0.92
Veneto	3.49	*Piemonte*	0.89	*Trentino*	0.89	*Piemonte*	0.90
Piemonte	3.47	*Toscana*	0.86	*Sardegna*	0.89	*Trentino*	0.88
Sardegna	3.45	*Trentino*	0.86	*Piemonte*	0.87	*Toscana*	0.86
Friuli	3.40	*Marche*	0.82	*Toscana*	0.86	*Abruzzo*	0.85
Campania	3.39	*Sardegna*	0.81	*Abruzzo*	0.85	*Marche*	0.85
Sicilia	3.38	*Abruzzo*	0.81	*Marche*	0.85	*Umbria*	0.84
Marche	3.36	*Umbria*	0.81	*Umbria*	0.84	*Sardegna*	0.83
Umbria	3.35	*Sicilia*	0.76	*Sicilia*	0.81	*Puglia*	0.78
Abruzzo	3.24	*Puglia*	0.75	*Puglia*	0.79	*Sicilia*	0.78
Puglia	3.23	*Campania*	0.73	*Campania*	0.77	*Campania*	0.75
Calabria	3.21	*Molise*	0.68	*Basilicata*	0.72	*Molise*	0.73
Basilicata	3.17	*Calabria*	0.65	*Molise*	0.70	*Calabria*	0.68
Molise	3.06	*Basilicata*	0.64	*Calabria*	0.68	*Basilicata*	0.67

Notes:

ln(y) 1968 is the logarithm of GDP per worker in 1968

LSDV includes the regional individual effects estimated using the LSDV estimator (95 observations)

GMM-AB1 includes the regional individual effects calculated using the GMM-AB1 estimator

KIVIET includes the regional individual effects calculated using the LSDV estimator with the KIVIET correction

Table 5.2b: Regional TFP ranks by different estimation procedures

Regions	Rank with LSDV	Rank with GMM-AB1	Rank with GMM-AB2	Rank with KIVIET
Abruzzo	12	11	9	10
Basilicata	19	17	18	19
Calabria	18	19	19	18
Campania	16	16	15	16
Emilia Romagna	4	4	6	3
Friuli	5	3	1	4
Lazio	2	2	2	2
Liguria	3	6	4	5
Lombardia	1	1	3	1
Marche	10	12	12	11
Molise	17	18	17	17
Piemonte	7	9	10	7
Puglia	15	15	16	14
Sardegna	11	8	11	13
Sicilia	14	14	14	15
Toscana	8	10	13	9
Trentino	9	7	7	8
Umbria	13	13	8	12
Veneto	6	5	5	6

Notes:
LSDV includes the rank of regional individual effects estimated using the LSDV estimator (95 observations)
GMM-AB1 includes the rank of regional individual effects calculated using the GMM-AB1 estimator
KIVIET includes the rank of regional individual effects calculated using the LSDV estimator with the KIVIET correction

Table 5.4: Estimation of the augmented Solow model (two subsamples)

Sample: Italian regions 1963-978 and 1978-93

Dependent Variable $ln(y_{i,t})$

	1	2	3	4
	time span=5	*time span=5*	*time span=3*	*time span=3*
	1963-1978	**1978-1993**	**1963-1981**	**1981-1993**
	LSDV	**LSDV**	**KIVIET**	**KIVIET**
Observations	*57*	*57*	*95*	*95*
$ln(y_{i,t-1})$	.480	.015	.760	.386
	(.141)	(.124)		
$ln(s_{i,t-1})$	.055	-.051	-.068	-.061
	(.049)	(.036)		
$ln(n_{i,t-1}+g+d)$	-.061	-.069	-.047	-.062
	(.052)	(.027)		
human capital	-.051	.006	-.30	.013
	(.052)	(.044)		
λ	0.15	0.84	0.09	0.32

Notes:

19 Italian regions included (Val d'Aosta excluded)

Standard errors in parentheses.

LSDV is the Least Squares with Dummy variables estimator.

KIVIET is the LSDV estimator with the Kiviet (1995) correction and only corrects the bias in the estimated parameters.

It does not produce alternative or corrected standard errors. This is why they are not shown among results.

Lambda is the corresponding (conditional) convergence coefficient

Table 5.5: Estimated Relative regional TFP levels 1963-78 and 1978-93

REGIONS	Relative TFP levels 1963-78	Relative TFP levels 1978-93	*Change of rank*
Piemonte	0.907	0.885	+1
Lombardia	1.000	1.000	+1
Trentino Alto Adige	0.925	0.849	-2
Veneto	0.891	0.882	+2
Friuli Venezia Giulia	0.926	0.892	-1
Liguria	0.996	0.952	-2
Emilia Romagna	0.926	0.932	+1
Toscana	0.904	0.858	0
Umbria	0.732	0.792	-1
Marche	0.814	0.800	0
Lazio	1.103	0.946	-2
Abruzzo	0.707	0.796	+3
Molise	0.523	0.721	+2
Campania	0.710	0.741	-2
Puglia	0.654	0.758	+1
Basilicata	0.553	0.644	-1
Calabria	0.561	0.666	-1
Sicilia	0.728	0.767	-1
Sardegna	0.787	0.797	0
Variance	0.027	0.010	

Notes:
The initial TFP level correspond to the TFP estimated using the sample 1963-1978, subsequent TFP level correspond to the sample 1978-1993.

APPENDIX V-B: FIGURES

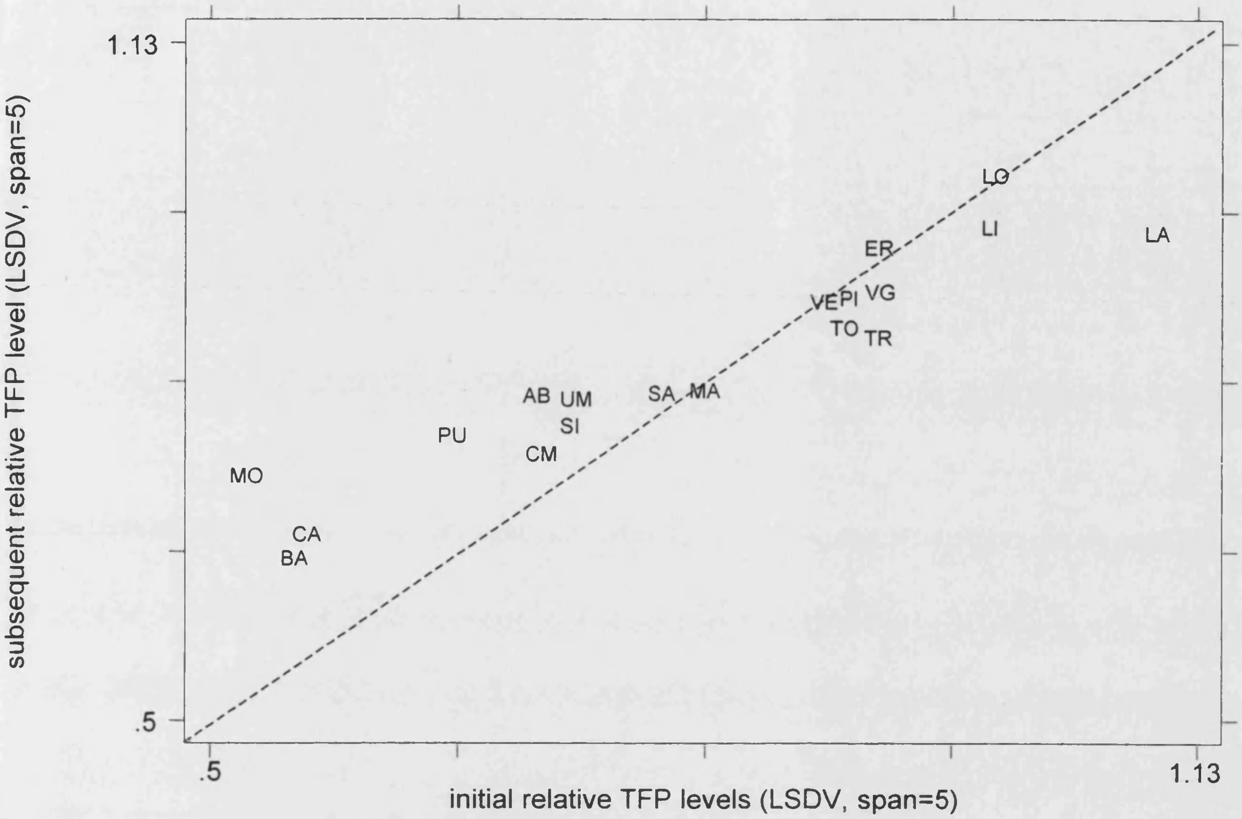

Figure 5.1: Productivity dynamics (LSDV)

