Marta Simões

Levels of Education, Technology and Growth

The OECD evidence from a country and industry-level perspective

IMPRENSA DA UNIVERSIDADE DE COIMBRA
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PREFACE

At last! A new book from the 2009 vintage not devoted to the worldwide financial crisis, but that deals with a very important question, the question of the fundamentals of economic growth: education, technical progress and international technology spillovers through international trade and FDI in relation with long run economic growth conditions. And, also, a book dealing with the prominent part of public economic policy, that which is able to insure (or restore) satisfactory and stable long-term economic development.

The source of this book is an excellent doctorate thesis in economics defended at the prestigious University of Coimbra, in 2006, by Marta Cristina Nunes Simoes, in front of a committee in which I had the pleasure and the great honor to sit.

In her research, and now in this book, Marta Simoes demonstrates a very high level of proficiency in economic theory and a great aptitude for the implementation of the most modern techniques of empirical data processing in the fields of economics of education, economics of technology and growth theory.

The Author carries out an economic analysis of the role and the effects of the investment in education on economic growth. This analysis is based on the scope of endogenous growth theories , which appeared and developed in the United States more than two decades ago, with the works of Romer (1986, 1990), Lucas (1988), Grossman and Helpman (1991), Aghion and Howit (1992) and many others. More precisely, the relationships between education, technical progress and growth are the heart of this research. Even if the field of the empirical work was restricted to the case of OECD countries, the analysis covers basic questions concerning the growth of the real economy that are essential for industrialized countries as well as for developing or transition countries.

The book is divided in five chapters. The first and introductory chapter presents the objectives, the motivation and the structure of the study. Chapter two is a detailed and, at the same time, synthetic presentation of the theoretical and empirical recent literature, which deals with the role and importance of education to ensure productivity growth and identifies the transmission channels going from capital expenditures in education to economic growth. At the same time, this chapter proposes a detailed survey on the more recent and efficient empirical methods dealing with the links between education, technology and growth (particularly by means of panel data econometrics) but also with measurement methodology questions (like puzzles on Total Factor Productivity (TFP) calculation or on human capital evaluation according to the diversified effects of investment in education, etc.). Chapter 2 ends with the exposure of the analytical approach developed in three steps by the Author and the announcement of the following three chapters that present the original and innovative results obtained from the empirical work.

Thus, Chapter 3 exposes the empirical research on a sample of twenty-three OECD countries from 1960 to 2000, which is specified in a formal model in the spirit of Benhabib and Spiegel (1994)'s work. But the Author adds various technological change determinants as exogenous variables, in her panel data framework, like R&D efforts, international trade and foreign direct investment. Her empirical results, summarized at the end of the chapter, are very rich but too numerous to be briefly summed up here. Still, they bring her to state extremely interesting recommendations as regards economic policy and, especially, the problem of its coherence.

The aim of chapters 4 and 5 is to carry on the analysis of the relationships between investment in education, technology and growth at a more disaggregated level, i.e. at the level of industries of the manufacturing sector. Thus, the goal of chapter 4 is to refine the analysis of these links for fifteen manufacturing industries, this time from eleven OECD countries over the 1980-2000 period. The tested econometric model connects, as endogenous variable, the productivity growth rate of each of these fifteen industries, in each country, with eleven exogenous variables a priori considered as explanatory, and chosen after a study of several empirical works of reference. Among these variables, one finds expenditure in education and in R&D, and country openness to international trade (openness assumed to enable international diffusion of technical progress). After a first test gathering the data related to all the industrial branches considered in her study, the Author arranges these industries in two groups, according to their investment in R&D: a group of nine industries considered as having a weak technological level, and a group of five other ones displaying high technology. So the global analysis performed on the fifteen manufacturing industries taken as a whole, then the disaggregated analysis treating the low-tech and high-tech industries separately reveal both very interesting and original results, which cannot be shortly summarized in this Preface. Many implications, however, concerning public policy for education can be deduced from these very rich results and are to be meditated by the public authorities of these countries.

Chapter 5 is devoted to an analysis of the manufacturing sector in Portugal, the home country of the Author. She tests the relationships between the efforts in education and the growth of productivity estimated at the industry level. Due to limited data availability, the sole variables used for estimating productivity growth are the level of education and international trade, this one being considered as a vector of ideas developed abroad. Fourteen manufacturing industries constitute the studied sample. A first global study was performed, then the industries were arranged in two groups, one gathering nine low-technology industries and the other group five high-tech ones. The major result of this econometric work is the relevance of the technology spillovers in Portugal through imports from OECD countries. There is, however, no empirical evidence concerning a direct influence of education on TFP growth. The Author then concludes that Portugal has to "concentrate its efforts at the secondary education level", a truth which is very sound for many other industrialized as well as developing or transition countries. She also adds that her country requires a highly educated labour force (eodem loco) for being able to carry out imitation activities.

In this fast presentation of this work, a presentation which is certainly too succinct and even impoverishing compared to the richness of the new results and the conclusions stated by the Author in each one of the three last chapters of her book, I want to insist on the scientific quality of the approach and on the width of the empirical evidence that she advances.

The quality of the scientific approach led by Marta Simoes, I don't wonder at it! On the one hand, her PhD research has been performed in a small but very efficient high level research group in macroeconomics, located at the Faculty of Economics from the University of Coimbra, GEMF, Grupo de Estudos Monetários e Financeiros. On the other hand, this research was supervised by a high level and also extremely demanding Academic from this Faculty, Professor Maria Adelaide P. Silva Duarte, who excels in growth economics. Two grounds that account for the high quality of the book, which is among the best ones on these topics, at the present time, in the worldwide literature.

And, as far as the macroeconomic lessons of her empirical results are concerned, in the three chapters relating the discoveries of her research, Marta Simoes is fully aware that the vocation of the macroeconomic theory is to provide bases for the implementation of useful "good steps" for policymakers, particularly, in her field of research, for authorities in charge of public policies concerning education and R&D investment programs. These policies must be coordinated and coherent with openness policies as regards international trade, especially as far as transfer of technology and know-how are concerned. The "free market" by itself is not efficient in providing these kinds of investment stocks bearing fruit in the long run, and to insure these synergies at the international level. Finally, it is true that a cautious and well-managed public education system remains the cornerstone for any efficient growth progress, everywhere.

For all these reasons, I hope that this book gets a wide diffusion, notably at the international (and not only academic) level.

Nice, the 1st of August 2009,
Claude BERTHOMIEU
Professor at the University of Nice-Sophia Antipolis
France

ACKNOWLEDGMENTS

In writing this book I benefited from the support of numerous persons and entities to which I am very grateful.

Special thanks are due to Prof. Maria Adelaide Duarte, my PhD thesis supervisor, that first showed me the importance of studying the causes of economic growth and with whom I discussed the research at every stage. I have drawn extensively on her advice and experience. I also thank Prof. João Sousa Andrade and Prof. Claude Berthomieu for specific suggestions.

The financial support fom the Faculty of Economics of Universidade de Coimbra and the Grupo de Estudos Monetários e Financeiros (GEMF) allowed me to discuss this work in several national and international conferences and workshops. I also benefited from a Marie Curie fellowship at the Faculty of Economics of the University of Cambridge, UK.

Personally, my deepest thanks go to Rui Pedro and my parents for their constant support.

Chapter 1
INTRODUCTION

1.1. Research Objectives

According to the OECD's publication, Education at a Glance 2008, OECD countries spent on average 5.8 per cent of its GDP on education in 2005, 5.0 per cent of which was publicly funded, and devoted 13.2 per cent of its total public expenditure to education. These numbers are quite impressive in a time of tight fiscal constraints since education has to compete with other major areas of public expenditure such as health, social security, or defence. It is therefore important to evaluate the economic benefits of educational investments since, as stated in the 1998 OECD report on human capital investment: "The widespread acknowledgment of the benefits of education and other forms of learning should not lead governments and others to invest indiscriminately in human capital. In deploying finite resources, they need to know which forms of investment produce the best value for money." ((OECD, 1998), p.53).

At the theoretical level, the adoption of measures that stimulate investments in education has been justified by the endogenous growth literature where human capital is in many models the engine of growth (e.g., (Lucas, 1988), (Romer, 1990a) and (Romer, 1990b)).

Although only one of the many possible sources of human capital, defined by the OECD as the "knowledge, skills, competences and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being" ((OECD, 2002c), p.119), formal education is at the centre of the evaluation of the contribution of human capital for economic growth and development, as well as bringing about important economic benefits at the individual level (e.g., increased productivity reflected in higher earnings, lower unemployment risk) but also social non-economic benefits (e.g., better personal health, expanded capacity to enjoy leisure, increased efficiency in job search and other personal choices, greater social equity, increased community involvement, slower population growth, reduced risks from infectious diseases, crime reduction), as can be seen in Figure 1.1.

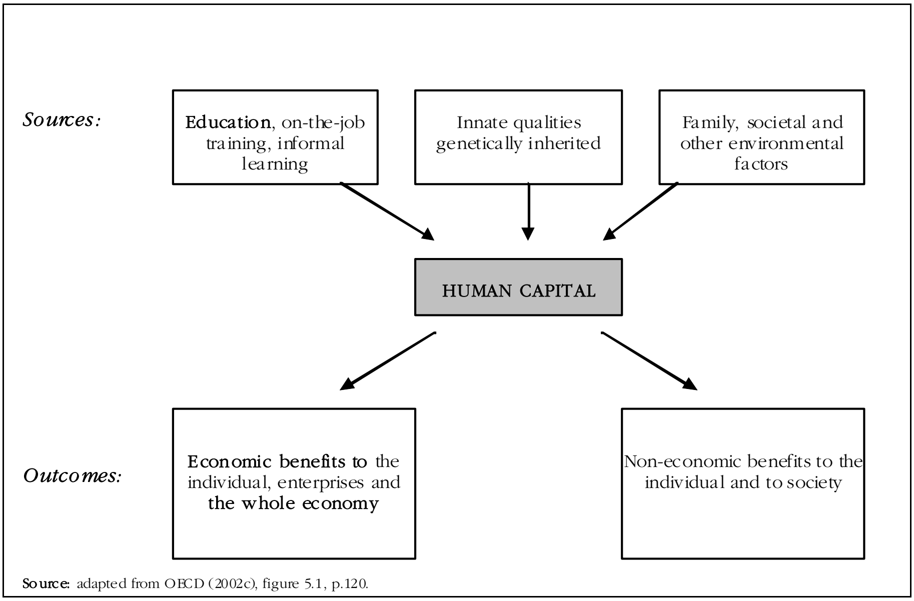

Figure 1.1. Education and human capital

The central goal of this thesis is to evaluate if and how education contributes to productivity growth. For this purpose, we analyse a group of OECD countries over the last decades of the twentieth century. Our work is empirical in its nature and concern. The analyses presented in the next chapters are set within the boundaries of new growth theory or endogenous growth models that form a segment in the broader field of the economic analysis of long run growth.

The main contributions of the thesis within the analysis of economic growth are three. First, the fact that it conducts a systematic empirical investigation of the role of human capital acquired in the formal education sector in productivity growth in light of endogenous growth theory analysing potential complementarities with several additional technological change determinants, which are usually studied independently. Second, we place greater emphasis on the role played by specific educational categories instead of focusing solely on overall educational attainment. Third, the assessment of the importance of the different channels through which education influences growth is conducted at different aggregation levels: cross-country, cross country-industry, and single country-industry.

The next section aims at positioning our work within its proper context. The last section presents the structure of the thesis and introduces, in a more detailed manner, the four subsequent chapters.

1.2. Scope of the study

The economic analysis of the importance of investing in education may be sub-divided into two broad categories: the microeconomic analysis that focus on the economic benefits for the individuals and the macroeconomic analysis that focus on the benefits to society as a whole.

The first category finds its roots in the theoretical analyses of Theodore Schultz and Gary Becker in the 1960's (see e.g., (Schultz, 1961), (Becker, 1964), (Becker, 1993)) and the empirical analysis of Jacob Mincer in the 1970's (see e.g., (Mincer, 1974)) on the economic benefits to the individuals of human capital acquired in the formal education sector.

The extensive empirical literature on rates of return to education has evolved from the work of (Mincer, 1974) that showed that it is possible to relate average years of schooling of individuals to their wages, assuming that the only cost for the individuals of attending school an additional year are the foregone wages.

The most often estimated rate of return to education equation, known as the Mincerian wage equation is,

$$\ln W_i = a + bS_i + cX_i + dX^2_i + Z_i'g + u_i \tag{1.1}$$

where lnW is the natural logarithm of individual wages, S is years of schooling, X is years of work experience, Z is a vector of other wage determinants (e.g. tenure, gender, sector, geography) and u is an error term. The coefficient b is identified as the rate of return to one additional year of schooling. The techniques for this evaluation are by now much more sophisticated involving a much wider set of control variables and empirical techniques, such as experiments aiming at controlling for unobserved individuals ability that might bias the results by looking at data on twins[1].

(Psacharopoulos, 1994) and (Psacharopoulos & Patrinos, 2004) provide a comprehensive review of the results of the labour economics literature on rates of returns to education. From the analysis of a vast number of studies for most of the countries in the World they reach the conclusion that the Mincer log-linear specification fits the data quite well. For instance, in the average OECD country, the rate of return to one additional year of primary education is 13.4%, to one additional year of secondary education 11.4%, and to one additional year of tertiary education 11.6%. The same figures but for the average World economy are 26.6%, 17.0%, and 19.0%, respectively.

The second category of studies of the economic implications of investing in education concentrates on the benefits of education for the aggregate economy and originates from growth theory. It can in turn be sub-divided into two categories: one that views education as just another input into final goods production, based on the predictions of exogenous growth models in the spirit of (Solow, 1956) and (Swan, 1956), and another that views technological change as the main engine of growth and education as a crucial source of technological

[1] For a review of the main methodological problems associated with this kind of estimation see e.g. (Card, 1999).

change, in the spirit of endogenous growth models or new growth theory originally developed by (Romer, 1990a), (G. M. Grossman & Helpman, 1991), and (P. Aghion & Howitt, 1992). The present work is based on this second analytical framework.

Figure 1.2 summarizes the sources of technological change that emerge from key theoretical and empirical studies on the importance of technological change for long run growth and its interactions with education. Among the determinants one can distinguish between those that influence innovation activities from the ones that influence imitation activities or technology spillovers. Education is present in both activities either directly or through its complementarity with the other technological change determinants.

While in neoclassical growth models technological change is taken as exogenous, in endogenous growth models it often depends on human capital through its effect on innovation, as in the (Romer, 1990a), (G. M. Grossman & Helpman, 1991), or (P. Aghion & Howitt, 1992) models, and/or technology adoption, as in the (Nelson & Phelps, 1966), (G. M. Grossman & Helpman, 1992), or (Barro & Sala-i-Martin, 1997) models.

But the importance of endogenous technological change for long run growth also lead to the development of a vast empirical literature aimed at measuring the rate of return to investments in R&D whose classical references include (Griliches, 1980) and (W. Cohen & Levinthal, 1989) that highlight the role of R&D efforts both directly in innovation activities and indirectly through its influence on the absorptive capacity of technology from abroad.

(Rivera-Batiz & Romer, 1991), on the other hand, emphasize the role of intermediate goods imports that embody new knowledge in determining technological change through technology diffusion, a transmission channel extensively empirically investigated by, among others, (Coe & Helpman, 1995) and (Coe, Helpman, & Hoffmaister, 1997).

Recent literature has also devoted much attention to the role of foreign direct investment (FDI) in technology diffusion, e.g. (Potterie & Lichtenberg, 2001), (Xu, 2000), and (Li & Liu, 2005). Education, as a determinant of the absorptive capacity of the economies, influences technological change through its complementarity with these different technological diffusion mechanisms.

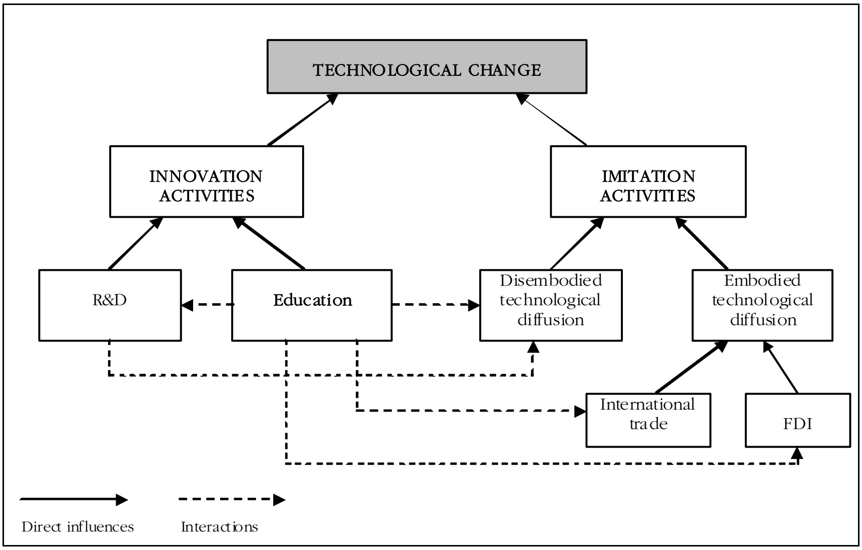

Figure 1.2. Education and technological change

1.3. Structure of the research

Chapter 2 of this thesis aims at establishing the methodological approach that is to be used in the subsequent three chapters. First, it presents in greater detail some endogenous growth models that provide insights on the channels through which education determines technological change. Second, it addresses general empirical issues regarding growth studies and the evaluation of the importance of education for economic growth. More precisely, these issues concern the use of panel data econometrics to overcome some common problems faced by empirical growth research.

The next three chapters present empirical evidence on the importance of education for productivity growth at three levels of aggregation: cross-country, cross country-industry, and single country-industry. The methodology adopted is first to survey the existing empirical literature on the topic at the aggregation level under analysis in each chapter. Second, the empirical specification that underlies the evaluation is outlined. Third, the data used is presented and summarized. Finally, the empirical analysis is implemented and the results discussed aiming primarily at deriving policy implications. The robustness of the econometric results is tested through the use of alternative estimation procedures, fixed effects and instrumental variables techniques, and educational attainment data sets, (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002) and (De la Fuente & Doménech, 2006).

Chapter 3 intends to evaluate how education influences technological change at the cross-country level in a sample of OECD countries over the last four decades of the twentieth century. Different empirical specifications allow us to assess the relative importance of education through innovation and imitation activities and how it relates to the other technological change determinants. For each specification tested the results associated with the use of an overall educational attainment measure are compared with those associated with the use of a specific educational attainment measure. The econometric results lead to the observation that education matters for productivity growth through both innovation and imitation activities mainly through its interaction with the other technological change determinants.