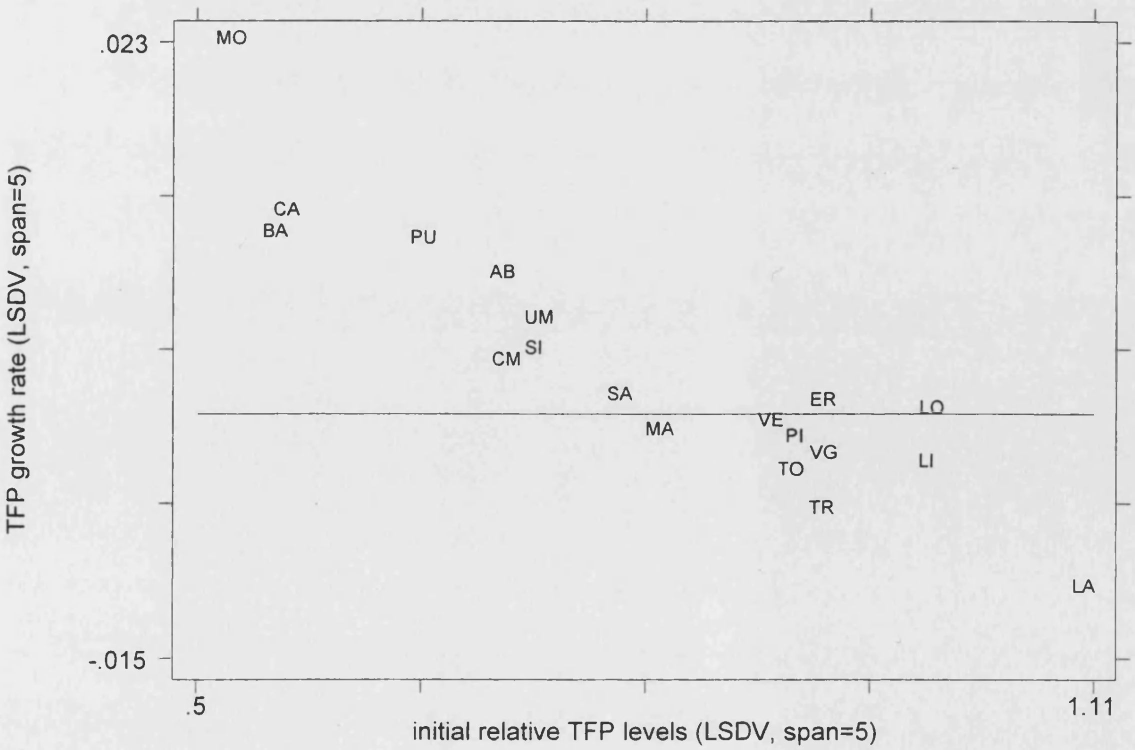

Figure 5.2: Productivity dynamics (LSDV), growth-initial level relationship

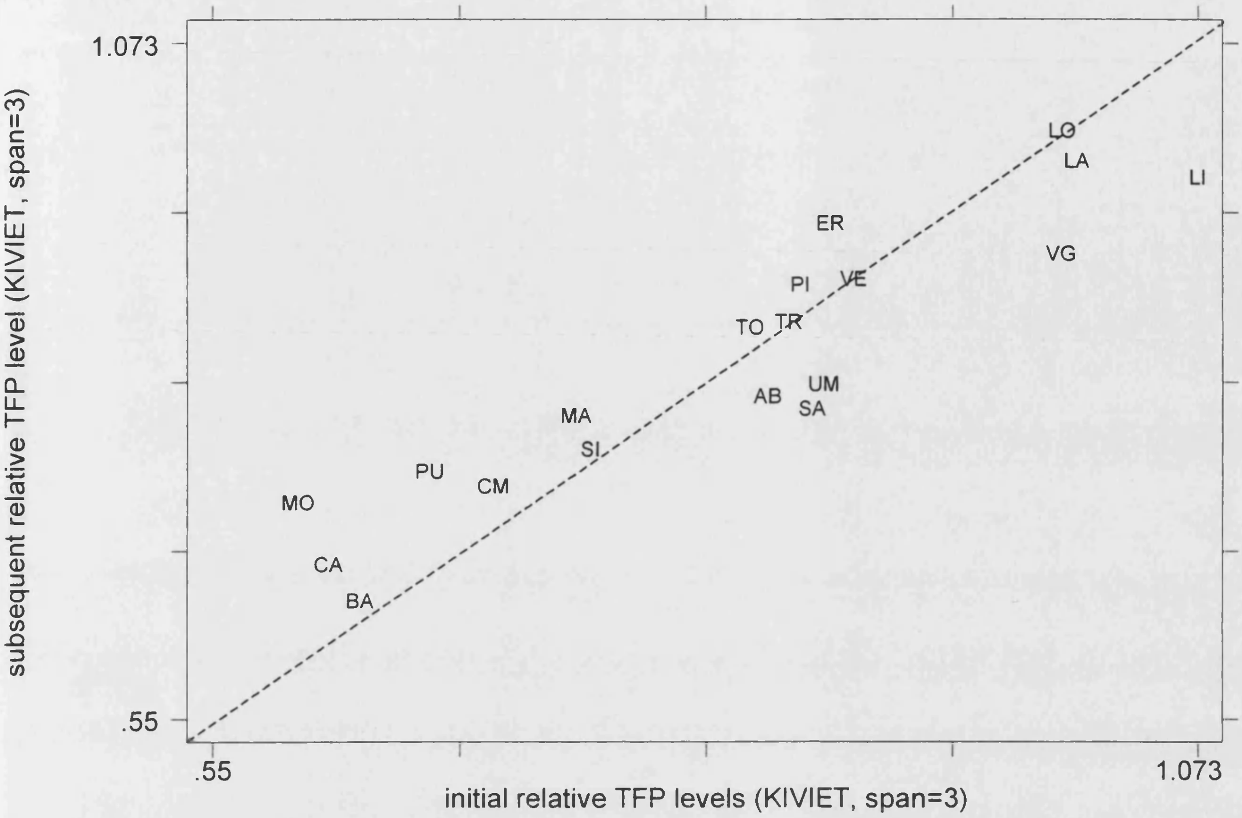

Figure 5.3: Productivity dynamics (KIVIET)

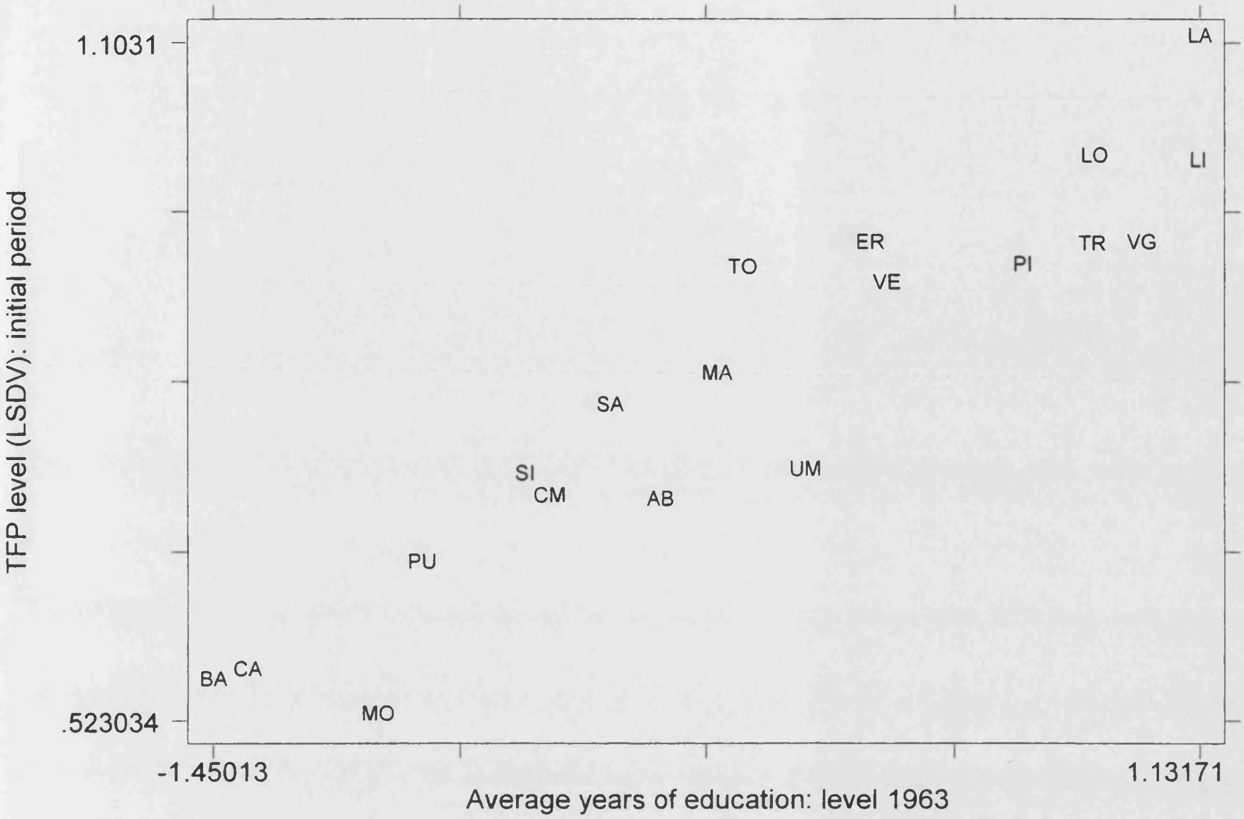

Figure 5.4: human capital and TFP (LSDV), initial period

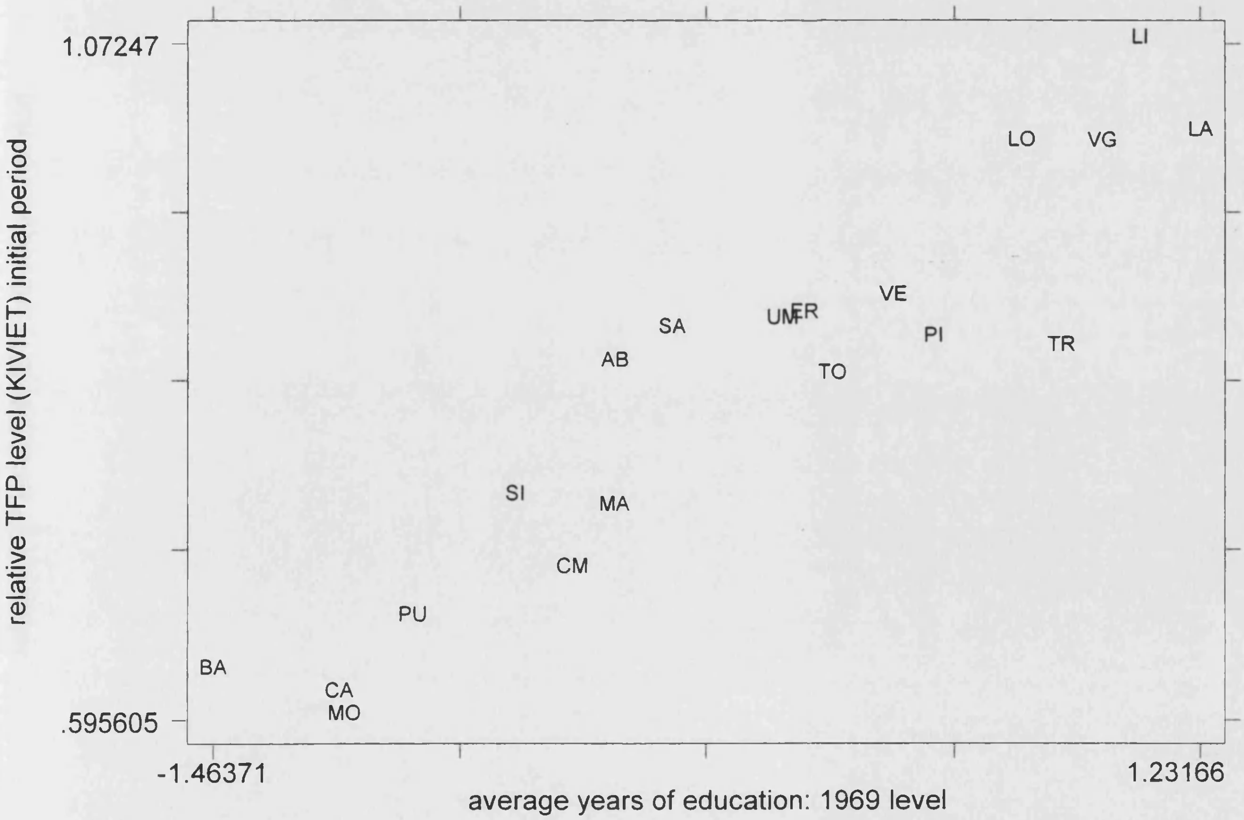

Figure 5.5: human capital and TFP (LSDV), final period

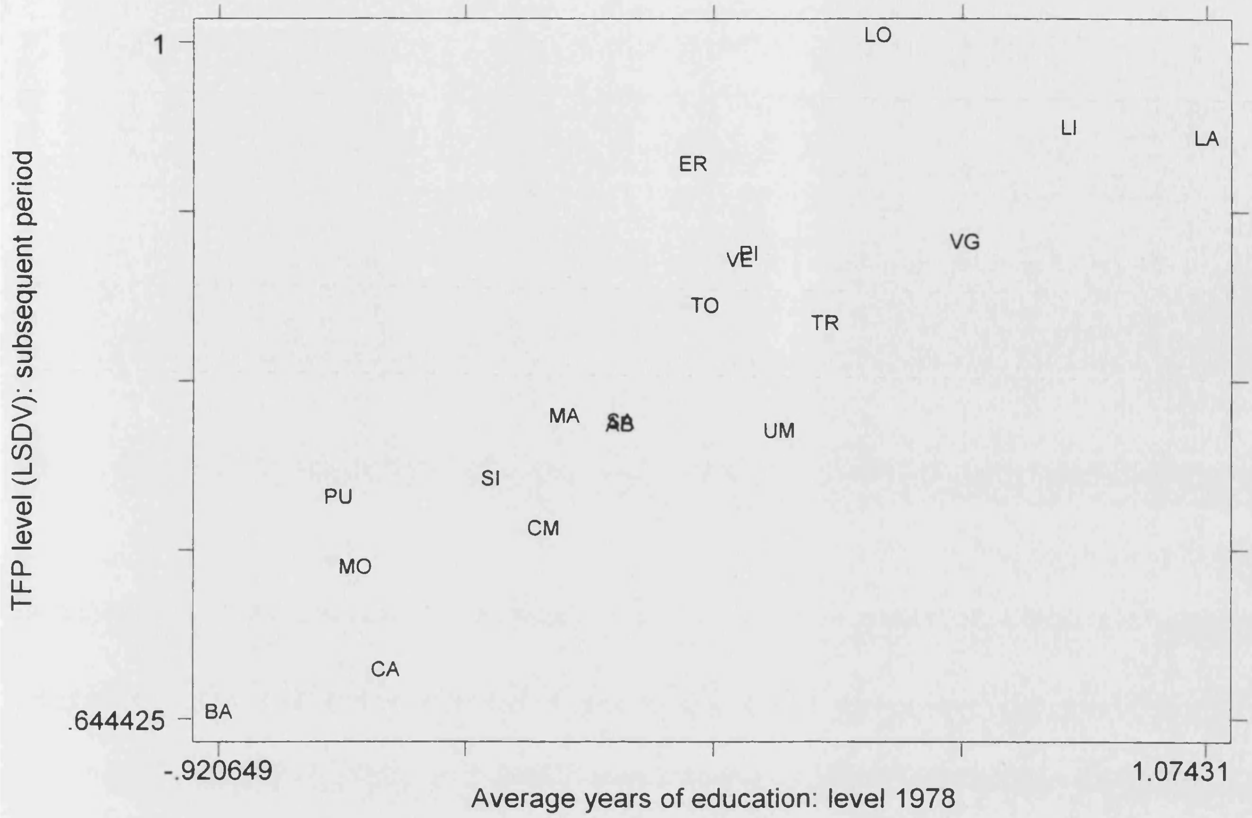

Figure 5.6: human capital and TFP (KIVIET), initial period

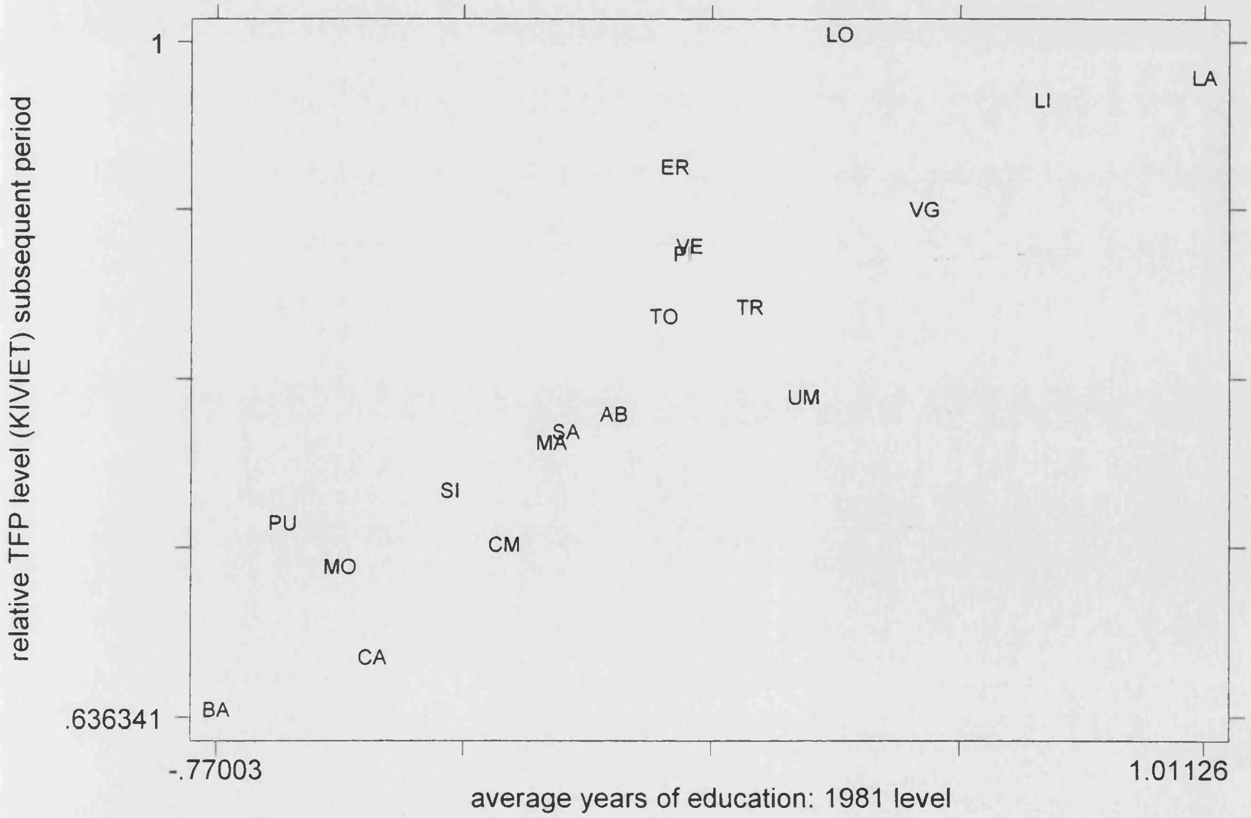

Figure 5.7: human capital and TFP (KIVIET), final period

CONCLUDING REMARKS

This study examines different issues concerning the estimation of the convergence equation. First of all, we underline a few problems in the econometric methodologies proposed so far for estimating the convergence parameter and propose an alternative approach. In fact, despite the abundance of different econometric techniques introduced in the empirical literature on convergence, it is usually assumed that shocks are uncorrelated across countries. This is surely unlikely for most of the data sets considered and we investigate a possibility so far ignored, namely the annual panel estimator where shocks are allowed to be correlated. Our analysis is restricted to the case of more time periods than countries (T>N) which allows us to estimate by Maximum Likelihood with an unrestricted variance-covariance matrix of cross-country shocks. The thesis examines by Monte Carlo the robustness against certain possible mis-specifications, namely measurement error and heterogeneity of the convergence coefficients. Our analysis indicates that Maximum Likelihood estimators are robust to plausible measurement error and variation of convergence rates across countries and are more efficient than conventional estimators for plausible values of cross-country error correlation. We consider in detail the relationship between the distribution of the Maximum Likelihood estimator and the initial conditions. Applying our findings to a panel of OECD countries for the post-war period, we show that Maximum Likelihood is effectively unbiased and more efficient than conventional panel estimators or OLS on a cross-section of countries. We argue that the reason this estimator is so well behaved is that many OECD countries were far from their equilibrium values at the beginning of the period.