The results achieved reveal the importance of education as a determinant of absorptive capacity for productivity growth through technology diffusion in our sample of OECD countries, a result contrary to that of (Benhabib & Spiegel, 1994), but the importance of education is not exhausted in this role. We find that to fully exploit the productivity growth benefits from R&D expenses through the domestic rate of innovation OECD countries need a sufficient level of education at the secondary and tertiary levels. Additionally, to benefit from technology incorporated in imports of machinery OECD countries need an educated population at all levels of schooling. On the contrary, technology incorporated in FDI exerts no influence in productivity growth. Finally, the positive direct role of education is never confirmed. In the next two chapters we test the robustness of these findings to the consideration of more disaggregate levels of analysis.

Chapter 4 is concerned with the education-productivity growth link at the more disaggregated cross country-industry level concentrating on potential differences according to technological characteristics. Since R&D intensities vary greatly across industries it is legitimate to wonder whether and how technological characteristics affect the influence of education on productivity growth in low technology and high technology industries. The empirical analysis is carried out for a panel of fifteen manufacturing industries from eleven OECD countries over the last two decades of the twentieth century.

Although the empirical results clearly show that education matters for productivity growth of manufacturing industries, the channels through which this influence occurs are not exactly the same as for the aggregate economy. Education influences the rate of innovation and technology diffusion in the samples of low technology and high technology industries considered but the relevant schooling level for each activity differs across technology groups.

In low-tech industries only tertiary education matters for imitation activities and overall educational attainment interacts with R&D. In high-tech industries, secondary and tertiary education together influence the domestic rate of innovation but all schooling levels together influence technology diffusion. The dominant effect of R&D on productivity growth is felt through the rate of innovation in high-tech industries and through its complementarity with education in low-tech industries. Finally, in low-tech industries, increased international trade only affects positively productivity growth if the countries have a sufficient level of tertiary education, while in high-tech industries increased international trade has a direct positive impact on productivity growth.

These results are robust to the use of instrumental variables techniques (except for the direct influence of education in low-tech industries and the direct impact of international trade in high-tech industries) but the results concerning the direct impact of education on productivity growth do not survive the use of the alternative human capital data set (nor does the impact of tertiary education through disembodied technology diffusion in low-tech industries).

The objective of chapter 5 is to explore the importance of education for productivity growth in a single country, Portugal, characterized by its low relative productivity levels. Portugal can be defined basically as a technological follower differing in this respect from the eleven OECD countries analysed in chapter 4 that devote significant shares of its GDP to R&D activities. The level of aggregation of the analysis is again the industry level considering fourteen manufacturing industries over the period 1986-1997. The low educational levels of the Portuguese workforce can constitute impediments to higher rates of productivity growth if a skilled workforce contributes to higher productivity growth through its influence on the domestic rate of innovation and to the exhaustion of catch up gains from imitation.

Empirical evidence for the Portuguese manufacturing industries favours the hypothesis that education is crucial to exploit the productivity growth benefits from embodied technology diffusion in all industries. Distinguishing between low technology and high technology industries renders the influence of TFP growth of the leader insignificant in high technology industries. Our most robust finding concerns the relevance of technology spillovers embodied in imports from OECD countries for productivity growth, as long as manufacturing industries employ workers with skills provided by secondary education.

Chapter 6 begins with a summary of each chapter and underlines their findings. Then policy implications induced by the empirical results are discussed. The last section of this chapter discusses open fields for further research.

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Chapter 2
Theoretical and Empirical Analyses of Education, Technology and Growth: An overview

2.1. Introduction

This chapter provides an overview of the theoretical and empirical framework that we will use to analyse the role of education and of the different schooling levels in the process of economic growth. The first part considers how the endogenous growth literature models the relationship between education, technology and growth, either as an input in the production function for new ideas, or as a determinant of the absorptive capacity of technological change from abroad, or both. The second part focuses on some typical issues that confront the empirical analysis of growth, and especially the empirical analysis of education and growth, and on the panel data econometric analysis of this relationship.

2.2. Theoretical Analyses of Education, Technology and Growth

Endogenous growth theory developed in the last two decades as an answer to the exogenous technological change explanation of long-term growth provided by the neoclassical growth theory proposed by (Solow, 1956) and (Swan, 1956). This growth literature revived the role of the State in promoting economic growth – one of its key conclusions is that policy intervention, namely educational policies, and the nature of institutions, including the education sector, can influence the long-run growth rate of the economy (see Figure 2.1).

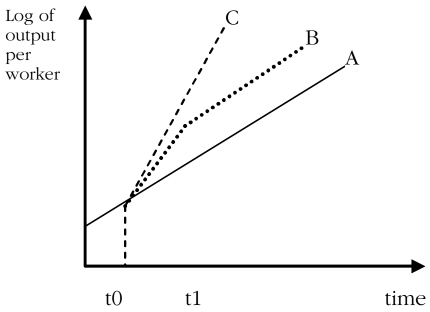

Figure 2.1. Impact of increased investment in education in the neoclassical and endogenous growth models[2]

Decisions to increase investment in education in some period t0 (see Figure 2.1) will have two quite different implications whether we are thinking in the framework of an exogenous growth model (path B) or in the framework of an endogenous growth model (path C). In the first case, the higher human capital will increase the growth rate of output per worker but only temporarily. Eventually in t1 the economy will return to its long run growth path A. On the contrary, the endogenous growth models originally developed by (Romer, 1986), (Lucas, 1988), (Barro, 1990), (Romer, 1990a), (P. Aghion & Howitt, 1992), and (G. M. Grossman & Helpman, 1991), predict that a higher investment in education will change the long run path of the economy making it grow according to a new steeper path C.

The focus of this section is on endogenous growth models that postulate that growth is driven by technological change, which in turn is the result of the decisions of individuals that respond to market incentives. This means that we will not deal with the so-called AK models that endogenize growth by relaxing the assumption of diminishing returns to capital accumulation of the neoclassical growth model, while maintaining the perfectly competitive markets assumption since technological change is viewed as resulting from externalities in capital (physical or human) accumulation.

An early example is the "learning-by-doing" model proposed by (Arrow, 1962) and subsequently developed by (Romer, 1986) where individual firms face diminishing returns to capital but, due to knowledge spillovers or technological externalities associated with investment in physical capital, the economy as a whole can face constant returns to capital and thus exhibit positive long run growth[3]. In (Barro, 1990) it is the provision of public goods by the State that leads to non-decreasing returns to capital accumulation.

[2] Source: (Dowrick, 2002).

[3] If the technology level, A, is a function of the economy-wide capital stock, K, so that $A=K^{\phi}$, and the aggregate production function faced by the economy is, for instance, $Y=K^{\alpha}(AL)^{\beta}$, then

The most interesting model within this class to our analysis is that of (Lucas, 1988) according to which it is human capital accumulation that drives long-run economic growth even in the presence of diminishing returns to physical capital accumulation. Human capital accumulation is a function of the existing human capital and the time spent studying: endogenous growth is possible as long as there are non-diminishing returns to human capital accumulation and output growth is a positive function of human capital accumulation.

(Lucas, 1988) considers the following Cobb-Douglas aggregate production function, $Y=AK^{\alpha}(uhL)^{1-\alpha}(h_a)^{\gamma}$, where h is individual human capital, 1-u is the time devoted to human capital accumulation, and h_a is the average human capital level. Human capital accumulation, dh/dt, is a function of the human capital already acquired and of the time spent accumulating it: $dh/dt=h^{\xi}G(1-u)$, $G'>0$. Endogenous growth is only possible if there are non-decreasing returns to human capital accumulation and (1-u)>0, so (Lucas, 1988) assumes that $\xi=1$. In this case per capita output growth is possible to maintain in the long run even in the presence of diminishing returns to physical capital accumulation.

A shortcoming of these models however had to do with the fact that they ignored that, as (Romer, 1994), p.12 puts it: "(…) Technological advance comes from things that people do."[4], i.e. they do not take into account that technological change results from intentional decisions of economic agents that respond to market incentives. This shortcoming was closely related to the lack of modelling instruments that allowed for the relaxation of the perfect competition assumption and the introduction of imperfect competition: agents innovate because they can earn a monopoly profit although technology has the nature of a public good in the sense that it is non-rival, while it is possible to exclude others from its use through, for instance, patent rights or technological means such as encryption.

This endogenous growth literature emphasizes technological change as the main source of growth and human capital as the main input in the technological change production sector. According to the benchmark endogenous growth models of (Romer, 1990a), (G. M. Grossman & Helpman, 1991), and (P. Aghion & Howitt, 1992) economic growth is determined by the rate of technological change: in the first case technological change corresponds to the introduction of new intermediate goods (horizontal differentiation), while in the latter corresponds to an improvement in the quality of the existing intermediate goods (vertical differentiation). In all the models however technological change results from the activity of an R&D sector that uses the existing knowledge stock and human capital as inputs.

The above-mentioned models treat technological change as the result of innovation activities but technological change also occurs through imitation

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substituting A by its expression gives $Y= K^{\alpha+\phi\beta}L^{\beta}$ so, as long as $\phi>0$, there will be non-decreasing returns to scale to capital accumulation. The assumption of perfectly competitive markets is maintained since non-decreasing returns to capital accumulation are due to knowledge spillovers, i.e., individual firms still face diminishing returns to capital accumulation due to the fact that they take *A* as fixed. See e.g. (Rogers, 2003), chapter 3, and (Barro & Sala-i-Martin, 2004), chapter 4.

[4] Italics from the original.

activities or technological diffusion, i.e., it also results from the use of technology developed originally in another country[5]. Some of the models that emphasize this type of technological change are (Nelson & Phelps, 1966), (G. M. Grossman & Helpman, 1991), and (Barro & Sala-i-Martin, 1997)[6] according to which a follower economy has potential for technological catch-up by imitating the more advanced technologies developed by the leader countries. (Nelson & Phelps, 1966) in particular emphasize the role played by education in imitation activities: "To put the hypothesis simply, educated people make good innovators, so that education speeds the process of technological diffusion." p.70.

Our analysis of the role of education, and especially that of the different schooling levels, in the process of economic growth will be guided by the predictions of the endogenous growth literature since this is the theoretical framework that provides us with, quoting (P. Aghion & Howitt, 1998): "(…) interesting insights as to the growth effects of various educational policies. (…) questions such as (i)' should governments emphasize primary/secondary or higher education, (ii)' should governments subsidize formal education versus on-the-job training and apprenticeship, (iii)' should educational policy be elitist or broadly based, (…) these last questions gain substance when addressed in the context of a model with endogenous technological change, following a Nelson-Phelps approach."p.327.

Our description of the relevant predictions of endogenous growth models as to the relationship between education, technological change and growth will be divided in two parts. We begin by presenting the predictions of an endogenous growth model where human capital drives the domestic rate of innovation. Next, we present the predictions of endogenous growth models that attribute to human capital a fundamental role in the process of technological catch-up through imitation activities. We focus on the predictions of endogenous growth models where technological change corresponds to the introduction of new varieties of intermediate goods, although the same predictions concerning the education-technological change-growth relationship could be obtained in a model with vertical differentiation, in the spirit of (G. M. Grossman & Helpman, 1991) and (P. Aghion & Howitt, 1992)[7].

We conclude the section with the presentation of the empirical specification that we use throughout this thesis to analyse the impact of education on

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[5] According to the (OECD, 1997), "Technology diffusion is essentially the widespread adoption of technology by users other than the original innovator." p.7.

[6] For early empirical analysis of the technological catch-up hypothesis see (Abramovitz, 1986), (Baumol, 1986), and (Dowrick & Nguyen, 1989). The latter conduct a systematic empirical analysis of convergence due to technological catch-up in OECD countries analysing the sensitivity of the results to the data sets used, period coverage, and countries included in the sample. They conclude that: "(…) the weight of the evidence clearly supports the proposition that catching up has been a dominant feature of post-war growth, along with the common rise and subsequent fall in average rates of growth of productivity and per capita GDP."p.1028. Also, "Even though TFP catching up is yet to be fully explained, we feel that it has been well established as an important phenomenon to warrant being taken into account in any attempt to explain differences between growth rates of member countries of the OECD."p.1029.

[7] See e.g. (M. Connolly, 1999), (P. Aghion & P. Howitt, 2005).

productivity growth inspired by the predictions of the endogenous growth models described below.

2.2.1. Education, Innovation and Growth

In this section, we start by presenting the more general model proposed by (Jones, 1995) and developed in (Jones, 2005) that nests the (Romer, 1990a) and (Romer, 1990b) models, the latter explicitly dedicated to the analysis of the relationship between human capital and growth where schooling levels assume quite specific and different roles.

R&D-based endogenous growth models such as the ones in (Romer, 1990a), (P. Aghion & Howitt, 1992), (G. M. Grossman & Helpman, 1991), (Jones, 1995), and (Jones & Williams, 2000) incorporate both positive and negative externalities to innovation efforts, the key long run determinant of productivity and growth, that may lead to under- or over-investment in research activities.

It is possible to identify four key externalities associated with innovation (see e.g. (Jones & Williams, 2000), (Cameron, 2000)), two positive and two negative. The positive externalities come from the fact that new ideas add to the existing stock and facilitate the discovery of yet new inventions (the *standing on shoulders* effect) and the fact that an innovator cannot fully appropriate the social gains from innovation (the *surplus appropriability* problem). The negative externalities are due on the one hand to the fact that new ideas render old ones obsolete (the *creative destruction* effect), and on the other hand to the existence of duplication efforts (the *stepping on toes* effect). In the second-generation or ideas-based endogenous growth models human capital produces externalities due to its role in innovation activities so it can produce any of the four externalities described above.

The model analysed here considers three sectors: a research sector that produces the designs of new intermediate goods, an intermediate goods production sector that uses the designs produced in the research sector and capital to produce intermediate goods, and a final goods production sector that uses the set of intermediate goods available and human capital to produce final output. The final goods production sector is perfectly competitive while the intermediate goods production sector is characterized by imperfect competition, where intermediate goods producers have a monopoly right to a differentiated intermediate good whose blueprint is acquired in the research sector. The incentive to undertake R&D thus derives from the perspective of earning a monopoly profit.

The production of final goods, Y, uses as inputs human capital, H_Y, and a continuum of intermediate goods, x_i, and can be described by the following Cobb-Douglas technology:

$$Y = H_Y^{1-\alpha} \int_0^A x_i^{\alpha} di, 0 < \alpha < 1 \tag{2.1}$$

There are constant returns to scale in H_Y and the intermediate goods in producing output for a given A, the range of intermediate goods available at any point in time. However, there are non-decreasing returns to scale to all reproducible inputs once A is treated as a variable.

Technological change corresponds to the invention of a design of a new producer good. The invention of a design for a new intermediate good uses as inputs human capital, H_A, and the existing knowledge stock, A:

$$\dot{A} = \frac{dA}{dt} = g(H_A, A) \tag{2.2}$$

The more resources devoted to research, the higher the number of new designs discovered, i.e., dg/dH_A is expected to be positive, higher or lower than 1 depending whether there is duplication effort or not. The sign of dg/dA is less obvious: it is positive if the discovery of new ideas increases with the existing knowledge stock. (Jones, 2005) calls this hypothesis the "standing on the shoulders of giants" hypothesis in reference to Isaac Newton's quote *"If I have seen farther than others, it is because I was standing on the shoulders of giants."* If however the most obvious ideas are discovered first so that it is increasingly difficult to discover new ideas, dg/dA is negative. (Jones, 2005) calls this the "fishing out" effect, an analogy with a fishing pond.

(Jones, 2005) proposes the following Cobb-Douglas functional form for the production function of new knowledge:

$$\dot{A} = \delta H_A^{\lambda} A^{\phi}, \delta > 0, \lambda > 0, \phi \leq 1 \tag{2.3}$$

where δ is a productivity parameter, λ is the elasticity of the production of new ideas with respect to human capital ($\lambda<1$ means that there is duplication in research), and ϕ determines the influence of the existing knowledge stock in the production of new ideas. The value taken by the parameter ϕ will determine whether there are decreasing, constant or increasing returns to scale to knowledge in goods production, i.e., determines whether there is continuous growth in per capita output, as we will see below.

Physical capital is accumulated by foregoing consumption according to the standard formulation:

$$\dot{K} = Y_t - C_t - dK_t \tag{2.4}$$

where C represents consumption of final goods and d is the depreciation rate, constant and exogenous.

After buying the design produced in the research sector, the production of one unit of any intermediate good requires 1 unit of output and assuming that there is symmetry in the production of x_i, i.e., $x_i=x$ $\forall i$, all intermediate goods firms produce the same quantity. The total physical capital stock, K, is thus equal to:

$$K = \int_0^A x_i \, di = Ax \tag{2.5}$$

since A, the level of technology of the economy corresponds to the range of intermediate goods available for final goods production.

A number of resource constraints applies to this economy. Regarding human capital, total human capital available in the economy, H, is allocated either to the final goods production sector or the production of new designs so that:

$$H = H_Y + H_A \tag{2.6}$$

(Romer, 1990b) distinguishes between human capital used in the final goods production sector, H_Y, and human capital used in the R&D sector, H_A. In the first case, H_Y corresponds to "educational skills acquired in primary and secondary education" (p.253), while in the latter H_A corresponds to "scientific talent acquired in post-secondary education" (p.253).

Total human capital is equal to human capital per worker, h, times the total number of workers L:

$$H = hL \tag{2.7}$$

and the labour force is assumed to grow at a constant and exogenous exponential growth rate n:

$$L = L(0)e^{nt} \tag{2.8}$$

To investigate how the growth rate of technology influences the behaviour of output per worker, Y/L, we have to analyse how resources are allocated in this economy. For the sake of simplicity we consider, as in (Jones, 2005), that the allocation of resources obeys the following rules of thumb (simple, exogenous rules defined by the researcher) for allocating resources:

$$1 - \frac{C_t}{Y_t} = s_k \in [0,1] \tag{2.9}$$

$$h = \bar{h} \tag{2.10}$$

$$\frac{H_A}{H} = s_A \in [0,1] \tag{2.11}$$

The first rule tells us that agents allocate a constant fraction of output, s_K, to investment. The last two rules mean that, as in (Romer, 1990a) the stock of human capital per worker is fixed and the fraction supplied to the research sector, s_A, is also fixed.

Given the above defined resource allocations we can now analyse the behaviour of output per worker, y=Y/L. In order to do this we assume for now that $\phi<1$ (positive or negative) so that a balanced growth path in which all the variables grow at the same constant rate exists. What we want to know is what determines the balanced growth path growth rate of output per worker.

Let us begin by writing the aggregate production function as:

$$Y = A^{1-\alpha}K^{\alpha}H_Y^{1-\alpha} \tag{2.12}$$

after substituting for x in the final goods production function[8].

Output per worker is equal to:

$$y = A^{1-\alpha}k^{\alpha}\left[(1-s_A)\bar{h}\right]^{1-\alpha} \tag{2.13}$$

where k=K/L is capital per worker.