Secondly, in this study we investigate the connection between growth and human capital in a convergence regression framework. The relationship between human capital and development has always been considered as a close one. Despite the importance placed on this relationship by both the theoretical growth literature and development strategists, empirical evidence on aggregate returns to schooling is weak: econometric analysis that uses international data sets usually find that human capital is insignificantly or even negatively correlated with the process of development. This study estimates the social returns to education at regional level for two different Southern European countries: Italy and Spain. In the case of Italian regions, we introduce a new data set on human capital. We use measures of the stock of regional human capital and estimate the social returns to schooling by including measures of average primary, secondary, tertiary years of education and a measure of total average years of schooling. It is well known that convergence in the South slowed after about 1975. We deal with this problem by two different methods. First, we allow the convergence rate to slow after 1975; and then we allow the South to converge to its own, potentially different level. We find marginally significant returns to total education by both methods. When we allow the parameters to differ between regions, however, we find that increased education seems to contribute to growth only in the South. Dividing total schooling into its three constituent parts, we find that primary education in the South seems to be important. We also find weak evidence of positive results for secondary education in the North. Thus, these results suggest that Italian growth mainly benefited from the elimination of illiteracy in the South, during the '60s.

Differences in the characteristics of the two data sets do not permit us to exactly replicate for Spain the analysis conducted for Italian regions. Nonetheless, we are still able to find comparable results. Overall, Spanish regional evidence is similar to that found for Italian regions. In particular, thanks to their sectoral disaggregation, Spanish data enables us to investigate more thoroughly if excluding the human capital allocated in the public sector influences the analysis of returns to schooling. Some results seem to stress the importance of allocation of human capital in the public sector in the analysis of returns to education. In particular, when we divide the total stock of human capital into components corresponding to primary secondary and tertiary education we find that only primary school seems to have an unambiguous positive role for growth, but when we exclude the public sector from our human capital variables, the tertiary education coefficient becomes positive and marginally significant.

However, the analysis on clubs does not confirm all these results and suggests a different and possibly more consistent picture. When we allow for some parameter heterogeneity and analyse separately the effect of education in two clubs of poor and rich Spanish regions we observe that the coefficients on human capital variables do not change significantly when we take the public sector into account. Thus, this relationship needs to be further investigated. In future work, it would be interesting to extend our analysis on the relationships between sectoral allocation of human capital and growth using more disaggregated data sets. Moreover, we find that returns to education are different in the two areas. In particular, human capital computed as average years of education is positive and significant only in the more developed regions club. Further, when we divide human capital into the three different levels of education we find significant differences in the two clubs. Among poor regions only primary schooling seems to positively affect growth rates: as in the Italian case, our estimates indicate high returns to basic education in the poorest areas of the country. Conversely, for rich regions we find a positive result only for secondary schooling. Again, these results are similar to those obtained for Italian regions, even if the positive coefficient on secondary schooling in Italy is only marginally significant.

Thus, overall these results seem to confirm one standard result on the effects of education on earnings in microeconometric literature which, however, has hitherto been difficult to confirm and even to properly investigate with macroeconomic data. That is, we find high returns to primary education in low developed, disadvantaged areas. However, we also find evidence that suggests the existence of a relationship between the level of development of an economy and returns to different levels of education: if primary schooling seems to contribute to growth in poorly developed areas, skilled human capital has a stronger growth-enhancing effect in more developed economies. In other words, our evidence emphasizes that there is likely to be heterogeneity in rates of returns to education across economies since the effect of schooling in growth regressions is influenced by the level of development of an economy. Failing to take this heterogeneity into account in empirical analysis may produce misleading results.

Finally we propose a fixed-effect panel methodology based on Islam (2000) to assess the existence of technology convergence across the Italian regions between 1963 and 1993. Our results find strong support for both the presence of TFP heterogeneity across Italian regions and for the hypothesis that TFP convergence has been a key factor in the process of aggregate regional convergence observed in Italy up to the mid-seventies. However, this period of TFP convergence has not generated a significant, persistent decrease in the degree of cross-region inequality in per capita income. Our human capital measure has been found to be highly positively correlated with TFP levels. This evidence confirms one of the hypothesis of the Nelson and Phelps approach, namely that human capital is the main determinant of technological catch-up. Our results are robust to the use of different estimation procedure such as simple LSDV, Kiviet-corrected LSDV, and GMM à la Arellano and Bond (1991). To the best of our knowledge, this is the first time that evidence on TFP convergence across Italian regions has been produced in a context in which the traditional Solovian-type of convergence is simultaneously taken into account.

REFERENCES

Abramovitz, M. 1986. "Catching Up, Forging Ahead, and Falling Behind." *Journal of Economic History* 46: 385-408.

Adam, C. S. 1998. "Implementing Small-Sample Bias Corrections in Dynamic Panel Data Estimators Using Stata." Mimeo, University of Oxford, Oxford.

Aghion, P., and Howitt, P. 1992. "A Model of Growth Through Creative Destruction." *Econometrica* 60: 323-352.

Aghion, P., and Howitt, P. 1996. "Research and Development in the Growth Process." *Journal of Economic Growth* 1: 49-73.

Aghion, P., and Howitt, P. 1998. *Endogenous Growth Theory.* Cambridge: MIT Press.

Aghion, P., Howitt, P., and Mayer-Foulkes D. 2003. "The Effect of Financial Development on Convergence: Theory and Evidence." Mimeo.

Aiello, B., and Scoppa, V. 2000. "Uneven Regional Development in Italy: Explaining Differences in Productivity Levels." *Giornale Degli Economisti e Annali di Economia* 59: 270-98

Aiyar, S., and Feyrer, J. 2002. "A Contribution to the Empirics of Total Factor Productivity." Mimeo, IMF, Washington.

Amemiya, T. 1967. "A Note on the Estimation of Balestra-Nerlove Models." Institute for Mathematical Studies in Social Sciences Technical Report No. 4. Stanford University, Stanford.

Arellano M., and Bond S., 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* 58: 277-97

Arrow, K. J. 1961. "The Economic Implication of Learning by Doing." *Review of Economic Studies* 29: 155-73.

Attanasio, O., and Padoa Schioppa, F. 1989. "Regional Inequalities, Migration and Mismatch in Italy, 1960-86." In F. Padoa Schioppa, (ed.), *The Economic of Mismatch.* London: CEPR.

Azariadis, C., and Drazen, A. 1990. "Threshold Externalities in Economic Development." *Quarterly Journal of Economics* 105: 501-526.

Baier S. L., Dwyer G. P., "Tamura R. (2002) How Important are Capital and Total Factor Productivity for Economic Growth?." Working Paper, Federal Reserve Bank of Atlanta.

Baltagi, B. H. 1995. *Econometric Analysis of Panel Data*. Chichester: John Wiley and Sons.

Barro, R. J. 1991. "Economic Growth in a Cross-Section of Countries." *Quarterly Journal of Economics* 106: 407-43.

Barro, R. J. 1997. *Determinants of Economic Growth: a Cross-Country Empirical Analysis*. Lionel Robbins Lecture. Cambridge: MIT Press.

Barro, R. J., and Sala-i-Martin, X. 2004. *Economic Growth*. New York: McGraw-Hill. First edition 1995.

Barro, R.J., and Sala-i-Martin, X. 1991. "Convergence Across States and Regions." *Brookings Paper of Economic Activity* 0: 107-182.

Baumol, W. J. 1986. "Productivity Growth, Convergence and Welfare: What the Long-Run Data Show." *American Economic Review* 76: 1072-85.

Becker, G., Murphy, K., and Tamura, R. 1990. "Human Capital, Fertility and Economic Growth." *Journal of Political Economy* 98: S12-S37.

Becker, S. G. 1976. *The Economic Approach to Human Behaviour*. Chicago: The University of Chicago Press.

Benabou, R. 1996. "Heterogeneity, Stratification, and Growth: Macroeconomic Implications of Community Structure and School Finance." *American Economic Review* 86: 584-609.

Benhabib, J., and Spiegel, M.M. 1994. "The role of human capital in economic development. Evidence from aggregate cross-country data." *Journal of Monetary Economics* 34: 143-173.