Denoting variables along the balanced growth path by an asterisk and the growth rate of a variable w by g_w, the expression for output per worker along the balanced growth path is given by:

$$y^* = A^*\left(\frac{s_k}{n+g_k+d}\right)^{\frac{\alpha}{1-\alpha}}\left[(1-s_A)\bar{h}^*\right] \tag{2.14}$$

In a balanced growth path all the variables in the right hand side (RHS) are constant, except for A* so output per worker grows according to the growth rate of technology:

$$g_y = g_k = g_A \tag{2.15}$$

The fundamental question now is what determines the growth rate of technology. Going back to the production function for knowledge let us rewrite it as:

$$g_A = \frac{\dot{A}}{A} = \delta\frac{H_A^{\lambda}}{A^{1-\phi}} \tag{2.16}$$

For g_A to be constant both the numerator and the denominator of the RHS have to grow at the same rate:

$$\frac{\dot{g}_A}{g_A} = \lambda\frac{\dot{H}_A}{H_A} - (1-\phi)\frac{\dot{A}}{A} = 0 \tag{2.17}$$

$$g_A = \frac{\lambda}{1-\phi}g_{H_A} \tag{2.18}$$

Finally, the growth rate of H_A along the balanced growth path is equal to the labour force growth rate since by assumption the fraction of human capital allocated to the research sector is constant, as well as average human capital per worker:

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[8] This production function is similar to that of a neoclassical growth model since, for A constant, there are diminishing returns to the reproducible inputs, while if A grew at an exogenously given rate, K and Y would grow at that same rate.

$$H_A = s_A H = s_A \bar{h} L$$
$$g_{H_A} = g_L = n \qquad (2.19)$$

We can now write the expression for the growth rate of output per worker along the balanced growth path:

$$g_y = g_A = \frac{\lambda}{1-\phi} g_{H_A} = \frac{\lambda}{1-\phi} n \qquad (2.20)$$

The growth rate of output per worker is proportional to the growth rate of human capital allocated to the research sector (not its level) and perpetual output growth of output per worker is only possible if there is labour force growth. (Jones, 1995) calls this a semi-endogenous growth model since, although the growth rate of output per worker is explained within the model, in the long run growth it is determined by the labour force growth rate, assumed exogenous.

Notice that the equilibrium growth rate of output per worker depends also on the parameters of the production function for knowledge, λ and ϕ, which in turn determine the extent of returns to scale in the research sector. We assumed until now that $\phi<1$ implying that there are decreasing returns to scale to the existing knowledge stock in the production of new ideas. This is not however the assumption made by (Romer, 1990a), which in turn assumes that $\lambda=\phi=1$ so that there are constant returns to scale to both human capital and the existing knowledge stock in the knowledge production function. What are the consequences for the long run output per worker growth rate of these assumptions? Before answering this question let us write the new production function of new ideas, linear in A:

$$\dot{A} = \delta H_A A$$
$$g_A = \frac{\dot{A}}{A} = \delta H_A \qquad (2.21)$$

Now the growth rate of technology is proportional to the level of human capital allocated to the R&D sector not to its growth rate and thus the level of human capital also determines the growth of output per worker. Moreover, output per worker grows without bound even in the absence of labour force growth, i.e., there is no balanced growth path (with $\phi=1$ the denominator of the expression for technology growth in the Jones model explodes).

The key implication of the (Romer, 1990a) model for our analysis is that the growth rate of output is a positive function of the R&D efforts and the level of human capital of the economy, i.e., an economy can grow without bound by investing in R&D and human capital. Moreover, according to (Romer, 1990b) it is not total human capital that determines the long run growth rate of output but only human capital acquired through higher education since this is the level of formal education that provides the scientific talent necessary for the discovery of new designs.

The assumption that ϕ=1 means that (Romer, 1990a) model exhibits scale effects since the growth rate of output per worker depends positively on the level of human capital devoted to research. The implication is that larger economies, i.e. economies with more researchers devoted to R&D, will grow faster, a prediction that according to (Jones, 1995) is not supported by the data. For instance, between 1950 and 1988 the number of researchers engaged in R&D in the USA grew by a factor of more than five while the growth rate of TFP remained relatively constant. The same happened in countries like West Germany, Japan and France. This empirical evidence was at the heart of the semi-endogenous growth model proposed by (Jones, 1995) developed above and motivated a number of other studies aimed at eliminating scale effects from endogenous growth models (see for instance (Dinopoulos & Thompson, 1998) and (Kortum, 1997)). In these models it is the level, not the growth rate, of output per worker that depends on the level of human capital, i.e. there are, according to (Jones, 2005), “weak” scale effects as opposed to the ‘strong’ scale effects in the (Romer, 1990a) type models.

A final quite distinct implication of the two types of models concerns its policy implications. In the (Jones, 1995) model policies affect the growth rate of output per worker along a transition path and determine the long run level of output per worker. In the (Romer, 1990a) model on the contrary, policy decisions have a lasting effect on the long run growth rate of output per worker. Hence, a policy decision that increases the level of human capital allocated to the research sector leads to a permanent increase in the growth rate of output per worker in the latter models, but to a transitory increase in the former. Nevertheless, transition periods can go on for a long time so the growth rate effects of a policy decision can be felt during a significant period of time.

2.2.2. Education, Imitation and Growth

In this section we focus on the predictions of technological catch-up growth models as to the role of education in technological change and growth. The models analysed in the previous section are more suitable to explain economic growth in countries that mostly innovate and forget that most of the World R&D research effort is carried out in a small group of countries and so most countries depend on imitation for technological progress. In technological catch-up growth models education influences economic growth by speeding up the rate at which new inventions are adopted.

This complementarity between technological backwardness and education was highlighted by (Abramovitz, 1986), designating it by “social capability”: “(…) One should say, therefore, that a country’s potential for rapid growth is strong not when it is backward without qualification, but rather when it is technologically backward but socially advanced.”p.388. Education is viewed as one of the determinants of the absorptive capacity of an economy that enable it to fully exploit the advantages from technological backwardness.

One of the first models that highlights technology diffusion as the main source of economic growth and education as a main determinant of the pace of technology diffusion is the (Nelson & Phelps, 1966) model.

The basic equation of this model is the equation for the rate of growth of the level of technology:

$$\frac{\dot{A}}{A} = \Phi(H)\left(\frac{T(t) - A(t)}{A(t)}\right), \qquad \Phi(0)=0,\ \Phi'(H) > 0 \tag{2.22}$$

where *T(t)* is the theoretical or best practise level of technology, i.e., the stock of knowledge available for innovators at time t evolving at the constant and exogenous exponential growth rate γ[9]. Equation (2.22) states that the growth rate of A depends on the gap between its level in practice and the theoretical level of knowledge, $\left[T(t) - A(t)\right]/A(t)$, but also on the available human capital, $\phi(H)$ – the higher the educational attainment the faster the gap will be closed – so the function $\phi(H)$ reflects the absorptive capacity of the economy.

Given the exponential growth rate of T(t), the equilibrium path of technology is given by:

$$A(t) = \left(\frac{\Phi(H)}{\Phi(H) + \gamma}\right)T(0)e^{\gamma t} \tag{2.23}$$

For a positive and constant H, the growth rate of A will reduce to γ in the long run and the steady state technology gap is equal to:

$$\frac{A}{T} = \frac{\Phi(H)}{\Phi(H) + \gamma} \tag{2.24}$$

constant as long as H remains constant. If the level of education increases over time the technology gap disappears since the level of technology in practice, A, will approach the theoretical level of technology, T. A higher level of human capital or educational attainment will also increase the path of A in the long run. On the other hand, a greater supply of human capital will have no effect on the level of output generated with conventional inputs unless new technology is introduced, and skill accumulation will continue only when technical progress is sustained.

(Benhabib & Spiegel, 1994) extend the (Nelson & Phelps, 1966) model to a leader-follower model with a domestic innovation component in order to include predictions useful for cross-country comparisons. In this spirit, the growth rate of A depends now on an innovation term, g(H), the endogenous growth component that states that the production of new knowledge is a positive function of the level of human capital, and on a catch-up term relative to the technology level of the leader country and not to a theoretical level of knowledge that grows exogenously, as before:

$$\frac{\dot{A}}{A} = g(H) + c(H)\left(\frac{A_{max}(t) - A(t)}{A(t)}\right), \qquad g'(H),\ c'(H) > 0 \tag{2.25}$$

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[9] The set up of the model is thus equivalent to the standard neoclassical model of growth in the sense that in the limit the process of knowledge creation is exogenous.

where g(H) and c(H)[10] are non-decreasing functions of H corresponding to the idea that the level of education not only enhances the ability of a country to develop its own technological innovations, but also its ability to adapt and implement technologies developed elsewhere, with A_{max} representing the technology level of the technological leader, i.e. the country with the highest A, which in the model corresponds to the country with the highest education level.

An important consequence of the model is that in the long run the country with the higher education level will be the leader unless it looses the educational advantage. If $A_{max}(0)$ is the technology level of the country with the highest initial level of A we can write:

$$A_{max}(t) = A_{max}(0)e^{g(H_{max})t} \tag{2.26}$$

since the leader country grows at the rate $g(H_{max})$.

If country i has a higher level of education then its growth rate will be higher than $g(H_i)$ due to the positive influence of the catch-up term:

$$A_i(t) > A_i(0)e^{g(H_i)t} \tag{2.27}$$

and it will eventually overtake the initial leader since $g(H_i)>g(H_{max})$.

(Benhabib & Spiegel, 2005) provide some micro foundations for the former model based on the technology diffusion model of (Barro & Sala-i-Martin, 1997) where a few leading economies are responsible for the discovery of new products and thus for growth while the remaining countries depend on imitation to grow, assuming that imitation is cheaper than innovation but the cost of imitation is decreasing with the distance to the leader. Applied to the study of the behaviour across economies the model implies convergence of the follower countries to the technological leader, with the follower growing faster during the transition period.

The main aim of the model is to reconcile the long run growth implications of endogenous growth models with the convergence predictions of the neoclassical model, supported by the evidence. The mechanism that drives convergence however is conceptually different: in the neoclassical model convergence is due to diminishing returns in capital accumulation while in the technology diffusion models it is the consequence of rising imitation costs as the follower catches up with the leader. In the long run all the economies grow at the technological change growth rate of the leader and thus long run output growth is governed by the forces that drive the production of new ideas described by the (Romer, 1990a) model.

The (Barro & Sala-i-Martin, 1997) model is a two-country model composed of a technological leader, country l, where innovation is relatively cheap, and a follower, country f, where imitation is cheaper than innovation. As in the (Romer, 1990a) model, technological change corresponds to the introduction of a new variety of intermediate goods.

[10] Similar to $\phi(H)$ in the (Nelson & Phelps, 1966) model.

There are three sectors operating in each economy: a perfectly competitive final goods production sector, an intermediate goods production sector that buys the perpetual right to produce an intermediate good from the research sector where it is invented or adapted from abroad.

The technology for the production of final goods for each representative firm is the same in both countries and equal to:

$$Y_i = B_i L_i^{1-\alpha} \int_0^{A_i} x_{ij}^{\alpha} dj, \quad 0 < \alpha < 1 \qquad i = l, f \tag{2.28}$$

where Y_i is output, L_i is labour input assumed to be fixed in both countries, x_{ij} is the quantity employed of the jth type of intermediate good, and A_i is the number of types of intermediates available in country i. B_i is a productivity parameter that reflects variations in policies and institutions across countries.

Since country l is the leader and country f the follower, we have initially $A_l(0)>A_f(0)$, and we assume that the follower relies solely on imitation for the introduction of new varieties of intermediate goods, i.e. the leader receives no diffusion from the follower.

Assuming that all the j intermediate goods are used in the same amount ($x_j=x$),

$$Y_i = B_i L_i^{1-\alpha} A_i x^{\alpha} = B_i L_i^{1-\alpha} (A_i x)^{\alpha} A_i^{1-\alpha} \tag{2.29}$$

The final goods production function exhibits constant returns to scale in L and Ax, the total amount of intermediate goods used, considering A is fixed. There are diminishing returns to Ax if it occurs through an increase in x but non-decreasing returns if it occurs through an expansion of the number of varieties, A.

Final goods output can be used for consumption, C_i, the production of intermediate goods, x_{ij}, or research that leads to invention or adaptation of an intermediate good. Prices are measured in units of final goods, with both C_i and x_{ij} requiring one unit of Y_i and the cost of inventing a new variety of intermediate goods is equal to η_i units of final output. Since η_i is assumed to be fixed there are constant returns to the discovery of new types of products as in (Romer, 1990a) and this is what makes perpetual long run growth possible.

In the leader country, the inventor of a new producer good has a perpetual monopoly right over its use in production with profits, π_{lj}, equal to:

$$\pi_{lj}=(P_{lj}-1)x_{lj} \tag{2.30}$$

where P_{lj} is the price of intermediate good j. Profit maximization implies setting P_{lj} equal to $1/\alpha$. To arrive at this result consider that perfect competition in final goods production implies that each input is paid its marginal product so that:

$$\frac{\partial Y_l}{\partial x_{lj}} = \alpha B_l L_l^{1-\alpha} x_{lj}^{1-\alpha} = P_{lj} \tag{2.31}$$

From this result we can derive the demand function of intermediate goods from all producers in the leader country:

$$x_{lj} = L_l \left(\frac{\alpha B_l}{P_{lj}} \right)^{1/(1-\alpha)} \tag{2.32}$$

Substituting in the profit function for this expression and maximizing it in order to the price yields the desired result. Since $(1/\alpha)>1$, the price is thus higher than the (assumed) marginal cost.

The monopoly price is the same for all intermediate goods j at all points in time so the total quantity produced of each intermediate good is:

$$x_{lj} = x_l = L_l \left(B_l\right)^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} \tag{2.33}$$

Substituting into the production function we arrive at the expression of output per worker in the leader country, $y_l=Y_l/L_l$:

$$y_l = \left(B_l\right)^{1/(1-\alpha)} \alpha^{2\alpha/(1-\alpha)} A_l \tag{2.34}$$

rising in B_l and A_l. Increases in A_l lead to a equiproportionate rise in y_l.

In equilibrium, (Barro & Sala-i-Martin, 1997) show that Y_l, C_l and A_l all grow at the same constant rate g_l, which is also the growth rate of output per worker.

In the follower country, f, the technology for final goods production is the same as in the leader although it can differ in terms of L_f and B_f, and also η_f, the cost of innovation in the follower. Initially imitation is more attractive than innovation for the follower so that $v_f(0)<\eta_f$, where v_f is the cost of adapting an intermediate good invented by the leader.

Imitation costs are assumed to increase as the pool of uncopied intermediate goods invented by the leader decreases, i.e., as A_f gets closer to A_l so that:

$$v_f= v_f(A_f /A_l),\ v'_f >0 \tag{2.35}$$

If $A_f /A_l<1$, v_f will in principle be lower than η_f unless the remaining pool of uncopied intermediate goods from the leader is difficult to adapt making it cheaper for the follower to innovate instead of imitating. We will assume that $v_f <\eta_f$ as long as $A_f /A_l<1$[11].

(Barro & Sala-i-Martin, 1997) assume the following functional form for v_f:

$$v_f = \eta_f \left(\frac{A_f}{A_l}\right)^{\sigma}, \qquad \sigma > 0 \tag{2.36}$$

that can be slightly transformed in order to reflect the importance of human capital for technology diffusion, as suggested by (Rogers, 2003), chapter 5.

[11] (Barro & Sala-i-Martin, 1997) show that the main results apply even if $v_f >\eta_f$ for a range $A_f /A_l<1$ values. Under this assumption v_f will approach η_f as A_f/A_l approaches 1.

(Rogers, 2003) considers that the cost of imitation depends not only on the technology gap but also on the absorptive capacity of the follower economy, represented by the absorptive capacity function Φ(.). The function Φ(.) is influenced by all the determinants of the capacity of the follower economy to imitate the leader's technology, such as openness to trade and human capital, as suggested by (Abramovitz, 1986) and formalized in the (Nelson & Phelps, 1966) and the (Benhabib & Spiegel, 1994) models.

The function for the cost of imitation can thus be written as:

$$v_f = \eta_f \left(\frac{A_f}{A_l}\right)^{\sigma} \frac{1}{\Phi(H)}, \quad \Phi' > 0 \tag{2.37}$$

where we assume that the function Φ that reflects the absorptive capability of the economy depends only on the human capital available in the follower economy, for ease of exposition. Now the imitation costs declines not only with the technology gap (the higher the gap the lower the imitation cost) but also with H: follower countries with higher levels of human capital can imitate and adapt the leader's inventions at lower costs.

After paying v_f for the jth intermediate good from country l, the imitators in country f gain a perpetual right to use it, so they set its price as a mark-up over the marginal cost as the inventors in country l, i.e. $P_{fj}=P_f=1/\alpha$. The formulas for quantity produced, x_{fj} , total output, Y_f, and flow of profit, π_{fj} , therefore parallel the expressions for country l, just substituting subscript l for subscript f.

Substituting into the production function we arrive at the expression of output per worker in the follower country, $y_f=Y_f/L_f$:

$$y_f = \left(B_f\right)^{1/1-\alpha} \alpha^{2\alpha/1-\alpha} A_f \tag{2.38}$$

so the growth rate of output per worker is the growth rate of A_f.

In the steady state, A_l/A_f remains constant so both A_l and A_f have to be growing at the same rate g_l. Out of the steady state (Barro & Sala-i-Martin, 1997) show that the growth rate of y_f is greater than g_l, imitation grows faster than innovation, but declines monotonically to g_l, due to the rising costs of imitation as A_f approaches A_l. The implications for output growth are thus similar to that of (Nelson & Phelps, 1966): in the short run countries behind the leader/theoretical level of knowledge will grow faster but eventually in the long-run all will grow at the same growth rate, the growth rate of the theoretical level of knowledge/technology of the leader. Furthermore, the higher the human capital level available in the follower the faster it will grow during transition due to lower imitation costs. In the long run, the country with the higher education level will be the leader unless it looses the educational advantage.

2.2.3. A testable empirical specification

The models reviewed in this section provide the background theoretical framework for the empirical analysis that follows, allowing us to define a testable empirical specification for the education-productivity growth link based on their predictions of the importance of human capital for economic growth. The basic ideas for the empirical modelling of the relationship between education and growth are: (i) growth is driven by technological change; (ii) technological change is determined by the production function of new ideas whose inputs are the existing knowledge stock and human capital and by the ability to absorb technology develop abroad, which in turn is influenced by the availability of human capital.

The strategy followed to derive a testable empirical specification is similar to that of (Benhabib & Spiegel, 1994): we begin by setting up a simple, empirically tractable model that allows us to examine the importance of education for technological change and growth through innovation and technological diffusion but we modify and extend it in order to consider additional technological change determinants suggested by theoretical and empirical growth studies (see chapters 3 and 4) and their complementarity with education[12]. In particular we want to assess whether the effect of education on productivity growth is robust to the inclusion of other technological change determinants.

Consider a standard neoclassical production function, which uses the traditional productive factors (equation (2.39)),

$$Y_{it} = A_{it}F(K_{it}, L_{it}) \tag{2.39}$$

where Y is real output, A is an index of technical efficiency, L is a measure of labour input, and denoting as usual individuals (countries/industries, depending on the aggregation level of the analysis) by the subscript i and time by subscript t.

Our main purpose is to understand how education influences technological change and thus growth, so we want to find a suitable specification for the growth of A, the index of technological efficiency.

As originally proposed by (Benhabib & Spiegel, 1994), the specification for $\log A_{it}$, the rate of technological change, as can be seen in equation (2.40) is:

$$\Delta \log A_{it} = c + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) \tag{2.40}$$

where H is the stock of human capital, $\log A_{\max t-1}$ is the level of technological efficiency of the leader country/industry, and $\log A_{it-1}$ is the level of technological efficiency of the country/industry analysed. In this model, human capital and the technological gap or disembodied technology diffusion, proxied by

[12] It should be noted that we do not consider human capital as a standard input of production as has been done extensively in the empirical growth literature (e.g., (Mankiw, Romer, & Weil, 1992), (Islam, 1995), (Temple, 2001b)) since the focus of this thesis is on the importance of education for growth through technological change and our dependent variable is the growth rate of technology not output growth.

$\log(A_{maxt-1}/A_{it-1})$ the distance to the leader country in terms of technological efficiency, are the engines of growth.

Human capital plays a dual role in the model: it determines both the endogenous capacity to generate new knowledge, represented by the term gH_{t-1} and technology absorption, represented by the term $mH_{t-1}\log(A_{maxt-1}/A_{it-1})$. This last aspect means that for foreign technology to have an impact on productive efficiency conditions for its absorption also have to prevail, which are identified in the model with the level of human capital.

Not denying the originality and importance of the (Benhabib & Spiegel, 1994) study the fact is that it ignores some important issues when specifying the determinants of the behaviour of technological change that we believe can shed additional light on the relationship between education and productivity growth.

The (Benhabib & Spiegel, 1994) model ignores other determinants of technological change that have been widely emphasized by the empirical literature on R&D and productivity growth, some of which we review in the next chapters, namely R&D expenses. The innovation component of $\Delta \log A$ should therefore also include this additional determinant of the rate of innovation as a possible technological change explanation, bearing also in mind its complementarity with education.

Besides the role played as an input in innovation activities the different schooling levels also influence the absorptive capacity of the economy, i.e., its ability to benefit from international technology spillovers. As pointed out in section 2.2.2, the complementarity between technological backwardness and education was highlighted by (Abramovitz, 1986). (Abramovitz, 1994) also describes several conditions for the "realization" of the potential for catching up of a follower economy and refers to "social capability" as one of them describing it as: "a vague complex of matters, few of which can be clearly defined and subjected to measurement. It includes personal attributes, notably levels of education, an attribute that is subject to measurement, however imperfectly (…)."p.88.

Although OECD countries represent a rather homogeneous group of countries the fact is that research efforts worldwide are carried out by a small number of countries, a fact highlighted by several authors. For instance, (Jones, 2002) develops an endogenous growth model to study the sources of growth of the US economy where technological change is determined by the human capital levels of the G-5 countries, assumption justified by the fact that these countries are responsible for most of the World's research effort.

(Keller, 2004) compares R&D expenditures and GDP levels of the G-7 countries with world R&D expenditures and GDP levels in 1995 and concludes that these countries share of R&D expenditures (84%) is much higher than their GDP share (64%), numbers that render the analysis of technological diffusion processes of primary importance even for homogeneous groups of countries like the OECD.

In fact, (Eaton & Kortum, 1996) develop a model to explain productivity growth in OECD countries that they fit to aggregate data and conclude that: "(…) international trade in ideas is a major factor in World growth: every OECD country other than the United States obtains more than 50% of its productivity growth from ideas that originated abroad, and for all but the five leading research economies (the United States, Japan, Germany, France, and the United Kingdom) the figure is more than 90%. As for the source of these innovations, the United States, Japan, and Germany together drive more than half of the growth of every country in our sample." p.252.

Technological diffusion can essentially assume two different natures: disembodied transfers of technology, i.e., that are not directly related to the pace of investment, and embodied ones. In the last case technology spillovers are considered to be embodied in a particular transmission channel. (Benhabib & Spiegel, 1994) only consider disembodied technology diffusion, i.e. they do not consider the specific way in which technology is transmitted, when a number of studies show the importance of embodied technological diffusion. Besides disembodied technological diffusion and its interaction with education, the growth regression should thus also include forms of embodied technology diffusion and their interaction with education[13].

From what has been said we can think of the following specification for the growth rate of technology, $\Delta \log A_{it}$:

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + nZ_{it-1} + \omega W_{it-1} + \varepsilon_{it} \qquad (2.41)$$

According to equation (2.41), the growth rate of technology for each individual (country/industry) i at time t depends on: **i)** an individual-specific component, c_i, that represents changes in the efficiency with which inputs are used associated with individual characteristics, that remain constant over time; **ii)** a time-specific component, c_t, common to all individuals; **iii)** the level of human capital allocated to the R&D sector translating its influence on the domestic rate of innovation, H_{it-1}; **iv)** an interaction term between the level of human capital and disembodied technology diffusion, proxied by the distance in technological efficiency terms to the technological leader, $\log(A_{maxt-1}/A_{it-1})$, since the more backward is a country the higher the potential to catch-up and human capital exerts a positive influence on the absorptive capacity of the economy, i.e. it speeds up technology diffusion, $H_{t-1}\log(A_{maxt-1}/A_{it-1})$; **v)** a vector Z_{it-1} that includes the influences of additional innovation activities determinants on productivity

[13] Although the literature on technological spillovers basically points to trade and FDI as channels of embodied technology diffusion there are other channels that have been considered in the literature, such as technological payments made by countries, publications in scientific and technical journals, or migrations of scientists or engineers. (Park, 2004) is an example of the study of these alternative channels for the transfer of technology considering in this case student flows as the vehicle for the transmission of technology. He constructs the foreign R&D stock as a student flows-weighted average of domestic R&D stocks of other countries and assesses its importance for the level of TFP concluding that this new foreign R&D stock measure is more important for TFP than the traditional measures. (Rogers, 2003) analyses, separately, the importance of sending students to study abroad, international business links and communication infrastructures for growth in GDP per worker in a sample of developed and developing countries between 1965 and 1995, based on the idea that these variables either may proxy knowledge flows, costs of imitation and the intensity of spillovers, i.e., determine the absorptive capacity of the economies. He concludes that these proxies are more relevant for growth than the widely used trade openness or foreign direct investment proxies.

growth both through the domestic rate of innovation, a direct influence, as well as the possible influence of interaction terms between human capital and these variables, and the transfer of technology that translates into the introduction of an interaction term between these variables and disembodied technology diffusion so that they also exert a positive influence on the absorptive capacity of the economy; **vi)** a vector W_{it-1} that includes the influences of embodied technology diffusion both directly and through its interaction with human capital due to the above-explained relationship with the absorptive capacity; and **vii)** an i.i.d. error term, ε_{it}.

Equation (2.41) is the general specification that will be implemented empirically for different variables in Z and W in each chapter according to data availability at each aggregation level. In each chapter we will present the specification with the actual additional technological change determinants used to check the robustness of the education results and the strategy followed to investigate the importance of the different education sub-categories or schooling levels.

2.3. Empirical analyses of education, technology and growth

The empirical analysis of the importance of education for economic growth developed here is based on the estimation of this relationship as opposed to the growth accounting methodology that imposes the parameters (based on factor shares or micro evidence) of an aggregate production function to determine the importance of education for growth.

The basic idea in growth accounting is to decompose output growth into the growth rate of inputs (physical and human capital) and a residual commonly designated by total factor productivity growth, i.e. a combination of growth in the efficiency with which these inputs are used and changes in technology.

This approach thus only considers the importance of human capital accumulation for growth as an input in the aggregate production function not taking into account the effects of education on growth through technological change highlighted by the endogenous growth literature. Furthermore, it does not allow deriving any conclusions about the direction of causality among variables[14]. Although an useful approach to gain insights into the process of economic growth it is not however the one that best suits our purposes.

The empirical methodology we use consists in estimating the relationship between education and productivity growth by exploring the cross-country time-series variation in the data using panel data econometrics, an approach also known as growth regressions. The exact way to do it is in itself subject to continuous discussion so we examine the most common problems facing the

[14] Interesting examples of the use of the growth accounting methodology to analyse the importance of education for growth can be found in (R. E. Hall & Jones, 1999), (Pritchett, 2001), (Woessmann, 2002), and (Jones, 2002).

estimation of empirical growth models[15] focusing on the issues concerning the identification of the education-growth link.

We start by examining the most common concerns with the estimated education coefficients from growth regressions and then focus on the utility of panel data econometrics to overcome some of these issues. Finally, we analyse in more detail the measurement error problem in two key variables, Total Factor Productivity (TFP), the proxy for technological efficiency used in this thesis, and educational attainment and how it can be attenuated.

2.3.1. Common problems facing growth econometrics

The assessment of the importance of education for growth requires an empirical formulation of the time-series cross-country growth differences in order to identify the effects of various factors on growth. Inspired by the work of (Barro, 1991) that regresses output growth on a set of variables considered relevant growth determinants based on the intuition from several theoretical growth models, a vast number of empirical growth studies emerged to analyse the importance of several factors (economic policy, institutions, inequality, etc.) for growth.

This raises the immediate question of which growth determinants should be included in the model, an issue known as *model uncertainty*, since different empirical models lead to different conclusions concerning growth determinants, especially for the ones that are common across studies.

A number of authors, (Levine & Renelt, 1992), (Sala-i-Martin, 1997), and (Doppelhofer, Miller, & Sala-i-Martin, 2004), conducted empirical searches of the robust growth determinants using different techniques. For instance, (Sala-i-Martin, 1997) wants to determine, from 62 growth determinants identified in the empirical growth literature, which are robust to the inclusion of different sets of explanatory variables. He defines a fixed set of growth determinants, initial income, life expectancy, and primary school enrolment rate, and combines the remaining variables in different sets. The human capital variable is found to be robust across specifications.

Our focus is on the evaluation of the role of education for productivity growth and we deal with the issue of model uncertainty in this work in some way by testing the robustness of the education results to the introduction of additional technological change determinants identified by the theoretical and empirical growth literature. To the extent that we are analysing a rather homogeneous group of countries, the OECD, this issue is also not as important as if we were dealing with a sample of countries at different stages of development.

The accurate assessment of the importance of education for growth has also to take into consideration the probable *endogeneity* of the schooling variables, a

[15] For a more thorough and technical discussion see (Temple, 1999a), (S. N. Durlauf & Quah, 1999), (Brock & Durlauf, 2001) and (S. Durlauf, Johnson, & Temple, 2005). We focus here on the problems that are most acutely felt when estimating the education-growth relationship.

problem common to most of the explanatory variables included in growth regressions, as emphasized by Caselli, Esquivel and Lefort (1996), p.367: “At a more abstract level, we wonder whether the very notion of exogenous variables is at all useful in a growth framework (the only exception is perhaps the morphological structure of a country’s geography).”

If education is a consumption good, high-income countries will demand more education. Also, skill-biased technological change in advanced industrialised countries requires a better qualified labour force. There can also be forces that influence positively both schooling and output growth.

If the explanatory variables are endogenously determined this means that they are correlated with the disturbances violating classical assumptions, and thus making it impossible to obtain consistent coefficient estimates in growth regressions using Ordinary Least Squares (OLS). When schooling is endogenous, an estimated positive coefficient on the schooling variable does not allow any conclusion on the direction of causality: it can be the result of a positive growth impact of exogenous changes in schooling or/and the result of a positive impact on education of higher growth.

For instance, (Bils & Klenow, 2000) analyse this issue in great detail concerning the education-growth link. They start by developing a model where faster technology-driven growth can induce more schooling by raising the effective rate of return of investment in schooling. Next they calibrate the model and conclude that the positive correlation between schooling and growth in (Barro, 1991) and other studies is due mainly to the fact that growth causes schooling and not the other way around. To overcome the endogeneity bias issue many studies use initial values of the explanatory variables (predetermined variables). Another option is to use instrumental variable procedures.

The impact of *measurement error* on the estimated coefficients of the explanatory variables included in growth regressions is another frequent concern. If a variable is measured with error the corresponding estimated coefficient would suffer from attenuation bias, i.e. there will be a tendency to underestimate its true value. Empirical studies of the education-growth link are especially sensitive to this problem due to the potential poor quality of the schooling data most commonly and widely used, from school enrolment rates to the educational attainment series of (Barro & Lee, 1993). This lack of quality is due not only to possible errors in data collection but also to the methodologies and underlying assumptions used to derive comparable education series. For instance, (Krueger & Lindahl, 2000) show that measurement error in education data severely attenuates estimates of the effect of the change in schooling on GDP growth. One way of dealing with this problem is to conduct a sensitivity analysis of the growth regression estimates to alternative human capital data sets. For this reason, we analyse the issue of the quality of the education series used in greater detail in a specific section of this chapter later on.

The ultimate goal in estimating the impact of education in economic growth is to be able to extrapolate results in order to derive policy prescriptions for specific countries/industries. This leads us to one final problem facing growth regressions, that of *parameter heterogeneity*. Growth regressions are based on the information from a cross-section of countries/industries and so the estimated coefficients are averages that apply to the representative country/industry in the sample. To be able to retrieve consistent estimates of the relevant coefficients the researcher has thus to impose certain restrictions about the equality of the parameters. If the restrictions do not apply however there may be very serious consequences that invalidate the policy implications derived from such estimated models. The estimation of growth regressions should thus include some form of parameter heterogeneity. In this work we consider country/industry specific effects, i.e. the growth rate of technology depends on country/industry characteristics that remain constant over time so that we allow for intercept heterogeneity while maintaining the assumption of common slopes.

Having identified some of the most serious concerns regarding the estimation of growth regressions aimed at clarifying the importance of education for growth we turn now to the analysis of the use of panel data econometrics to overcome these problems. Since the measurement error problem can also be dealt with by checking the robustness of the growth regression results to the use of alternative proxies we dedicate a specific section of this chapter to the analysis of the technological efficiency measure used, TFP, and of the quality of the education data used in growth regressions in general and the ones used in this thesis in particular.

2.3.2. Panel data econometrics for growth analysis

When conducting empirical growth analysis it is possible to choose between different econometric approaches: cross-section, time series, or panel data. Panel data is currently the most common approach to growth analysis and is the approach adopted in this thesis[16]. The focus of this section is thus on the specificities of panel data econometrics for growth analysis highlighting its advantages in the resolution of the problems facing growth econometrics described in the previous section and identifying possible shortcomings. Within panel data econometrics there are also different estimation procedures that can be used so we describe the adequacy of selected panel data procedures for the estimation of growth regressions. A more complete analysis of the issues involved in empirical growth analysis can be found in (S. N. Durlauf & Quah, 1999), (Temple, 1999a), and (S. Durlauf, Johnson, & Temple, 2005)[17].

Cross-section regression analysis was, until recently, the most common econometric approach used in growth analysis. Growth regressions were estimated considering a sample of countries and averaging growth over a long period of time of about 25 to 30 years, assuming homogeneity of all parameters. Examples of applications of this procedure can be found in (Abramovitz, 1986), (Baumol, 1986), (Barro, 1991), (Barro & Sala-i-Martin, 1991), (Kyriacou, 1991),

[16] (Temple, 1999a), p. 131 is of the opinion that "(…) panel data studies will increasingly offer the best way forward for many questions of interest, especially as longer spans of data become available."

[17] See also (Baltagi, 2001), (Johnston & Dinardo, 1997) and (Wooldridge, 2002).

(Levine & Renelt, 1992), (Barro & Lee, 1994), (Mankiw, Romer, & Weil, 1992), and (Benhabib & Spiegel, 1994), just to name a few.

From the mid 1990's onwards however panel data became the most widely used econometric approach in the study of growth. An obvious advantage is that with panel data it is possible to explore more information since it combines between and within-country variation and thus allows for more degrees of freedom increasing the efficiency of the estimators.

Another important advantage of panel data is the fact that it allows to control in some way for country heterogeneity. Islam (1995) criticised the use of single cross-country regressions to study cross-country growth since they do not allow controlling for unobserved differences across countries and the omission of these variables leads to biased OLS estimates if they are correlated with the explanatory variables. He suggests using panel data and static fixed effects estimators to control for unobserved country-specific effects, i.e. imposing common slopes but allowing for different intercepts, and in this way reduce the biases in the estimated coefficients.

For ease of exposition consider the following equation explaining the growth rate of the level of technology,

$$\Delta a_{it} = \alpha a_{it-1} + \beta x_{it} + c_i + c_t + v_{it}, \quad i = 1,\dots,N \text{ and } t = 2,\dots,T \qquad (2.42)$$

where a_{it} is the logarithm of the level of technology, x_{it} is a determinant of productivity growth, c_i is an individual effect that accounts for any time invariant individual specific effect not included in the regression, c_t is a period-specific constant, and v_{it} is an IID(0, σ_v^2) error term.

If we only have observations on a cross section of countries at time t (corresponding to averages for 25 years or more) we can only estimate:

$$\Delta a_i = \alpha a_{i1} + \beta x_i + \varepsilon_i \qquad (2.43)$$

where the variables are now measured as period averages or initial values for each individual, and $\varepsilon_i = c_i + v_i$.

Single cross-country regressions assume that the error term is uncorrelated with the explanatory variables and so the equation can be estimated using OLS. But if $E(c_i x_i) \neq 0$ then $E(\hat{\beta}) \neq \beta$, i.e. if the unobserved individual specific effects are correlated with the explanatory variables, a situation likely to occur in growth analysis, then one of the classical assumptions will be violated and OLS can not be used to recover the true estimates of the parameters of interest.

The alternative, as suggested by (Islam, 1995), is to move to panel data and use the time series information to eliminate the individual-specific effects from the regression. This can be done either by introducing dummy variables for each individual or by subtracting from each observation the respective time mean and proceed with OLS estimation of the regression defined in this way. Both estimators are static fixed effects estimators. The first is known as the least squares dummy variable estimator (LSDV) and the second is known as the within-groups (WG) estimator since it exploits the differences within countries.

Allowing for country-specific effects enables us to eliminate the bias resulting from the omission of other growth determinants that are correlated with the educational attainment variables. The results will be biased if the educational attainment variables are acting as proxies for unobservables or omitted growth determinants that are relatively constant over time and we fail to account for these omitted country characteristics. In particular, technological efficiency depends on specific features of each country such as institutions and culture, constant over time. The consideration of country-specific effects is especially important when studying the growth influence of educational variables since these change very slowly over time, i.e. are relatively constant for each country across time, so we must check if they survive the introduction of fixed effects, in which case we prove that they are not serving as proxies for other omitted country characteristics.

A second source of bias in empirical growth studies is the possible endogeneity of the regressors that occurs when some of the variables in the right hand side are correlated with the error term. This correlation might be due to reverse causation, i.e., shocks to output growth that affect the explanatory variable, or to the omission of variables that jointly determine both growth and the explanatory variables.