Benhabib, J., and Spiegel, M.M. 2002. "Human Capital and Technology Diffusion." forthcoming in *Handbook of Economic Growth*.

Bernard, A. B., and Durlauf, S. N. 1995. "Convergence in International Output." *Journal of Applied Econometrics* 10: 97-108.

Bernard, A. B., and Durlauf, S. N. 1996. "Interpreting Tests of the Convergence Hypothesis." *Journal of Econometrics* 71: 161-73.

Bernard, A. B., and Jones, C. 1996. "Productivity Across Industries and Countries: Time Series Theory and Evidence." *The Review of Economic Statistics* 78: 135-46.

Bernard, A. B., and Jones, C. 1996. "Technology and Convergence." *Economic Journal* 106: 1037-1044.

Bianchi, C., and Menegatti, M. 1997. "Differenziali Regionali di Produttivita' e Crescita Economica: un Riesame della Convergenza in Italia nel Periodo 1970-94." *Studi Economici* 52: 15-42.

Bils, M., and Klenow, P. J. 1995. "Does Human Capital Drive Growth or The Other Way Around?" Mimeo. Department of Economics. Rochester University.

Blanchard, O. J. 1991. In Comments and Discussion on "Convergence Across States and Regions." *Brookings Paper of Economic Activity* 1: 159-174.

Blaug, M., Layard, P. R. G., and Woodhall, M. 1969. *The Causes of Graduate Unemployment in India*. London: Allen Lane The Penguin Press.

Blundell R., and Bond S. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87: 115-143.

Boldrin M., and Canova F. 2001. "Inequality and convergence: reconsidering European regional policies." *Economic Policy* 32: 205-245.

Boltho, A., Carlin, W., and Scaramozzino, P. 1997. "Will East Germany Become a New Mezzogiorno?" *Journal of Comparative Economics* 24: 241-264.

Bond, S., Hoeffler , A., and Temple, J. 2001. "GMM Estimation of Empirical Growth Models." Mimeo, Institute for Fiscal Studies, London.

Brunello, G. Comi, S., and Lucifora, C. 1999. "Returns to Education in Italy: a Review of the Literature". in *Returns to Human Capital in Europe. A literature Review*, eds. Asplund R. and P Telhado Pereira, ETLA.

Cannon E. 2000. "Human Capital: levels versus growth effects." *Oxford Economic Papers* 52: 670-676.

Canova, F., and Marcet, A. 1995. "The Poor Stay Poor: Non-Convergence Across Countries and Regions." CEPR Discussion Paper No. 1265. London.

Caselli, F., Esquivel, G., and Lefort, F. 1996. "Reopening the Convergence Debate: a New Look at Cross Country Growth Empirics." *Journal of Economic Growth* 1: 363-89.

Cellini, R., and Scorcu, A. 1997. "How Many Italies? What Data Show About Growth and Convergence Across Italian Regions, 1970-91." *Rassegna dei Lavori dell'ISCO* 14: 93-124.

Chamberlain, G. 1982. "Multivariate Regression Models for Panel Data, Journal of Econometrics 18: 5-46.

Coe, D. T., and Helpman E. 1995. "International R&D Spillovers." *European Economic Review*,39: 363-390.

Coe, D. T., Hoffmaister A. W., and Helpman E. 1997, "North-South R&D Spillovers." *The Economic Journal* 107: 134-149.

Comin, D. Hobijn, B. 2003 "Cross-Country Technology Adoption: Making the Theories Face the Facts." *Federal Reserve Bank of New York Staff Reports* No. 169.

CRENoS, Centro Ricerche Nord-Sud. 2004. *XI Rapporto CRENoS*. Università di Cagliari, Cagliari.

De la Fuente, A. 1995. "The Empirics of Growth and Convergence: a Selective Review." CEPR Discussion Paper No. 1275. London.

De la Fuente, A. 1997. "The empirics of growth and convergence." *Journal of Economic Dynamics and Control*, 21, 23-77

De la Fuente, A. 2001. "Regional Convergence in Spain: 1965-95" EEE 120, Fundacion de Estudios de Economia Aplicada.

De la Fuente, A. 2002. "On the Sources of Convergence: a Close Look at the Spanish Regions." *European Economic Review* 46:569-599.

De la Fuente, A., da Rocha, J. M. 1996. "Capital humano y crescimiento: un panorama de la evidencia empirica y algunos resultados para la OCDE" *Moneda y Credito* 203: 43-86.

De la Fuente, A., Vives, X. 1995. "Infrastructure and Education as instruments of regional Policy: Evidence from Spain". *Economic Policy* 20: 13-51

Di Liberto, A. 1994. "Convergence Across Italian regions." Nota di Lavoro Fondazione ENI Enrico Mattei No. 68/94. Milano.

Di Liberto, A. 2001. "Stock di Capitale Umano e Crescita delle Regioni Italiane: un Approccio Panel." *Politica Economica* Il Mulino, 17: 159-184.

Di Liberto, A., and Symons, J. 2003. "Some Econometric Issues in Convergence Regressions." *The Manchester School*, 71: 293-307.

Dolado, J. J., Gonzalez-Paramo, J. M., Roldan, J. M. 1994. "Convergencia Economica entre las Provincias Espanolas: Evidenzia Empirica." *Moneda y Credito* 198: 81-110.

Dowrick, S., and Nguyen, D. T. 1989. "OECD Comparative Economic Growth 1950-85: Catch-up and Convergence". *American Economic Review*, 79: 1010-1030.

Dowrick, S., and Rogers, M. 2002. "Classical and Technological Convergence: Beyond the Solow-Swan Growth Model." *Oxford Economic Papers*, 54: 369-385.

Durlauf, S. N. 1996. "On the Convergence and Divergence of Growth Rates." *Economic Journal* 106: 1016-1018.

Durlauf, S. N., and Quah, D. T. 1998. "The Empirics of Economic Growth." In J. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*. Amsterdam: North Holland.

Easterly, W., and Levine, R. 2001. "It's Not Factor Accumulation: Stylized Facts and Growth Models, *World Bank Economic Review* 15: 177-219.

Evans, G.B.A., and Savin, N.E. 1983. "Testing for Unit Roots: 2, *Econometrica* 52, 1241-69.

Evans, P., and Karras, G. 1996. "Convergence Revisited." *Journal of Monetary Economics* 37: 249-265.

Fagerberg J., and Verspagen B. (1996), Heading for divergence. Regional growth in Europe riconsidered, *Journal of Common Market Studies*, 34, 431-48.

Friedman, M. 1992. "Do Old Fallacies Ever Die?" *Journal of Economic Literature* 30: 2129-32

Funkhouser, E. 1998. "Changes in the Returns to Education in Costa Rica." *Journal of Development Economics* 57: 289-317.

Cameron, G., Proudman, J., and Redding, S. 1999. "Productivity, Growth, Convergence and Trade in a Panel of Manufacturing Industries." CEP Discussion Papers No. 428, Centre for Economic Performance, LSE

Galor, O. 1996. "Convergence? Inferences from Theoretical Models." *The Economic Journal* 106: 1045-1055.

Geroski, P., Lazarova, S., Urga, G., and Walters, C. 2003. "Are differences in firm sizes transitory or permanent?" *Journal of Applied Econometrics* 18: 47-59.

Golini, A., Clucci, L., and Caselli, G. 1978. *Ricostruzione della Popolazione residente per sesso, età e regione.* ISTAT, Roma.

Gollin, D. 2002. "Getting Income Shares Right." *Journal of Political Economy* 110: 458-74.