For instance, (Rodrik, 2003), chapter 1, defends that geography is the only growth factor that can be considered truly exogenous. (Bils & Klenow, 2000) develop a model where growth induces more schooling by raising the rate of return to investments in schooling and find empirical evidence that the effect of growth on schooling is more important than the reverse channel.

Additionally, if the productivity growth regression includes in the RHS initial productivity as an explanatory variable static fixed effects estimators will produce biased estimates of the parameters of interest, as pointed out by (Nickell, 1981). The bias becomes negligible as T becomes large but in growth studies T is usually small since observations are usually averaged over 10 or 5-year periods to eliminate business cycle effects.

To solve this problem we need to use dynamic panel data estimators. One solution is to use the first differenced GMM estimator proposed by (Arellano & Bond, 1991) and applied to growth regressions by, among others, (Caselli, Esquivel, & Lefort, 1996) and (Bond, Hoeffler, & Temple, 2001). The first differenced GMM estimator starts by differencing the growth regression to eliminate the country-specific effects and then uses lagged values of the variables as instruments to overcome the bias due to the presence of the lagged dependent variable or endogenous regressors.

To illustrate how the first differenced GMM estimator works notice that we can write equation (2.42) as an AR(1) model for the level of technology,

$$a_{it} = \tilde{\alpha} a_{it-1} + \beta x_{it} + c_i + c_t + v_{it}, \quad \tilde{\alpha} = 1 + \alpha \tag{2.44}$$

The first differenced GMM estimates the relevant coefficients based on assumptions on the population moments of the explanatory variables and the error term using the respective sample moments, and instruments the endogenous variables with its past values (internal instruments).

After accounting for time-specific effects, to eliminate the country-specific effects, c_i, we take first differences of equation (2.44):

$$\Delta a_{it} = \tilde{\alpha}\Delta a_{it-1} + \beta\Delta x_{it} + \Delta v_{it} \tag{2.45}$$

Notice that, by construction, the new error term $\Delta v_{it}=v_{it}-v_{it-1}$ is correlated with the lagged dependent variable, $\Delta a_{it-1}=a_{it-1}-a_{it-2}$, so we need to instrument for it in the regression.

Assuming that the error term is serially uncorrelated and independent across countries:

$$E(v_{it}v_{is})=0, \text{ for } i=1,\ldots,N \text{ and all } s\neq t \tag{2.46}$$

and that the initial conditions, a_{it}, are predetermined,

$$E(a_{i1}v_{it})= 0, \text{ for } i=1,\ldots,N \text{ and } t=2,\ldots,T \tag{2.47}$$

it is possible to use values of a_{it} lagged two periods or more as instruments for Δa_{it-1} since a_{it-2} and earlier values are correlated with Δa_{it-1} but not with Δv_{it}. This implies exploiting the following moment conditions,

$$E(a_{it-j}\Delta v_{it})= 0, \text{ for } t=3,\ldots,T \tag{2.48}$$

Strict exogeneity of the additional explanatory variable implies that:

$$E(x_{it}v_{is})= 0, \text{ for } i=1,\ldots,N \text{ and all } s,t \tag{2.49}$$

Since in a growth framework strict exogeneity is quite a strong assumption we relax it considering that x_{it} is weakly exogenous in the sense that there is a correlation between its current values and current shocks to output, as well as feedback from past shocks to output, so:

$$E(x_{it}v_{is})= 0, \text{ for } i=1,\ldots,N \text{ and } s>t \text{ only} \tag{2.50}$$

and

$$E(x_{it}v_{is})\neq 0, \text{ for } i=1,\ldots,N \text{ and } s\leq t \tag{2.51}$$

Valid instruments for Δx_{it} are x_{it} lagged two periods or more since x_{it-2} and earlier values are correlated with Δx_{it} but not with Δv_{it}. Assuming that x_{it} is weakly exogenous is thus equivalent to exploring the following moments:

$$E(x_{it-j}\Delta v_{it})= 0, \text{ for } j=2,\ldots,(t-1) \text{ and } t=3,\ldots,T \tag{2.52}$$

Table 2.1 describes the valid GMM instruments for the different time periods when x_{it} is weakly exogenous.

Period	Equation	Instruments for Δait-1 and Δx it
t=2	Δai2= αΔai1+βΔxi2+Δvi2	not possible to estimate since there are no instruments available for Δai1 and Δxi2.
t=3	Δai3= αΔai2+βΔxi3+Δvi3	ai1 valid instrument for Δai3 xi1 valid instrument for Δxi3
t=4	Δai4= αΔai3+βΔxi4+Δvi4	ai1 ai2 valid instruments for Δai4 xi1 xi2 valid instruments for Δxi4
…	…	…
t=T	ΔaiT=αΔaiT-1+βΔxiT+ΔviT	ai1 ai2… aiT-2 valid instruments for ΔaiT-1 xi1 xi2 ,…, xiT-2 valid instruments for ΔxiT

Table 2.1. Instruments available for the first-differenced GMM estimator: x_{it} weakly exogenous

If however the productivity growth determinant, x_{it} is predetermined, i.e., current shocks to output are uncorrelated with x_{it} but past shocks are correlated with these variables, we can write:

$$E(x_{it}v_{is})= 0, \text{ for } i=1,\dots,23 \text{ and } s\geq t \qquad (2.53)$$

and

$$E(x_{it}v_{is})\neq 0, \text{ for } i=1,\dots,23 \text{ and } s< t \qquad (2.54)$$

Assuming that x_{it} is predetermined is equivalent to exploring the moments assumption:

$$E(x_{it-j}\Delta v_{it})= 0, \text{ for } j=1,\dots,(t-1) \text{ and } t=3,\dots,T \qquad (2.55)$$

so valid instruments for Δx_{it} are x_{it} lagged one period or more since x_{it-1} and earlier values are correlated with Δx_{it} but not with Δv_{it}.

For the GMM estimates to be consistent we have to check whether the lagged values of the explanatory variables are valid instruments. Two specification tests proposed by (Arellano & Bond, 1991) can be used to address this issue.

For lagged values of the explanatory variables to be valid instruments the error term, v_{it}, must be serially uncorrelated. The first specification test corresponds thus to testing whether the first-differenced equation error term is second-order serially uncorrelated which is equivalent to the null hypothesis that the errors in the levels equation are first-order serially uncorrelated. First-order serial correlation of the differenced error term is expected even if the original error term (in levels) is uncorrelated. Second-order serially uncorrelated differenced residuals indicate that the original error term is serially uncorrelated otherwise we would have to reject the appropriateness of the proposed instruments. The second-order serial correlation test-statistic follows the standard normal distribution.

The second test is a Sargan test of over-identifying restrictions, which tests the overall validity of the instruments used by analysing the sample analog of the moment conditions used in the estimation process. The model specification is supported when the null hypothesis is not rejected. Under the null hypothesis the Sargan Statistic follows a χ^2 distribution with M-K degrees of freedom, where M is the number of columns in the instrument matrix and K is the number of explanatory variables[18,19].

Despite the advantages of panel data in dealing with some of the most common problems that empirical growth analysis has to face, namely the endogeneity problem and to some degree the parameter heterogeneity problem, some care has to be taken when interpreting the results. Notice that in order to overcome the omitted variable problem the panel data estimators rely on within-country variation eliminating the long-run variation across countries. This means also that the influence of variables that are fairly constant over time cannot be identified since it will be thrown away when eliminating the country-specific effects[20]. Another problem has to do with the averaging of data over time periods. How does the researcher know what is the time horizon over which the growth model is supposed to apply? According to (S. N. Durlauf & Quah, 1999), p.54 "In growth work, one can plausibly argue that misspecification is greater at higher frequencies." Averaging over long time periods also means reducing the time series variation, an advantage of panel data in the first place.

A recent concern of panel data econometrics is nonstationary panels (see e.g. Baltagi and Kao (2000)). The econometric analysis of time series data as for long worried about the problems associated with nonstationary variables. In regressions with nonstationary variables, i.e. variables that display a mean, variance or covariances that are not constant over time the statistical inference based on t, F and χ^2 statistics cannot be applied since the coefficient estimates follow non-standard distributions and the problem of spurious correlation arises. If the dependent variable and at least one of the explanatory variables exhibit a distinct trend we are likely to obtain highly significant estimated coefficients and high values for R^2 even if there is no causal relationship between the variables, so that the regression results are completely spurious, i.e. meaningless. To avoid this problem time series tests of stationarity of a variable or unit root tests were

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[18] If the number of individuals is small relative to the number of instruments the Sargan test statistic cannot be computed given the near singularity of the variance-covariance of the moment conditions. In this case we have to rely on the serial correlation test to draw conclusions on the consistency of the GMM estimates.

[19] Econometric software packages used were GiveWin 2.02 and Stata 8.0.

[20] For instance, (S. Durlauf, Johnson, & Temple, 2005) suggest exploring the information content of country-specific effects to uncover the influence of these variables.

developed, such as the popular (augmented) Dickey-Fuller test (see e.g. (Dickey & Fuller, 1979)).

Since panel data combines time series and cross-section information of the variables of interest[21] it is not surprising that econometricians dealing with panel data have also tried to develop panel unit root tests (which are often extensions of the time series unit root tests) although comparably much less attention has been devoted to this issue at both theoretical and empirical levels[22] so we can say that the literature on panel unit root tests is still on its infancy and thus open to several critiques (e.g. how to deal with the variety of models possible in a panel setting[23]).

Bearing in mind these caveats we nevertheless decided to submit the annual series used in chapters 4 and 5 to two panel unit root tests, the ones most often used in the empirical literature. These are the Levin, Lin and Chu (2002) and the Im, Pesaran and Shin (2003) tests that we describe in greater detail in the appendix to chapter 4, section 4.6.5. If the variables used are stationary the econometric methodology for stationary panels applied in chapters 4 and 5 is the suitable one. If the series contain a unit root the regression results may be spurious unless the variables are cointegrated[24]. In any case the possible lack of power of the available panel unit root tests does not allow for definite conclusions (see e.g. (Jörg Breitung, 2000)). We present the results of the panel unit root tests as an appendix to each chapter.

2.3.3. Sources of measurement error in key variables

One possible way of dealing with the problem of measurement error in the empirical investigation of the role of education in productivity growth is to check the robustness of the results to the use of alternative measures or proxies of the theoretical concepts that underlie the empirical model under estimation. We will do so for two key variables in this thesis, the proxy used to measure the growth rate of technology, our dependent variable, and human capital acquired in the formal education sector, our key explanatory variable.

2.3.3.1. Measurement of TFP growth and levels

The empirical analysis uses Total Factor Productivity (TFP) growth as the measure of technological change or productivity growth. The growth rate of TFP is measured residually as the difference between the change in output and the observed change of combined inputs, where each input is weighted according to

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[21] Thus increasing the information available by adding the cross-section dimension and consequently improving the power of the time series tests.

[22] See e.g. (J. Breitung & Meyer, 1994), (Quah, 1994), (A. Levin & Lin, 1993), (K. Im, Pesaran, & Shin, 1997), and (Maddala & Wu, 1999).

[23] See e.g. (McCoskey & Kao, 1999), (Banerjee, Marcellino, & Osbat, 2004), (Bai & Ng, 2001), and (Strauss & Yigit, 2003).

[24] Panel cointegration analysis however is not possible in our analysis due to the different integration orders of the dependent (I(0)) and explanatory variables (I(1)).

its share in total output. We thus use a growth accounting framework to measure productivity growth in the tradition of (Solow, 1957), that assumes that production processes can be represented by a production function that relates the available inputs to the maximum possible output and that the markets are perfectly competitive so that the production function has constant returns to scale to all reproducible inputs and thus inputs can be weighted according to the respective, observable, income shares.

Consider a standard neoclassical production function with Hicks-neutral technological change,

$$Y = F(A, K, L) = A\overline{F}(K, L) \tag{2.56}$$

where Y is real output, A is the level of technology, K is the real physical capital stock, and L is the quantity of labour. The function $\overline{F}$ is homogenous of degree one due to the assumption of constant returns to scale to K and L and exhibits diminishing marginal products to the reproducible inputs.

Differentiating the production function with respect to time and dividing by Y we arrive at,

$$\frac{dY}{dt}\frac{1}{Y} = \frac{dA}{dt}\frac{1}{A} + \frac{F_K K}{Y}\frac{dK}{dt}\frac{1}{K} + \frac{F_L L}{Y}\frac{dL}{dt}\frac{1}{L} \tag{2.57}$$

where the growth rate of output can be decomposed into the growth rate of technology and the growth rates of the factor inputs and $F_K = A\overline{F}_K$ and $F_L = A\overline{F}_L$ are the marginal products of physical capital and labour, respectively.

In perfectly competitive markets factors are paid according to their marginal products so that F_K and F_L can be approximated by the observed factor prices. Assuming additionally constant returns to scale, $Y=F_K K+F_L L$, so that the contribution of the growth of each input to output growth is weighted according to the respective observed income shares.

The growth rate of technology can thus be computed as a residual,

$$\frac{dA}{dt}\frac{1}{A} = \frac{dY}{dt}\frac{1}{Y} - \frac{F_K K}{Y}\frac{dK}{dt}\frac{1}{K} - \frac{F_L L}{Y}\frac{dL}{dt}\frac{1}{L} \tag{2.58}$$

where (dA/dt)(1/A) is also known as the TFP growth rate or the Solow residual.

The (OECD, 2001a) manual on measuring productivity recommends the use of superlative index numbers[25] to compute TFP growth rates[26] since "they provide a reasonable approximation to an independent measure of technical change even when technologies in practice do not show the simple, output-augmenting layout of the constant returns to scale production function". To test the robustness of the results we use two different functional forms for the production function, the Cobb-Douglas specification since it is the most widely used in the growth literature, that assumes that income shares are constant

[25] An index that is exact for a flexible functional form of the production function.

[26] See also (Caves, Christensen, & Diewert, 1982a) and (Caves, Christensen, & Diewert, 1982b).

across countries and time, and the translog specification that allows factor shares to vary across countries/industries and time.

According to the Cobb-Douglas specification the production function can be written as (in logarithmic terms),

$$\log Y_{it} = \log A_{it} + (1-\alpha)\log K_{it} + \alpha \log L_{it} \qquad (2.59)$$

so that TFP growth is equal to:

$$\Delta \log A_{it} = \Delta \log TFP_{it} = \Delta \log Y_{it} - \alpha\Delta \log K_{it} - (1-\alpha)\Delta \log L_{it} \qquad (2.60)$$

where α is the labour income share, constant across countries/industries and time.

The translog specification on the other hand allows us to consider that factor shares vary across countries/industries and time (see (Harrigan, 1997)). According to the translog specification the production function can be written as (in logarithmic terms),

$$\log Y_{it} = \alpha_{0it} + \alpha_{1it}\log K_{it} + \alpha_{2it}\log L_{it} + \alpha_{3it}\left(\log K_{it}\right)^2 + \alpha_{4it}\left(\log L_{it}\right)^2 + \alpha_{5it}\log K_{it}\log L_{it} \qquad (2.61)$$

where constant returns to scale requires $\alpha_1+\alpha_2=1$ and $2\alpha_3+\alpha_5=2\alpha_4+\alpha_5=0$.

A proxy for the growth rate of technology is thus obtained according to the formula:

$$\Delta \log A_{it} = \Delta \log TFP_{it} = \Delta \log Y_{it} - (1-\frac{\alpha_{it}+\alpha_{it-1}}{2})\Delta \log K_{it} - \frac{\alpha_{it}+\alpha_{it-1}}{2}\Delta \log L_{it}$$

(2.62)

where α is allowed to vary across countries, industries and time.

The level of TFP can be computed using a superlative index number analogous to the one used to compute the TFP growth rate according to the formula:

$$\log TFP_{it} = \log\left(\frac{Y_{it}}{\bar{Y}}\right) - (1-\frac{\alpha_{it}+\bar{\alpha}}{2})\log\left(\frac{K_{it}}{\bar{K}}\right) - \frac{\alpha_{it}+\bar{\alpha}}{2}\log\left(\frac{L_{it}}{\bar{L}}\right) \qquad (2.63)$$

where $\bar{Y}$, $\bar{\mathbf{K}}$, $\bar{L}$, $\bar{\alpha}$ are the geometric means of real output, real physical capital stock, labour input, and labour income shares, respectively.

The distance of a country/industry from the technological frontier or relative TFP (RTFP) is simply calculated in any case by subtracting the level of TFP of the industry under analysis from the level of TFP of the frontier country/industry, the country/industry with highest value of TFP:

$$\log\left(\frac{A_{\max t}}{A_{it}}\right) = RTFP_{it} = \log TFP_{\max t} - \log TFP_{it} \tag{2.64}$$

In each chapter we will give details on the data needed to compute TFP growth and levels corresponding to the different aggregation levels.

2.3.3.2. Measurement of human capital acquired in the formal education sector

The analysis of the importance of human capital acquired in the formal education sector for economic growth implies the availability of comparable schooling data for a relatively large cross section of countries over time. The limited availability of this kind of data implied that empirical growth studies from the late 1980's and early 1990's had to depend on the readily available statistics, adult literacy rates (e.g., (Romer, 1990b), (Azariadis & Drazen, 1990), (Nunes, 1993)) and school enrolment ratios (e.g., (Barro, 1991), (Murphy, Shleifer, & Vishny, 1991), (Mankiw, Romer, & Weil, 1992), (Levine & Renelt, 1992), (S. Durlauf & Johnson, 1995)). Both proxies however can be shown to be poor proxies of the skills formal education provides workers with (see (Woessmann, 2002), chapter 2, and (Woessmann, 2003) for a detailed analysis of this issue).

The obvious major shortcoming of adult literacy rates as a measure of the educational attainment stock is the fact that it only considers skills provided by education at a very initial and basic level[27] thus ignoring all skills acquired at the subsequent stages of education such as numeracy, logical and analytical reasoning[28].

School enrolment ratios on the other hand are flow measures of educational attainment not stock measures. Using flow variables as proxies for stock variables is especially problematic in the case of educational attainment since the time lag between enrolment and participation in the workforce is very long and may even never translate into additions to the educational attainment of the labour force if the individuals do not enter the labour market.

These conceptual shortcomings led a number of authors to build education data sets more suitable on theoretical grounds for the estimation of empirical growth models. Early attempts include the works of (Psacharopoulos & Arriagada, 1986) and (Kyriacou, 1991) but it was the work by (Barro & Lee, 1993) (henceforth BL) that provided a human capital data set that enabled an explosion in empirical growth studies, since human capital is given a

[27] According to the UNESCO website "A person is literate who can, with understanding, both read and write a short simple statement on his or her everyday life."

[28] For other problems related to the use of adult literacy rates in international comparisons see (Barro & Lee, 1993), p.367.

fundamental role in economic growth by both exogenous and endogenous growth models[29].