Goria, A., and Ichino, A. 1994. "Migration and Convergence among Italian Regions." Working Paper FEEM No. 51/94. Fondazione Eni Enrico Mattei, Milano.

Gorostiaga, A. 1999. "Como afectan el capital publico y el capital humano al crescimiento? un analisis para las regiones espanolas en el marco neoclasico". *Investigationes Economicas* 23(1): 95-114.

Graziani, A. 1978. "The Mezzogiorno in the Italian Economy." *Cambridge Journal of Economics* 2: 355-72.

Griliches, Z. 1997. "Education, Human Capital and Growth: a Personal Perspective." *Journal of Labour Economics* 15: S330-S344.

Griliches, Z., and Regev, H. 1995. "Firm Productivity in Israeli Industry 1979-1988." *Journal of Econometrics* 65: 175-203.

Grossman, G., and Helpman, E. 1991. "Quality Ladders and the Theory of Growth." *Review of Economic Studies* 58: 43-61.

Grubb, D., and Symons, J. 1987. "Bias in Regressions with a Lagged Dependent

Variable." *Econometric Theory* 3: 371-86.

Hahn, F. H., and Matthews, R. C. O. 1964. "The Theory of Economic Growth: a Survey." *Economic Journal* 74: 779-901.

Hall, R. E. Jones (1999). "Why do Some Countries Produce so Much More Output per Worker than Others?" *Quarterly Journal of Economics* 114:83-116.

Hall, S., and St. Aubin, M. 1995. "Using the Kalman Filter to test for Convergence: a Comparison to Other Methods Using Artificial Data." manuscript, Centre for Economic Forecasting, London Business School, London.

Hargraves, D (1994), *The Mosaic of Learning*, Demos, London

Harrod, R. F. 1939. "An Essay in Dynamic Theory." *Economic Journal* 49: 14-33.

Howitt P. 1999. "Steady Endogenous Growth with Population and R&D Inputs Growing." *Journal of Political Economy* 107: 715-730.

Hsiao C. 1986, *Analysis of Panel Data*, Cambridge University Press.

Islam, N. 1995. "Growth Empirics: a Panel data Approach." *Quarterly Journal of Economics* 110: 1127-70.

Islam, N. 1998a. "Growth Empirics: a Panel Data Approach - a Reply." *Quarterly Journal of Economics* 113: 325-29.

Islam, N. 1998b. "Convergence: Variation in Concept and Empirical Results" Department of Economics, Emory University.

Islam, N. 1998c. "International Comparisons of Total Factor Productivity: a Review" Department of Economics, Emory University.

Islam, N. 2000. "Productivity Dynamics in a Large Sample of Countries: a Panel Study" Department of Economics, Emory University.

Islam, N. 2003. "What Have we Learnt from the Convergence Debate?." *Journal of Economic Survey* 17: 309-62.

ISTAT. *Annuario Statistico dell'Istruzione Italiana*. ISTAT, Roma, various years.

ISTAT. *Censimento della Popolazione*. ISTAT, Roma, various years

Jones, C. 1995. "R&D-Based Models of Economic Growth." *Journal of Political Economy* 103: 759-784.

Judson, R., and Owen, A. 1996. "Estimating DPD models: a Practical Guide for Macroeconomists." Federal Reserve Board of Governors Mimeo.

Kaldor, N. 1961. "Capital Accumulation and Economic Growth." In F. A. Lutz and D. C. Hague (eds.), *The Theory of Capital*. London: Macmillan.

Kaldor, N. 1970. "The Case for Regional Policy." *Scottish Journal of Political Economy* 17: 337-348.

King, R. G., and Rebelo, S. T. 1993. "Transitional Dynamics and Economic Growth in the Neoclassical Model." *American Economic Review* 83: 908-930.

Kiviet, J. 1995. "On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamicc Panel Data Models." Journal of Econometrics, 68: pp. 53-78.

Klenow, P. J., and Rodriguez-Clare, A. 1997a. "The Neoclassical Revival in Growth Economics: Has it Gone too Far?". In Ben S. Bernanke and Julio J Rotemberg, eds., *NBER Macroeconomics Annual 1997*, MIT Press, Cambridge.

Klenow, P. J., and Rodriguez-Clare, A. 1997b. "Economic Growth: A Review Essay". *Journal of Monetary Economics*, 40: 597-617.

Knight, M., Loayza, N., and Villaneuva, D. 1993. "Testing the Neoclassical Theory of Economic Growth." IMF Staff Papers No. 40. Washington, DC.

Krueger, A. B., and Lindahl, M. 2001. "Education for Growth: Why and for Whom?" *Journal of Economic Literature* 39: 1101-1136.

Kyriacou, G. A. 1991. "Level and Growth Effects of Human Capital: A Cross-Country Study of the Convergence Hypothesis." Economic Resaerch Reports No. 91-26. New York University, New York.

Lee, K., Pesaran, H. M., and Smith, R. P. 1997. "Growth and Convergence in a Multi-Country Empirical Stochastic Solow Model." *Journal of Applied Econometrics* 12: 357-92.

Lee, K., Pesaran, H.M., and Smith, R. 1998. "Growth Empirics: a Panel Data Approach - a Comment." *Quarterly Journal of Economics* 113: 319-23.

Levin, A., and Lin, C. F. 1993. "Unit Root Tests in Panel Data: New Results." Working Paper No. 93-56. University of California, San Diego.

Lodde, S. 1995. "Allocation of Talent and Growth in the Italian Regions." Working Paper CRENOS No. 95/3. Universita' di Cagliari, Cagliari.

Lodde, S. 1999. "Human Capital and Growth in the European Regions. Does Allocation Matter?" In J. Adams and F. Pigliaru (eds.), *Economic Growth and Change. National and Regional Patterns of Convergence and Divergence*. Cheltenham: Edward Elgar.

Lopez-Bazo E., and Moreno R. 2003. "Rendimiento Social del Capital Humano." Mimeo Universidad de Barcelona.

Lucas, R. E. 1988. "On the mechanics of economic Development." *Journal of Monetary Economics* 22: 3-42.

Lucas, R. E. 1993. "Making a miracle." *Econometrica* 61: 251-72.

Lucas, R. E. 2000. "Some macroeconomics for the 21st century." *Journal of Economic Perspectives* 14: 159-168.

Mankiw, N.G., Romer, D., and Weil, D. N. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107: 407-437.

Marrocu E., Paci R., and Pala R. (2001), Estimation of Total Factor Productivity for Regions and Sectors in Italy: A Panel Cointegration Approach, *Rivista Internazionale di Scienze Economiche e Commerciali*, 48, 533-558.

Mas, M., Pérez, F., Uriel, E., and Serrano, L. (various years): *Capital humano, series históricas*, Fundació Bancaixa, Valencia.

Mauro, L., and Podrecca, E. 1994. "The case of Italian Regions: Convergence or Dualism?" *Economic Notes* 24: 447-472.

Mincer, J., 1974. *Schooling, Earnings and Experience*. New York: Columbia University Press.

Mulligan, C. B., and Sala-I-Martin, X. 2000. "Measuring Aggregate Human Capital.", Journal of Economic Growth 5: 215-252.

Murphy, K. M., Shleifer, A., and Vishny, R. W. 1991. "The allocation of Talent: Implications for Growth." *Quarterly Journal of Economics* 106: 503-530.

Nelson, R. R., and Phelps, E. S. 1966. "Investments in Humans, Technological Diffusion, and Economic Growth." *American Economic Review* 56: 69-75.

Nickell, S. 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49: 1399-416.

OECD. 2001. *Education at a Glance*.

Paci, R., and Pigliaru, F. 1995. "Differenziali di Crescita tra le Regioni Italiane: un'analisi cross-section." *Rivista di Scienze Economiche e Commerciali* 85: 3-34.