The original BL dataset has been revised twice (1996 and 2001) and is still the most widely used human capital data set[30]. A major advantage of this human capital data set for empirical growth studies is that it covers almost the same sample of countries as the (Summers & Heston, 1991) Penn World Table data set that displays a set of national accounts economic time series covering many countries denominated in a common set of prices in a common currency and thus allows for real quantity comparisons, both between countries and over time.

A number of alternative human capital data sets have since been proposed although none of them has been as successful in terms of use in empirical growth studies. (Nehru, Swanson, & Dubey, 1995) build estimates of the stock of education for 85 countries; (Gemmell, 1996) provides data for 98 countries; (De la Fuente & Doménech, 2000), revised in (De la Fuente & Doménech, 2002) (henceforth DD) [31] focus on a sample of 21 OECD countries and (D. Cohen & Soto, 2007) build a measure of the educational attainment of the population for 95 countries.

A common feature of the above mentioned studies is the fact that they proxy human capital with the educational attainment of the population and ultimately compute a measure of the average years of schooling of that same population. This proxy is especially suitable for the empirical analysis of endogenous growth models that predict a positive relationship between the level of human capital, technological change and the growth rate of output. The use of average years of schooling of the population data also allows for more direct comparisons of empirical growth studies results on the quantitative growth impact of education with the labour economics literature results on rates of return to education.

One way we have to deal with the attenuation bias associated with measurement error in education data is to conduct a sensitivity analysis of the results to the use of two alternative educational attainment data sets, (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002). The (Barro & Lee, 2001) data set is an obvious choice since it is still the most widely used human capital data set in empirical growth studies. On the other hand, since this thesis focus on a sample of OECD countries, the (De la Fuente & Doménech, 2002) data set is the most adequate choice to check the robustness of the results to the use of alternative human capital data sets. This data was built with the specific aim of correcting the (Barro & Lee, 1996) data for OECD countries for quality issues in data collection[32].

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[29] Some examples of empirical growth studies that use the BL data are (Islam, 1995), (Klenow & Rodriguez-Clare, 1997), (Temple, 1998), (R. E. Hall & Jones, 1999).

[30] For instance, a search in the Social Sciences Citation Index for articles that cite Barro and Lee's work returns more than three hundred references.

[31] See also (De la Fuente & Doménech, 2006).

[32] (D. Cohen & Soto, 2007) also correct the BL data for quality issues. The major novelty in their education stock series is the use of educational attainment rates broken up into different age groups. However, they only provide data at 10-year intervals so we do not use it to check the robustness of the results.

In the next sections we briefly review the techniques used in both data sets to compute education stock series for a panel of OECD countries over time and provide some summary information on average years of schooling at the different levels for the average OECD country across data sets to identify differences and similarities, as well as an indicator of the quality of the data in each of them, the respective reliability ratio.

2.3.3.2.1. The Barro and Lee data set(s)

(Barro & Lee, 1993) uses census/survey data and estimation procedures to build a data set of the educational attainment of the population aged 25 and over for 129 countries at 5-year intervals from 1960 to 1985. The first step in their analysis consisted in gathering data on educational attainment of the population aged 25 and over from several issues of UNESCO's Statistical Yearbooks and some other sources that according to the authors "exhausts the census/survey figures on educational attainment that we know of."p.370.

The collected data corresponds to the six levels of the International Standard Classification of Education (ISCED) defined by UNESCO: no schooling; incomplete first level; complete first level; entered second level, first cycle; entered second level, second cycle; and higher level. The observations obtained in this way represent about 40% of the total observations. Additionally, BL use adult illiteracy data to estimate the no-schooling percentage, which provides them with 124 additional observations.

Taking this census/survey information and the estimated no-schooling percentages as benchmarks, BL then use a perpetual inventory method to estimate the missing observations at the various education levels using gross enrolment ratios and population by age data[33]. The basic idea is that the enrolment ratios represent investment rates in education, i.e., are the flow variable that adds over time, with an appropriate time lag, to the prior educational attainment stocks and in this way allow for the computation of the subsequent stocks[34].

Finally, BL construct their measure of average years of total schooling (TYR_BL) according to the formula:

$$TYR\_BL = \sum_{a}\left[n_a \left(\sum_{i=1}^{a} DUR_i\right)\right] \qquad (2.65)$$

[33] See (Barro & Lee, 1993), pp.373-375, for a description of the application of the perpetual inventory method to the computation of educational attainment figures. Data availability on gross enrolment ratios only allows to get the full time series of six observations for 106 out of the 129 countries.

[34] The estimates are obtained in three ways: forward-flow estimates when benchmark values from year t are used to estimate attainment in year t+10; backward-flow estimates when benchmark values from year t are used to estimate attainment in year t-10; and interpolation, when possible. This method was used to compute missing observations at four levels: no schooling; first level total, second level total, and higher level. To compute missing observations disaggregating each level into complete and incomplete educational attainment BL regress completion ratios (ratio of complete schooling at level j to total schooling at level j) on its past 5-year and 10-year lagged values and on regional dummies.

where n_a is the share of the population aged 25 and over for which the ath level of schooling is the highest level attained, DUR is the duration in years of schooling level a, and a corresponds to, respectively, incomplete primary, complete primary, first cycle of secondary, second cycle of secondary, incomplete higher, and complete higher education. The duration of each schooling cycle is derived for each country from the UNESCO Statistical Yearbook of 1965 and assumed to remain constant. It is assumed also that the population aged 25 and over with incomplete primary education received half the years of education corresponding to this schooling cycle. When the duration of each cycle of secondary education was not provided BL assigned one-half of the total duration of secondary school to the first cycle. For higher education BL assume a duration of four years for all countries and of two years for people who did not complete it.

(Barro & Lee, 1996) and (Barro & Lee, 2001) are updates of this first data set, covering a longer time period (up to 2000 in the second case) but using basically the same methodology to compute the educational attainment rates at the various schooling levels and the average years of schooling measure. In (Barro & Lee, 1996) the authors update the former data set until 1990 using data on net enrolment ratios and not gross enrolment ratios as before and provide information on the educational attainment of the population aged 15 and over, especially relevant for developing countries where a large proportion of the labour force is younger than 25. This data set covers 126 countries for the years 1960, 1965, 1970, 1975, 1980, 1985, and 1990 with full time series of seven data points for 105 countries. Census observations correspond to about 35% of the total number of observations.

A further update is provided in (Barro & Lee, 2001) with figures up to 1995 and projections for the year 2000. These updates improve the former two data sets in two important ways: to compute the missing educational attainment rates the authors now use gross enrolment rates adjusted for repeaters at the primary and secondary level and to construct measures of average years of schooling at all levels they take account of changes of each schooling cycle over time within each country[35]. The data set comprises at least one observation for 142 countries and a full time series of nine observations for 107 countries.

2.3.3.2.2. The De la Fuente and Domenéch data set

The concern with the quality of the education data used in the construction of education stock series lead (De la Fuente & Doménech, 2000) to build a new data set for 21 OECD countries[36] at 5-year intervals between 1960 and 1990,

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[35] If countries change the duration of each schooling cycle considering the 1965 duration is a source of measurement error. According to (Barro & Lee, 2001), p.547: "Over the last three decades, 32 countries have changed at least once the typical duration of schooling at the primary or secondary levels (see UNESCO, Statistical Yearbook, various years)."

[36] "One of the main reasons for this choice is that educational statistics for this set of advanced industrial nations are presumably of decent quality. Any deficiencies we find in them are likely to be compounded in the case of poorer countries." (De la Fuente & Doménech, 2002), p.6.

revised in 2002 and including data up to 1995 for most countries, using a higher number of census data, i.e. exploring data sources that had not been used by BL. They do not use the perpetual inventory method with enrolment data to fill in missing observations but interpolation and backward projection[37].

The first step in DD's study consists in verifying the existence of errors in the education stock series built by BL that justify the need for a new data set with a higher signal-to-noise ratio. They explore both the cross section and the time series discrepancies[38] in BL's 1996 data set by comparing it with data from the OECD for the most recent years.

Based on the evidence of potential measurement errors in the existing data sets, DD provide data on the fraction of the population aged 25 and over that has started but not necessarily completed one of six schooling levels (illiterates, primary schooling, lower secondary schooling, upper secondary schooling, higher education, first cycle or shorter courses, and higher education, second cycle or full-length courses) exploring this new information from OECD and national sources.

This information is then used to compute average years of total schooling (TYR_DD) based on the cumulative years of schooling for each schooling cycle in the different countries according to the formula:

$$TYR\_DD = \sum_{a} \left[n_a CUMYR_a \right] \tag{2.66}$$

where n_a is the share of the population aged 25 and over for which the ath level of schooling is the highest level attained, $CUMYR_a$ corresponds to the cumulative years of schooling of level a (equal to the sum of the duration of each schooling level up to level a), and a corresponds to, respectively, primary schooling (L1), lower secondary schooling (L21), upper secondary schooling (L22), higher education, first cycle or shorter courses (L31), and higher education, second cycle or full-length courses (L32). Contrary to BL, DD assume that every person that started a given schooling level completed it.

With the information provided by the authors concerning the attainment series and the assumed duration of each schooling cycle it is straightforward to compute average years of schooling, by schooling level, primary (PYR_DD), secondary (SYR_DD) and tertiary (HYR_DD) for each country in the sample, according to the formulas[39]:

[37] As the authors acknowledge they "rely on a heuristic procedure to obtain plausible time profiles for attainment levels by removing sharp breaks in the data that can only be due to changes in classification criteria."p.2. Also, "We have avoided the use of flow estimates based on enrollment data because they seem to produce implausible time profiles." p.14.

[38] "(…) the schooling levels reported for some countries do not seem very plausible, while others display extremely large changes in attainment levels over periods as short as five years (particularly at the secondary and tertiary levels) or extremely suspicious trends." (De la Fuente & Doménech, 2002), p.6.

[39] (Barro & Lee, 2001) already provide data on average years of education by schooling level with no need for further computations.

$$PYR\_DD = (\sum_a n_a)CUMYR_{L1} \tag{2.67}$$

$$SYR\_DD = n_{L21}(CUMYR_{L21} - CUMYR_{L1}) + (n_{L22} + n_{L31} + n_{L32})(CUMYR_{L22} - CUMYR_{L1}) \tag{2.68}$$

$$HYR\_DD = n_{L31}(CUMYR_{L31} - CUMYR_{L22}) + n_{L32}(CUMYR_{L32} - CUMYR_{L22}) \tag{2.69}$$

(Bassanini & Scarpetta, 2001) and (Bassanini & Scarpetta, 2002) extended the DD data set to 1998 using more recent data on educational attainment rates from the OECD. We also extended the DD data set on average years of schooling, total and by schooling level, up to 2000, using data on educational attainment rates obtained directly from the OECD Statistics Division[40].

2.3.3.2.3. A brief comparison of the two data sets at the various schooling levels

In this section we analyse the cross section and time series similarities and differences between the BL and DD data sets highlighting what happens at the various schooling levels. In the tradition of (Krueger & Lindahl, 2000) we also analyse the quality of the data by computing the respective reliability ratio. This is an important issue since if an explanatory variable is measured with additive white noise errors the estimated coefficients of education variables in growth regressions will be biased towards zero.

Table 2.2 reports data on average years of schooling, total and by schooling level, for the average OECD country in the BL 2001 and the DD 2002 human capital data sets. The BL data refers to the average OECD country for a sample of 23 OECD countries used in the empirical analysis. The DD data refer to only 21 OECD countries, Iceland and Turkey not included, from 1960 to 2000.

In the time series dimension, all measures of years of schooling show an upward trend in both data sets. This trend is less marked for average years of primary schooling as expected since many countries had already universal coverage at the primary level in 1960.

The total growth rate of PYR is much lower than for the other education levels, and its annual average growth rate is close to zero. Average years of tertiary schooling show the highest total and annual growth rates in both data sets. Average years of secondary schooling also grew considerably with total growth rates around 100%, and annual growth rates of more than 1.5%.

Despite the high growth rates of average years of secondary and tertiary education there is still significant room for further expansion since the 2000

[40] We thank Manuela de Sousa from the OECD Education Indicators and Analysis Division for kindly providing this data.

figures are less than half the maximum value for secondary and tertiary education.

The higher figures in the DD data are due to the assumption that everyone that started a given schooling level completed it. On the other hand, the behaviour of the DD series is smoother than the BL series, a result due mostly to the behaviour of the SYR series.

	BL data for the population aged 15 and over				DD data for the population aged 25 and over			
YEAR	TYR_BL	PYR_BL	SYR_BL	HYR_BL	TYR_DD	PYR_DD	SYR_DD	HYR_DD
1960	6.587	4.722	1.713	0.151	8.360	5.454	2.717	0.189
1965	6.696	4.752	1.782	0.163	8.691	5.478	2.975	0.238
1970	7.132	4.862	2.067	0.203	9.025	5.502	3.234	0.288
1975	7.428	4.860	2.292	0.276	9.449	5.525	3.559	0.365
1980	8.056	4.971	2.741	0.344	9.871	5.549	3.881	0.441
1985	8.285	5.039	2.859	0.386	10.272	5.569	4.189	0.514
1990	8.747	5.138	3.151	0.459	10.633	5.587	4.460	0.586
1995	9.127	5.254	3.330	0.543	11.157	5.640	4.766	0.751
2000	9.399	5.283	3.486	0.631	11.828	5.571	5.248	1.009
Total growth	42.7%	11.9%	103.5%	318.0%	41.5%	2.2%	93.1%	434.5%
Average annual growth	0.9%	0.3%	1.8%	3.6%	0.9%	0.1%	1.6%	4.2%

Notes: TYR_BL is average years of total schooling for the population aged 15 and over from BL2001,
PYR_BL is average years of primary schooling for the population aged 15 and over from BL2001,
SYR_BL is average years of secondary schooling for the population aged 15 and over from BL2001,
HYR_BL is average years of tertiary schooling for the population aged 15 and over from BL2001.
TYR_DD is average years of total schooling of the population aged 25 and over from DD2002,
PYR_ DD is average years of primary schooling of the population aged 25 and over from DD2002,
SYR_ DD is average years of secondary schooling of the population aged 25 and over from DD2002,
HYR_ DD is average years of tertiary schooling of the population aged 25 and over from DD2002.
BL2001 data refers to the 23 OECD countries used in the empirical analysis. Data from DD2002 does not include Iceland and Turkey. DD values for the year 1995 for France, Japan, Portugal, Spain and the UK and all the values for the year 2000 were computed with data provided by the OECD Education Indicators & Analysis Division.

Table 2.2. Average years of schooling for the average OECD country from the BL 2001 and DD 2002 data sets, 1960-2000

In the cross-section dimension[41], the DD estimates lie above the BL's estimates since they assume that every person that has attained a certain school level completed it. In terms of country rankings, in 1960 the highest figure for TYR was registered by Australia in BL and by Denmark in DD, while the last position was occupied by Portugal in both data sets. The USA were in the fifth position in BL and in the second in DD. Regarding PYR, the first place was occupied by New Zealand in BL and by Australia in DD. The USA were in the seventh and nineteenth positions in BL and DD, respectively, and again Portugal was always in the last position. In fact this country always occupies one of the last two positions in the ranking of SYR and TYR in the two data sets. In the SYR

[41] See Tables 2.5 and 2.6 in the Appendix for data by country for the years 1960, 1980, 1990 and 2000.

ranking, the fist position is for Germany in BL and for the USA in DD. The USA was in the sixth position in BL. As for HYR, the USA was in the first position in DD and in third in BL.

In 1990, Portugal came in last in BL and DD regarding all measures of schooling years except PYR (and was second to last regarding HYR in BL) which is probably due to differences in the duration assumed for this schooling cycle by the different authors. In the TYR ranking, the USA was first in BL and fourth in DD. Regarding PYR nothing much changes due to universal coverage, i.e., the first place was again occupied by New Zealand in BL and by Australia in DD, the USA were in the sixth, and nineteenth position in BL and DD, respectively. As for SYR, Germany occupied the first position in both data sets, and the USA occupied the second position. In the HYR ranking, the USA occupied the first position and Canada the second in BL, and the position between the two changed in DD.

Finally, in the year 2000 nothing changed in the last position. In the first position of the TYR ranking, the USA was first in BL and Germany was first in DD. Nothing much changes in the PYR and SYR ranking. In the HYR ranking, the first position is occupied by the USA in BL and Finland in DD. The USA is in the third position in DD.

To sum up, we can say that the time profiles of the two data sets are similar with fewer breaks in the DD data set. In the cross-section dimension, there are no significant differences concerning the last positions in the rankings but there are some in the first positions. The differences are more notorious at the primary level, which is mainly due to classification problems and the techniques used to distinguish between primary and the first stage of secondary education.

The fact that the two data sets are closely related is supported by the high correlation coefficients registered between the different measures, in levels, of average years of schooling. Table 2.3 reports the correlation coefficients between the four education measures for the common 21 OECD countries between 1960 and 2000 at 5-year intervals. The high correlation coefficients for TYR are due to the high correlation coefficients for SYR and HYR. The lower values for PYR are probably due to the different duration assumed for this schooling cycle by the different authors. If we redo the calculations ignoring Greece, Spain and Portugal, the countries with the lowest values for the different measures, the correlation coefficients drop (although still higher than 0.68 for SYR and HYR).

	TYR_BL	TYR_DD		PYR_BL	PYR_DD
TYR_BL	1		PYR_BL	1	
TYR_DD	0.917	1	PYR_DD	0.438	1
	SYR_BL	SYR_DD		HYR_BL	HYR_DD
SYR_BL	1		HYR_BL	1	
SYR_DD	0.780	1	HYR_DD	0.833	1

Notes: 21 OECD countries, 1960-2000 at 5-year intervals.
TYR_BL is average years of total schooling for the population aged 15 and over from BL2001,
PYR_BL is average years of primary schooling for the population aged 15 and over from BL2001,
SYR_BL is average years of secondary schooling for the population aged 15 and over from BL2001,
HYR_BL is average years of tertiary schooling for the population aged 15 and over from BL2001.
TYR_DD is average years of total schooling of the population aged 25 and over from DD2002,
PYR_ DD is average years of primary schooling of the population aged 25 and over from DD2002,
SYR_ DD is average years of secondary schooling of the population aged 25 and over from DD2002,
HYR_ DD is average years of tertiary schooling of the population aged 25 and over from DD2002.

Table 2.3. Correlation coefficients between the BL and DD data sets in levels

Finally, we computed reliability ratios for each series to analyse in relative terms the quality of the different data sets, i.e. their information content, in the tradition of (Krueger & Lindahl, 2000).

Let us denote by TYR the true value of average years of schooling, by TYR_i the existing imperfect measures of average years of schooling (with i=BL,DD), and by e_{TYR_i} the respective measurement error term, an i.i.d. disturbance with zero mean and uncorrelated with TYR.

The reliability ratio of the variable TYR_i, R(TYR_i), measures the fraction of its variability that is due to the variability of the true variable (equation (2.70)):

$$R(TYR\_i) = \frac{\operatorname{var} TYR}{\operatorname{var} TYR + \operatorname{var} e_{TYR\_i}} \tag{2.70}$$

Having alternative imperfect measures of average years of schooling, TYR_i and TYR_j, then the covariance between these two measures can be used to estimate R(TYR_i) if the measurement error terms are uncorrelated with, so that (equation (2.71)),

$$R(TYR\_i) = \frac{\operatorname{cov}(TYR\_i, TYR\_j)}{\operatorname{var} TYR\_i} \tag{2.71}$$

To estimate the reliability of TYR_i we can thus run a regression of the form TYR_j=a+bTYR_i where b is the estimated value of R(TYR_i) since the formula above corresponds to the OLS estimator of the slope coefficient of a regression of TYR_j on TYR_i when all the countries are pooled together.

However, if the measurement errors of the two series are positively correlated, a strong possibility since the series rely to a greater or less extent on the same mismeasured enrolment or census data, R(TYR_i) will overestimate the reliability ratio and hence understate the extent of the attenuation bias induced by measurement error. Since reliability ratios must lie between zero and one, estimates that fall outside these bounds are an indicator that measurement error is likely to be correlated across data sets.

Table 2.4 reports the reliability ratios for the variables in levels when the 21 countries are pooled together between 1960 and 2000. As in (Serrano, 2003), we find that the reliability of the BL data set (91.9%) is higher than the reliability of the DD data set for TYR. When we analyse the reliability ratios of the average years of education by schooling level measures, the ratio for PYR is higher for the DD data and we cannot consider the SYR and HYR figures for BL since they are higher than one.

	BL	DD
	0.919	0.851
TYR	(0.071)	(0.069)
	0.487	0.785
PYR	(0.121)	(0.222)
	1.31	0.534
SYR	(0.144)	(0.032)
	1.01	0.688
HYR	(0.119)	(0.076)

Notes: 21 OECD countries, 1960-2000 at 5-year intervals.
Heteroscedasticity-consistent standard errors in parenthesis.
TYR is average years of total schooling, PYR is average years of primary schooling,
SYR is average years of secondary schooling, HYR is average years of tertiary schooling.

Table 2.4. Levels reliability ratios of the BL and DD data sets, 1960-2000

2.3.3.2.4. Comments

At the present the prevailing technique to construct education stock series across countries and over time is the one that combines census data on the educational attainment of the population with the perpetual inventory method, that uses the previous data and enrolment ratios to compute the missing observations. A major shortcoming of this technique is that only a small percentage of the observations are taken directly from census. For instance, (Woessmann, 2003) refers that in the DD data set only 27 percent of the observations on secondary attainment come directly from census. The remaining 73 percent are thus "statistically manufactured" in some way or another giving rise to the possibility of measurement error[42], which in turns gives rise to biases in the estimated coefficients of education variables in growth regressions. It is therefore important to have some idea of the relative degree of measurement error present in the available data sets.

We thus compared the education stock series in (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002) in order to get some perception of the quality of the data in each of them. The time profile of the series is similar in both data sets for all measures of average years of schooling, although smoother in the second case. Comparing the data across countries there are some differences regarding the countries that occupy the first positions in the rankings for the different schooling levels but the countries that appear last are basically the

[42] Besides the measurement error in the collection of the primary data.

same. The correlation coefficients between the different measures of average years of schooling in levels are quite high.

To analyse the information content of each data set we computed reliability ratios, an indicator that provides an upper bound for the quality of the data. The BL data set has the higher reliability ratios in levels. This is an important result since this is the most widely used data set to assess the impact of human capital accumulation in empirical growth studies. Nevertheless, this analysis supports our view that due to the likelihood of measurement error in education data in our empirical analysis we must conduct a sensitivity analysis of the results to the use of the two alternative data sets.

2.4. Summary and Conclusions

This overview of the theoretical and empirical analysis of education, technological change and growth focused on the predictions of the second-generation endogenous growth models as to the importance of education for growth and on the most common econometric problems and approaches used to test these predictions.

The theoretical literature reviewed considers technological change as a supply-driven phenomenon that uses primarily human capital and the existing knowledge stock in the production of new knowledge. Education determines growth through its influence on the technological progress growth rate both as a fundamental input in the ideas production function and as a facilitator of technology diffusion.

According to (Romer, 1990b) it is not total human capital that determines the long run growth rate of output but only human capital acquired through higher education since this is the level of formal education that provides the scientific talent necessary for the discovery of new designs, while human capital acquired in primary and secondary education are fundamental for the production of final goods. There can also be a distinction between the role of the different schooling levels in the determination of technological change either as determinants of the domestic innovation rate or speeding up technology diffusion: tertiary education can be viewed as the relevant schooling level in the first case, and secondary education as the relevant schooling level in the second case.

To test the empirical predictions of the endogenous growth models the researcher has to face some common problems and can choose between different econometric approaches. We highlighted model uncertainty, endogeneity, measurement error, and parameter heterogeneity among the most common problems facing empirical growth studies due to their relevance for the analysis of the importance of education for growth.

To deal with these problems panel data econometrics seems to be the most promising econometric approach although it raises some issues of its own. We use fixed effects and instrumental variables estimators to deal with the parameter heterogeneity and endogeneity problems.

The issue of measurement error is addressed in two ways. First, by analysing the TFP growth and levels measure used since it is subject to measurement error depending on the theoretical framework underlying its computation. Second, to address the problem of the presence of measurement error in education data we use alternative education capital data sets to check the robustness of the results of the empirical analysis. By giving a summary description of the (Barro & Lee, 2001) and the (De la Fuente & Doménech, 2002) data sets we concluded that despite their time series and cross country similarities the information content of the two can vary a great deal, especially regarding the data by schooling level, confirming the need to check the robustness of the results to the use of both data sets.

2.5. Appendix - The Barro and Lee (2001) and De la Fuente and Domenéch (2002) data sets

	1960								1980							
country	TYR	rank	PYR	rank	SYR	rank	HYR	rank	TYR	rank	PYR	rank	SYR	rank	HYR	rank
Australia	9.726	1	6.524	3	2.818	5	0.383	4	10.288	5	6.582	2	3.388	7	0.607	4
Austria	7.335	12	3.673	19	3.611	2	0.051	16	7.344	16	3.684	20	4.297	6	0.061	23
Belgium	7.668	10	6.061	4	1.447	11	0.160	8	8.244	11	5.922	3	2.707	17	0.297	13
Canada	9.111	3	5.512	5	3.147	3	0.452	1	10.315	4	5.559	6	4.527	5	0.877	1
Denmark	9.047	4	5.489	6	3.107	4	0.450	2	8.982	7	5.478	7	3.607	9	0.468	6
Finland	5.405	16	4.785	14	0.495	20	0.124	9	7.163	17	5.061	15	3.786	19	0.302	11
France	5.399	17	4.191	16	1.149	13	0.058	15	6.686	19	4.144	17	3.064	13	0.207	18
Germany	8.175	6	3.633	20	4.502	1	0.040	19	8.776	8	3.690	19	5.142	2	0.152	19
Greece	4.833	19	4.166	17	0.594	18	0.073	14	7.010	18	4.964	16	2.795	21	0.309	9
Iceland	5.790	15	4.854	13	0.830	17	0.106	10	7.371	15	5.157	14	2.994	18	0.213	17
Ireland	6.396	13	4.890	12	1.407	12	0.099	11	7.458	14	5.177	13	3.310	16	0.219	16
Italy	4.703	20	3.769	18	0.887	16	0.047	17	5.895	21	3.683	21	2.882	14	0.076	22
Japan	7.779	9	5.125	9	2.487	8	0.167	7	8.506	9	5.356	9	3.249	10	0.473	5
Netherlands	5.267	18	4.736	15	0.505	19	0.026	21	8.235	12	5.338	11	3.169	11	0.299	12
New Zealand	9.704	2	7.393	1	2.213	9	0.098	12	11.474	2	7.591	1	3.128	8	0.784	3
Norway	5.917	14	4.891	11	0.985	15	0.041	18	8.152	13	5.345	10	4.731	12	0.292	14
Portugal	1.860	23	1.583	23	0.251	22	0.025	22	3.779	22	2.524	23	2.242	22	0.093	20
Spain	3.672	21	3.301	21	0.281	21	0.091	13	5.984	20	3.963	18	2.642	20	0.223	15
Sweden	8.068	7	5.263	8	2.613	7	0.191	6	9.706	6	5.270	12	5.135	4	0.455	7
Switzerland	7.389	11	5.084	10	2.001	10	0.303	5	10.374	3	5.450	8	4.578	3	0.310	8
Turkey	1.915	22	1.687	22	0.214	23	0.014	23	3.412	23	2.609	22	1.273	23	0.084	21
United Kingdom	7.847	8	6.713	2	1.094	14	0.040	20	8.273	10	5.885	5	2.754	15	0.303	10
United States	8.492	5	5.293	7	2.768	6	0.431	3	11.865	1	5.896	4	4.773	1	0.819	2
Mean	*6.587*		*4.722*		*1.713*		*0.151*		*8.056*		*4.971*		*3.486*		*0.344*	
Stand. Dev.	*2.243*		*1.401*		*1.224*		*0.146*		*2.132*		*1.201*		*0.991*		*0.235*	

	1990								2000							
country	TYR	rank	PYR	rank	SYR	rank	HYR	rank	TYR	rank	PYR	rank	SYR	rank	HYR	rank
Australia	10.379	5	6.535	3	3.178	10	0.666	4	10.922	6	6.581	2	3.100	10	0.953	4
Austria	7.761	18	3.637	21	3.898	6	0.227	19	8.354	18	3.661	22	3.599	7	0.396	20
Belgium	8.872	12	6.009	4	2.396	19	0.466	7	9.338	15	5.949	5	2.025	20	0.682	5
Canada	10.990	4	5.609	7	4.284	5	1.098	2	11.617	4	5.805	7	3.879	6	1.285	2
Denmark	9.582	8	5.518	9	3.604	8	0.461	8	9.661	10	5.515	12	3.036	9	0.539	13
Finland	9.380	10	5.535	8	3.475	9	0.370	14	9.988	9	5.579	9	1.799	8	0.623	9
France	6.951	19	4.204	17	2.480	16	0.267	16	7.862	19	4.328	18	2.336	15	0.470	16
Germany	9.711	7	3.717	20	5.742	1	0.251	18	10.203	8	4.579	17	4.935	1	0.482	14
Greece	7.997	17	5.394	12	2.349	20	0.254	17	8.667	17	5.413	15	1.738	18	0.459	18
Iceland	8.115	16	5.271	16	2.530	15	0.315	15	8.830	16	5.373	16	2.002	16	0.462	17
Ireland	8.779	13	5.396	11	2.953	12	0.430	10	9.351	14	5.461	13	2.062	11	0.580	11
Italy	6.486	20	3.810	19	2.457	17	0.220	20	7.180	21	3.914	20	2.136	17	0.384	21
Japan	8.964	11	5.464	10	2.967	11	0.533	6	9.467	11	5.541	11	2.677	12	0.677	6
Netherlands	8.748	15	5.383	13	2.907	13	0.458	9	9.355	13	5.565	10	2.598	13	0.620	10
New Zealand	11.248	3	7.409	1	2.872	14	0.967	3	11.737	3	7.498	1	3.099	14	1.111	3
Norway	11.563	2	6.572	2	4.569	3	0.422	11	11.848	2	6.489	3	2.515	4	0.628	8
Portugal	4.908	22	3.019	22	1.681	22	0.208	21	5.873	22	3.272	23	1.161	22	0.358	22
Spain	6.442	21	4.197	18	2.046	21	0.199	22	7.280	20	4.214	19	1.798	21	0.424	19
Sweden	9.514	9	5.356	15	3.620	7	0.538	5	11.414	5	5.634	8	3.981	2	0.645	7
Switzerland	10.144	6	5.366	14	4.394	4	0.384	13	10.481	7	5.430	14	4.615	5	0.472	15
Turkey	4.145	23	2.999	23	1.006	23	0.140	23	5.289	23	3.781	21	0.719	23	0.235	23
United Kingdom	8.769	14	5.973	5	2.404	18	0.393	12	9.420	12	6.098	4	2.084	19	0.568	12
United States	11.742	1	5.794	6	4.653	2	1.295	1	12.049	1	5.824	6	5.150	3	1.451	1
Mean	*8.747*		*5.138*		*3.151*		*0.459*		*9.399*		*5.283*		*2.741*		*0.631*	
Stand. Dev.	*1.988*		*1.145*		*1.091*		*0.296*		*1.847*		*1.035*		*1.167*		*0.300*	

Notes: TYR is average years of total schooling of the population aged 15 and over; PYR is average years of primary schooling of the population aged 15 and over; SYR is average years of secondary schooling of the population aged 15 and over; HYR is average years of tertiary schooling of the population aged 15 and over.

Table 2.5. Average years of schooling of the population aged 15 and over from Barro and Lee (2001)

country	1960 TYR	rank	PYR	rank	SYR	rank	HYR	rank	1980 TYR	rank	PYR	rank	SYR	rank	HYR	rank	1990 TYR	rank	PYR	rank	SYR	rank	HYR	rank	2000 TYR	rank	PYR	rank	SYR	rank	HYR	rank
Australia	9.84	**7**	7	**1**	2.6	**10**	0.24	**6**	12.41	**1**	7	**2**	4.8	**7**	0.66	**3**	12.88	**2**	7	**1**	5.15	**7**	0.73	**3**	13.000	**4**	7.000	**1**	5.176	**11**	0.824	**17**
Austria	9.01	**9**	4	**18**	4.88	**3**	0.13	**15**	10.23	**10**	4	**21**	6	**3**	0.22	**20**	11.17	**9**	4	**20**	6.83	**3**	0.34	**17**	12.586	**10**	4.000	**18**	8.029	**3**	0.557	**19**
Belgium	7.73	**15**	6	**6**	1.45	**15**	0.27	**4**	9.36	**16**	6	**13**	2.8	**16**	0.54	**4**	10.08	**16**	6	**12**	3.36	**16**	0.72	**4**	11.253	**15**	6.000	**3**	4.170	**17**	1.083	**9**
Canada	10.4	**5**	6	**7**	3.97	**6**	0.4	**2**	12.13	**3**	6	**6**	5	**6**	1.18	**1**	12.74	**3**	6	**6**	5.31	**6**	1.44	**1**	12.815	**6**	6.000	**4**	5.216	**10**	1.599	**2**
Denmark	10.4	**4**	7	**2**	3.28	**8**	0.15	**9**	11.63	**5**	7	**1**	4.3	**9**	0.38	**12**	12.23	**5**	7	**2**	4.65	**10**	0.58	**10**	13.240	**2**	7.000	**2**	5.273	**8**	0.967	**12**
Finland	9.91	**6**	4	**20**	5.79	**2**	0.12	**17**	12.01	**4**	4	**19**	7.6	**1**	0.41	**11**	12.95	**1**	4	**21**	8.37	**1**	0.58	**9**	13.252	**1**	4.000	**20**	8.312	**1**	0.940	**13**
France	10.8	**1**	6	**8**	4.66	**4**	0.13	**16**	11.54	**7**	6	**3**	5.3	**4**	0.29	**16**	11.73	**7**	6	**7**	5.39	**5**	0.33	**18**	13.222	**3**	4.000	**19**	8.191	**2**	1.031	**10**
Germany	4.97	**20**	4.44	**17**	0.42	**20**	0.11	**19**	5.87	**20**	4.56	**18**	1.1	**20**	0.24	**17**	7.1	**20**	4.76	**18**	2.01	**20**	0.33	**19**	9.559	**20**	5.000	**17**	3.428	**19**	1.131	**8**
Greece	7.65	**16**	6	**5**	1.43	**16**	0.22	**7**	9.94	**11**	6	**7**	3.4	**13**	0.5	**6**	10.96	**11**	6	**13**	4.3	**12**	0.67	**7**	12.777	**7**	6.000	**5**	5.176	**12**	1.601	**1**
Ireland	8.13	**12**	5	**14**	2.89	**9**	0.24	**5**	9.86	**13**	5	**15**	4.4	**8**	0.43	**9**	10.45	**15**	5	**16**	4.89	**8**	0.56	**12**	11.016	**16**	5.000	**15**	5.134	**13**	0.882	**14**
Italy	8.57	**11**	6	**4**	2.43	**11**	0.13	**13**	9.77	**14**	6	**11**	3.5	**12**	0.31	**15**	10.52	**14**	6	**5**	4.1	**14**	0.43	**15**	12.503	**11**	6.000	**14**	5.476	**7**	1.027	**11**
Japan	5.56	**18**	4.56	**16**	0.85	**18**	0.15	**11**	7.09	**18**	5.28	**14**	1.5	**19**	0.34	**13**	7.91	**19**	5.45	**14**	2.02	**19**	0.43	**14**	10.060	**18**	6.000	**6**	3.357	**20**	0.703	**18**
Netherlands	7.36	**17**	6	**9**	1.25	**17**	0.12	**18**	8.49	**17**	6	**5**	2.3	**17**	0.23	**19**	9.41	**17**	6	**8**	3	**17**	0.42	**16**	10.902	**17**	6.000	**7**	4.029	**18**	0.874	**15**
Norway	5.41	**19**	4.57	**15**	0.74	**19**	0.1	**20**	6.98	**19**	4.79	**17**	2	**18**	0.24	**18**	8.04	**18**	4.89	**17**	2.83	**18**	0.32	**20**	9.980	**19**	5.000	**16**	4.511	**16**	0.469	**20**
New Zealand	8.62	**10**	6	**10**	2.41	**12**	0.21	**8**	10.42	**9**	6	**8**	4	**11**	0.47	**7**	11.24	**8**	6	**3**	4.56	**11**	0.68	**5**	12.820	**5**	6.000	**8**	5.484	**6**	1.336	**4**
Portugal	8.11	**13**	6	**11**	1.96	**13**	0.15	**12**	9.88	**12**	6	**9**	3.4	**14**	0.46	**8**	10.95	**12**	6	**9**	4.27	**13**	0.67	**6**	11.958	**14**	6.000	**9**	4.789	**15**	1.169	**6**
Spain	9.68	**8**	6	**3**	3.55	**7**	0.13	**14**	10.57	**8**	6	**4**	4.2	**10**	0.32	**14**	11.12	**10**	6	**4**	4.66	**9**	0.45	**13**	12.678	**9**	6.000	**11**	5.542	**5**	1.136	**7**
Sweden	10.5	**3**	6	**12**	4.18	**5**	0.28	**3**	11.6	**6**	6	**10**	5.1	**5**	0.51	**5**	12.11	**6**	6	**10**	5.53	**4**	0.57	**11**	12.070	**13**	6.000	**10**	5.229	**9**	0.841	**16**
Switzerland	4.37	**21**	3.96	**21**	0.36	**21**	0.05	**21**	5.73	**21**	4.9	**16**	0.7	**21**	0.16	**21**	6.41	**21**	5.23	**15**	0.95	**21**	0.23	**21**	7.745	**21**	6.000	**12**	1.391	**21**	0.354	**21**
UK	8.04	**14**	6	**13**	1.89	**14**	0.15	**10**	9.6	**15**	6	**12**	3.2	**15**	0.41	**10**	10.62	**13**	6	**11**	4.01	**15**	0.61	**8**	12.226	**12**	6.000	**13**	5.021	**14**	1.205	**5**
USA	10.6	**2**	4	**19**	6.08	**1**	0.48	**1**	12.15	**2**	4	**20**	7.2	**2**	0.98	**2**	12.67	**4**	4	**19**	7.46	**2**	1.21	**2**	12.726	**8**	4.000	**21**	7.267	**4**	1.460	**3**
Mean	*8.4*		*5.454*		*2.72*		*0.2*		*9.871*		*5.55*		*4*		*0.441*		*10.633*		*5.587*		*4.46*		*0.586*		*11.828*		*5.571*		*5.248*		*1.009*	
Stand. Dev.	*2*		*0.986*		*1.72*		*0.1*		*2.033*		*0.9*		*2*		*0.248*		*1.902*		*0.869*		*1.789*		*0.289*		*1.470*		*0.926*		*1.663*		*0.334*	

Notes: TYR is average years of total schooling of the population aged 25 and over; PYR is average years of primary schooling of the population aged 25 and over; SYR is average years of secondary schooling of the population aged 25 and over; HYR is average years of tertiary schooling of the population aged 25 and over.