Paci, R., and Pigliaru, F. 2002. Technological diffusion, spatial spillovers and regional convergence in Europe, in: J.R. Cuadrado-Roura and M. Parellada (eds), *Regional convergence in the European Union*, Berlin: Springer, 273-292.

Padula, M., and Pistaferri, L. 2001. "Education, Employment and wage risk." Working Paper CSEF, Salerno.

Palafox, J., Mora, J. G., Perez, F. 1995. *Capital Humano, Educacion y Empleo*.

Parente, S. L, and Prescott, E. C. 1994. "Barriers to Technology Adoption and Development." *Journal of Political Economy* 102: 298-321. Fundaciò Bancaixa and IVIE, Valencia.

Parente, S. L., and Prescott, E. C. 2000. *Barrier to Riches*. Cambridge, The MIT Press.

Pedroni, P. 1997. "On the Role of Human Capital in Growth Models: Evidence from a Nonstationary Panel of Developing Countries." Mimeo, Indiana University.

Pesaran, H. M., and Smith, R. 1995. "Estimating Long-run Relationships from Dynamics Heterogeneous Panels." *Journal of Econometrics* 68: 79-113.

Pigliaru, F. 2003. Detecting technological catch-up in economic convergence, *Metroeconomica*, 54, 161-178

Pritchett, L. 1996. "Where Has All the Education Gone?" World Bank Policy Research Working Paper No. 1581. Washington DC.

Psacharopoulos, G. 1985. *Education for Development: an Analysis of Investment Choices*. Oxford: Oxford University Press.

Psacharopoulos, G. 1994. "Returns to Investments in Education: a Global Update". *World Development*, 22:1325-43.

Pugno, M. 1998. "Rendita e Questione Meridionale." Mimeo, Università di Trento.

Quadrella, S., and Tullio, G. 1998. "Economic Convergence of Italian Regions: the Role of Organised Crime and of Public Expenditure." Mimeo, Università di Brescia.

Quah, D. T. 1993. "Galton's Fallacy and Tests of the Convergence Hypothesis." *Scandinavian Journal of Economics* 4: 427-443.

Quah, D. T. 1995. "Empirics for Economic Growth and Convergence." *European Economic Review* 40: 1353-75.

Quah, D. T. 1996. "Twin Peaks: Growth and Convergence in models of Distribution Dynamics." *The Economic Journal* 106: 1045-1055.

Quah, D. T. 1997. "Empirics for Growth and Distribution: Stratification, Polarisation and Convergence Clubs." *Journal of Economic Growth* 2: 27-59.

Quah, D. T. 1999. "Ideas Determining Convergence Clubs." Mimeo, LSE Economics Department.

Rebelo, S. 1991. "Long-Run Policy Analysis and Long-Run Growth." *Journal of Political Economy* 99: 500-521.

Robertson, D., and Symons, J. 1992. "Some Strange Properties of Panel Data Estimators." *Journal of Applied Econometrics* 7: 175-89.

Robertson, D., and Symons, J. 2000. "Factor Residuals and SUR Regressions, Estimating Panels Allowing for Cross-Sectional Correlation." , Mimeo.

Romer, D. 2001. *Advanced Macroeconomics*. New York: McGraw Hill.

Romer, P. M. 1986. "Increasing Returns and Long Run Growth." *Journal of Political Economy*, 94: 1002-1037.

Romer, P. M. 1990a. "Human Capital and Growth." In Carnegie-Rochester Conference Series on Public Policy 32: 251-286. Amsterdam: North Holland.

Romer, P. M. 1990b. "Endogenous Technological Change." *Journal of Political Economy* 98: S71-S102.

Romer, P. M. Rivera Batiz L. A. 1991. " Economic Integration and Endogenous Growth." *Quarterly Journal of Economics* 106: 531-555

Rutter, M., and Smith, D. 1995. *Psychological Disorders in Young People: Time Trends and their Causes.* Wiley, Chichester.

Sakellaris, P., and Spilimbergo, A. 1999. "Business Cycles and Investment in Human Capital: International Evidence on Higher Education." SSRN Electronic Library (http://papers.ssrn.com/paper.taf?abstract_id=188048).

Sala-i-Martin, X. 1996. "The Classical Approach to Convergence Analysis." *The Economic Journal* 106: 1019-1036.

Schultz, T. W. 1962. "Reflection on Investment in Man." *Journal of Political Economy* 70: S1-S8.

Segerstrom P. S. 1998. "Endogenous Growth without Scale Effects." *American Economic Review* 88: 1290-1310.

Serrano Martinez, L. 1996. "Indicatores del Capital Humano y Productividad". *Revista de Economia Aplicada* 11: 177-190.

Serrano Martinez, L. 1997. "Productividad y Capital Humano en la Economia Espanola". *Moneda y Credito* 205: 79-101.

Serrano Martinez, L. 1999. "Capital Humano, Estrucrura Sectorial y Crescimiento en la Regiones Espanolas" *Investigaciones economicas* 23(2): 225-249.

Sestito, P. 1991. "Sviluppo del Mezzogiorno e Capitale Umano." *Economia e Lavoro* 4: 3-13.

Shioji, E. 1997a. "Convergence in Panel Data: Evidence from the Skipping Estimation." Economic Working Paper No.235. Universitat Pompeu Fabra, Barcelona.

Shioji, E. 1997b. "It's still 2%: Evidence on Convergence from 116 Years of the US States Panel Data." Economic Working Paper No.236. Universitat Pompeu Fabra, Barcelona.

Shumpeter, J. A. 1942. *Capitalism, Socialism and Democracy.* New York: Harper.

Solow, R. M. 1956. "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics* 70: 65-94.

Solow, R. M. 1970. *Growth Theory: an Exposition.* London: Cambridge University Press.

Solow, R. M. 1994. *Lezioni sulla Teoria della Crescita Endogena.* Roma: La Nuova Italia Scientifica.

Spence, M. 1974. *Market Signalling.* Cambridge, Mass.: Harvard University Press.

Swan, T. W. 1956. "Economic Growth and Capital Accumulation." *Economic Record* 32: 334-361.

Temple, J. 1999a. "The New Growth Evidence." *Journal of Economic Literature* 37: 112-156.

Temple, J. 1999b. "A Positive Effect of Human Capital on Growth." *Economic Letters* 65: 131-134.

Temple, J. 2001. "Growth Effects of Education and Social Capital in the OECD Countries." Mimeo, University of Bristol.

Uzawa, H. 1965. "Optimal Technical Change in an aggregate model of Economic Growth." *International Economic Review* 6: 18-31.

Vandenbussche, J. Aghion, P., and Meghir, C. 2003. "Distance to Technological Frontier and Composition of Human Capital." Mimeo, UCL, London.

Wolff, E. N., and Gittleman, M. 1993. "The role of Education in Productivity Convergence: Does Higher Education Matter?." In Szirmai A., Van Ark B., Pilat D. (eds.), *Explaining Economic Growth*, Elsevier.

World Bank. 1991. *World Development Report.* World Bank, Washington DC.

Young, A. 1928. "Increasing Returns and Economic Progress." *Economic Journal* 38: 527-42.

Young, A. 1991. "Learning by Doing and the Dynamic Effects of International Trade." *Quarterly Journal of Economics* 106: 369-406.

Young, A. 1994. "Lessons from the East Asian NIC's. A Contrarian View." *European Economic Reviw* 38: 964-73.

Young, A. 1995. "Confronting the Statistical Realities of the East Asian Growth Experience." *Quarterly Journal of Economics* 110: 641-80.