Table 2.6. Average years of schooling of the population aged 25 and over from De la Fuente and Doménech (2002)

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Chapter 3

LEVELS OF EDUCATION, TECHNOLOGY AND GROWTH: A COUNTRY-LEVEL ANALYSIS OF THE OECD EVIDENCE

3.1. Introduction

The purpose of this chapter is to provide evidence on the importance of education for productivity growth in OECD countries at the cross-country level. As discussed in chapter 2, new growth theory views technological change as the main source of growth and differences in the rate of technological change as the principal cause of income differences across countries[43]. To put it simply, for technological change to occur countries need to engage in innovation and/or imitation activities that use primarily human capital as an input and since formal education is an important source of human capital, the study of the relationship between education and productivity growth can provide important insights on the causes of income differences across countries.

Moreover, a better understanding of the relationship between education and productivity growth taking into account the interaction effects between education and other determinants of technological change can help policy makers when defining educational policies since simultaneous reforms will have a greater impact on productivity growth, i.e., countries will benefit more by coordinating reforms in education and other technological change determinants than by focusing on each policy individually.

We review a selection of empirical growth studies of the relationship between education, technology and growth at the aggregate country-level in order to identify the additional technological change determinants to include in the testable empirical specification outlined in chapter 2, alongside the education variables. We emphasize the evidence on the importance of the different

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[43] For instance (Klenow & Rodriguez-Clare, 1997) state that: "We find that differences in productivity growth explain the overwhelming majority of growth rate differences."(p.3). Also, "Our results call for greater emphasis on models of technology diffusion and policies that directly affect productivity. (…) countries with high growth in A have had unusually high growth rates of schooling. Thus it could be that high growth in economy wide schooling attainment powerfully boosts growth through its effect on technology adoption."(pp.23-24).

(Jones, 1996) suggests: "Combining insights from Romer (1990), (Mankiw, Romer, & Weil, 1992), (Nelson & Phelps, 1966), and others to obtain a model that emphasizes the importance of technology transfer in understanding cross-country differences in income seems to be a promising avenue for future research. The analysis presented here suggests that a model emphasizing research and ideas can generate the relatively successful cross-country regression pursued by MRW." p.25.

educational sub-categories since, as (Storesletten & Zilibotti, 2000) put it "While the general notion of human capital accumulation would not discriminate between different types of education, the "generation-of-ideas" approach would emphasize the importance of supporting *higher* education and advanced research institutions to promote R&D-driven growth.", p.44[44].

Our contribution to the literature comes first from the fact that we carry out a systematic search of the productivity growth specification taking Benhabib and Spiegel (1994) as our benchmark but considering additional technological change determinants, R&D, international trade and FDI, and its interaction with education. The joint consideration of the different ways in which education influences productivity growth allows us to assess the relative importance of each channel for economic growth. We also depart from previous studies in that we check the robustness of the results to the use of alternative estimation procedures that allows us to tackle better the issue of endogeneity.

We test the different growth specifications using the within groups estimator to account for omitted country characteristics that may be correlated with the error term and obtain results robust to the possible endogeneity of the explanatory variables through the use of the first-differenced GMM estimator. Since the main focus of the analysis is on the education-growth link we also conduct a sensitivity analysis of the results to the use of alternative education data sets, (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002) to account to a certain extent for measurement error.

The results achieved reveal, first, the importance of education for productivity growth through technology diffusion as a determinant of absorptive capacity in our sample of OECD countries, a result contrary to that of (Benhabib & Spiegel, 1994) that only confirm a role for education through innovation activities, but in line with the results of (Engelbrecht, 2003).

Second, there is no evidence of a positive direct role of education in domestic innovation activities.

Third, these results are robust to the introduction of the additional technological change determinants, R&D efforts, international trade and FDI.

Fourth, the importance of education for TFP growth is not exhausted in the absorption of disembodied technology diffusion. Education at the secondary and tertiary levels is crucial to benefit from the investments in R&D in terms of productivity growth in OECD countries. Additionally, all schooling levels are equally important to benefit from technology incorporated in imports of machinery. Finally, technology incorporated in FDI seems to exert no influence in productivity growth, neither directly nor interacted with education.

[44] The authors also defend that "(…) the engine of growth lies not in education in general, but in a restricted subset of activities producing technological innovation. These activities demand intensively very specific and "advanced" skills, and the rate of growth of an economy will depend on the availability of these skills in the society. (…) for the purpose of promoting growth, it is not really important to have well-educated blue-collar workers, but, rather, to have some excellent higher education institutions which prepare competent managers, engineers, etc. who can engage in innovative activities.", (Storesletten & Zilibotti, 2000), p.51.

From the results obtained the more significant implications for economic policy that we can draw are the advisability of policies that encourage investments in education, for three reasons: it speeds disembodied technology diffusion, it allows to fully exploit the benefits from R&D efforts, and it allows for potential improvements in productivity growth entailed in international technology spillovers embodied in imports of machinery. The composition of human capital acquired in the formal education sector is also important to exploit the growth benefits of the different technological change determinants, with education at the secondary and tertiary levels allowing benefiting from growth due to domestic innovation. Moreover, the positive influence of the interaction effects between schooling levels and other determinants of technological change endorses the importance of simultaneous education, R&D and trade policy reforms as opposed to reforms that focus on each policy individually.

This chapter has three main parts. We begin with a selective review of the empirical evidence of the importance of education for output growth and TFP in order to identify the main channels through which education influences productivity growth. Next we present the empirical specification that includes the main additional technological change determinants identified in the previous section and provide an overview of the data used. In section 4, we present the results from the empirical analysis. The last section concludes.

3.2. Selective review of the empirical literature

Due to the vast amount of literature produced in the last two decades on the relationship between education and growth, a literature review has to depend on the selection criteria of the author, namely the focus on the importance of education for technological change emphasizing the role of the different schooling levels and its interaction with other technological change determinants.

Beginning with the benchmark study of (Mankiw, Romer, & Weil, 1992) (henceforth MRW), the empirical assessment of the importance of education for economic growth has been extensively dealt with within an exogenous neoclassical growth framework. Since this thesis focus on the predictions of endogenous growth literature, the strategy adopted will be to summarize briefly what has been learned from the empirical literature based on the exogenous growth literature predictions and look more closely at selected studies that consider the growth influence of education through technological change, i.e. empirical studies within the endogenous growth framework.

Neoclassical growth theory views human capital as just another input in final goods production, whose accumulation is subject to diminishing returns, so changes in human capital levels can only lead to temporary changes in income. MRW test an empirical formulation of the human capital-augmented exogenous growth model where income growth is determined by the rate of investment in human capital, proxied by the secondary enrolment rate of the fraction of population aged 15 to 19 in the working age population, finding evidence that human capital investment is significant for income growth[45].

Soon however these results were questioned by other studies using the same neoclassical theoretical framework but that deal with issues overlooked by MRW such as the quality of the proxy used and endogeneity problems. Examples of studies that invalidate MRW's conclusions include Islam (1995), Caselli, Esquivel and Lefort (1996), (Temple, 1998), (Pritchett, 2001), and (Temple, 2001a).

This lack of significance of human capital accumulation in growth regressions has not lead however researchers to dismiss its importance for economic growth but rather to search for its causes in areas such as that of measurement error, human capital formulation in growth regressions, and appropriate estimation procedures. For instance, (Krueger & Lindahl, 2000) argue that measurement error in the human capital proxy used is the major cause of the apparent lack of significance of human capital accumulation in growth regressions. The same argument is followed by De la Fuente and Doménech (2000) and is the main reason why they construct a revised human capital data set for OECD countries. In a recent working paper, (Soto, 2002) recovers a role for human capital accumulation in economic growth within a neoclassical framework by dealing with three issues deemed fundamental by the author: the formulation of human capital, the collinearity between physical and human capital accumulation, and the use of estimation procedures that deal with the measurement error and endogeneity problems.

In the next two sections we review in more detail some of the empirical literature that tries to empirically assess the importance of human capital for growth within an endogenous growth framework viewing human capital not just as another factor of production but as a determinant of productivity growth. We classify the empirical studies that test the endogenous growth literature predictions on the importance of education for economic growth through its influence on technological change in two groups: the first group tests directly the importance of education for output growth, while the second group tests its influence on TFP, the most widely used empirical proxy for technological change.

3.2.1. Education, technology, and output growth

The empirical studies reviewed in this section share the fact that they consider as their dependent variable a measure of output growth and some measure of education as the or one of the possible explanatory variables and adopt either solely an endogenous growth view of the role of education in economic growth or consider it alongside an exogenous growth view.

A pioneer work in this field of study is (Kyriacou, 1991) that contrasts the neoclassical view where human capital accumulation determines growth, with an endogenous growth explanation where the initial human capital stock is the

[45] Although the evidence is rather weak when the sample is restricted to include only OECD countries.

proxy for technological progress, using an aggregate production function approach to explain cross-country income differences. The empirical results favour the last explanation: "(…) the effect of human capital in the final goods sector is insignificant, whereas its effect as an input in the intermediate goods sector, which is the engine for technological growth, is significant." p.19.

The most cited empirical study on the importance of education for economic growth due to its impact on technological change is however (Benhabib & Spiegel, 1994). Additionally to the (Kyriacou, 1991) analysis they develop a model of the role of human capital in technological adoption and innovation inspired by the (Nelson & Phelps, 1966) and (Romer, 1990a) growth models and test the corresponding empirical structural specification in a cross-section regression. The results for the richest third of their sample, defined as countries with GDP per capita higher than 2520 USD in 1965, show that education influences output growth through innovation activities but not through imitation activities.

This study gave rise to numerous other studies some of which reversed the original results concerning the lack of support for the influence of human capital accumulation by overcoming problems with outliers (e.g., (Temple, 1999b)), specification (e.g., (Temple, 2001a)), and measurement error ((Krueger & Lindahl, 2000)), while others tried to improve the results from this pioneer work, as we will see below.

Although path breaking in the analysis of the importance of education for technological change and growth, the above mentioned studies are not concerned with whether each educational level has a distinct role in output growth. Robert J. Barro and his co-authors, responsible for the development of the large body of growth regression analysis in the last 15 years, have investigated in a systematic way the sources of income differences across countries by regressing the growth rate of income per capita on its initial level and a set of control variables that determine the steady state income level, among which we usually find an education variable, extending in this way the neoclassical growth framework in order to include the contributions of endogenous growth theory[46].

In this line of research, (Barro & Sala-i-Martin, 1995) regress income growth on initial income and a set of control variables that include several measures of the educational attainment of the population, as well as enrolment rates. Four measures of educational attainment are always present in the different regressions: average years of male secondary and higher schooling and average years of female secondary and higher schooling. The authors stress that the explanatory power of the regression is greater when the disaggregate influence

[46] "The recent endogenous growth models are useful for understanding why advanced economies – and the world as a whole – can continue to grow in the long run despite the workings of diminishing returns in the accumulation of physical and human capital. In contrast, the extended neoclassical framework does well as a vehicle for understanding relative growth rates across countries, for example, for assessing why South Korea grew much faster than the U.S. or Zaire over the last 30 years. So overall, the new and old theories are more complementary than they are competing." (Barro, 1999), p.240.

of education is considered than with average years of total schooling. The male education variables are jointly significant and have a significant impact on growth. The female education variables however enter significantly but with a negative sign[47]. Jointly the two variables are highly insignificant. Other regressions include in addition the following education variables: male and female average years of primary education, school enrolment ratios at the secondary and higher levels of education, and finally, changes in the male and female secondary and higher schooling. None of these were found to be significant. This study is an interesting piece of empirical work on economic growth but as far as the education variables are concerned it does not make very clear its interpretation distinguishing between exogenous growth and endogenous growth mechanisms.

(Barro, 1999) and (Barro, 2001), on the other hand, are specifically concerned with the impact of human capital on growth[48] and, again, the education variable that the evidence supports as relevant for output growth is average years of male secondary and higher schooling. Male primary years of schooling and female primary, secondary and tertiary years of schooling do not have any explanatory power. The author interprets these results as evidence that human capital facilitates the adoption of technology from abroad, speeding up the process of technology diffusion, and since technology adoption requires certain minimum skills, primary education alone is not sufficient to drive growth[49]. The next step in his analysis is to verify whether school quality is important for growth by introducing in the former regressions a proxy computed using the results in international student assessment tests. The main conclusion is that both quantity and quality matter for growth but the latter is more important[50]. These studies do not give particular attention to developed countries but include them in a much wider sample without a detailed analysis of the differences relative to developing countries, nor do they make clear the role of each education level given the lack of explanatory power of the above mentioned education variables.

(Gemmell, 1996), on the contrary, studies the separate role of each educational sub-category in economic growth with an application to OECD countries with two important features: a) it considers both initial levels and

[47] These results have given rise to an interesting strand of literature that tries to differentiate the impact of male and female education in growth. See for instance (Knowles, Lorgelly, & Owen, 2002).

[48] The second article is basically a revised and shorter version of the first that uses more recent data on average years of schooling ((Barro & Lee, 1996) in the first case, and (Barro & Lee, 2001) in the second) and international student assessment tests scores.

[49] Another argument that justifies these results is that technology is mainly produced in advanced countries that use highly-skilled workers so less developed countries can only adopt technology from abroad if they have a certain level of skills (see (Zilibotti, 1999), p.280).

[50] Another interesting exercise carried out by the author in the first study is the computation of the predicted growth rates for the 1996-2006 period controlling for the contribution of the different growth determinants. The prospects for the advanced economies are not very good with predicted growth rates not going beyond 1% and most European countries registering negative average growth rates. This is attributed mainly to the differences of human capital stocks of these countries *vis a vis* the US. However (Zilibotti, 1999) considers these estimates too pessimistic and attributes the results to measurement error in the quantity and quality of schooling that are especially prejudicial to European countries.

changes of educational attainment as possible explanations for economic growth, and b) analyses the separate influence of primary, secondary and higher educational attainment avoiding in this way the choice of arbitrary weights necessary to construct an aggregate measure of educational attainment. For the sample of OECD countries both the initial level and the growth rate of higher schooling are found to be positive and significant but the distinct influence of each schooling level is not analysed in detail.

(Wolff, 2000) is specifically concerned with the role of each education level in economic growth in OECD countries. He classifies the existing empirical studies of the relationship in three categories: "human capital" models according to which growth is driven by human capital accumulation; "catch-up" models where education is essential to benefit from the advantages of technological backwardness; and "interactions with technical change" models, inspired by the work of (Arrow, 1962) and (Nelson & Phelps, 1966)[51], according to which there are interaction effects between the educational level of the labour force and measures of technological activity such as R&D intensity.

Using cross section and pooled time series cross section data and a number of different education measures he estimates the corresponding growth specifications concluding that: in the "catch-up" model formulation only primary school enrolment rates and the rate of educational attainment at the primary level are positive and significant, an unexpected result due to the "sophisticated technology in use among OECD countries"(p.458); and in the specification corresponding to the "interaction with technical change" model the educational level is never significant and the same happens to the coefficient of the interaction term, whatever the educational measure considered. Wolff concludes then that although a descriptive analysis suggests a positive association between education and growth in OECD countries (both variables grow during the period and both converge) this conclusion is not supported by the econometric tests of the relationship. He suggests five possible reasons for these results: poor quality of the education data; problems of comparability in formal educational measures across countries; specification errors; reverse causality; and the fact that other forms of schooling and training are more relevant to growth in advanced industrialized countries than formal education.

This work of Wolff is very interesting for the comparative growth and education statistics it provides for OECD countries and for the analysis of the three main paradigms that underlie the empirical discussions of the role of education in economic growth, considering that each schooling level can have a

[51] This interpretation is different from the (Benhabib & Spiegel, 1994) interpretation of the (Nelson & Phelps, 1966) model: in this case education is seen as speeding up the closing of the distance between the theoretical level of knowledge and the actual level of technology and not as a facilitator of technology diffusion – "In this sense, of two countries with the same R&D intensity but different education levels, the one with the more educated labour force should adopt new technology more quickly and effectively and this should show up in higher measured productivity."(p.464). The author also acknowledges however the (Benhabib & Spiegel, 1994) interpretation and runs regressions corresponding to this interpretation concluding that they do not change the results.

separate impact and using different proxies for the education variables. It has however in our opinion two main shortcomings: (i) it does not test an encompassing growth specification that allows the mechanisms highlighted by the different models to work simultaneously; and (ii) it does not compare directly the relative importance of the different schooling levels. Furthermore, the available education proxies at the time have by now undergone substantial revisions so using these more recent proxies can help alleviate the comparability problems of formal education measures across countries.

(Dowrick & Rogers, 2002) also analyse specifically, although not solely, a sample of OECD countries in order to distinguish the importance of classical vs. technological convergence in explaining cross-country income differences. Based on the estimation of both a production function and a convergence regression where country-specific effects are found to be always significant, they conclude that the (Mankiw, Romer, & Weil, 1992) assumption of a common technology growth rate does not apply. They then proceed to examine the hypothesis that convergence is due to technological catch-up and not diminishing returns to reproducible inputs. Using a production function specification they confirm that education facilitates technology transfer in a sample of 57 countries and that restricting the analysis to OECD countries delivers a much higher rate of technology convergence confirming the hypothesis that technology diffusion is faster in countries with similar levels of technology. This paper does not however consider the importance of education for the domestic rate of innovation, which can lead to specification errors, especially in the case of developed countries, nor does it consider the role of primary and tertiary education.

(Engelbrecht, 2003), concerned with the lack of significance of the technology diffusion variable in the richest third of the sample in the (Benhabib & Spiegel, 1994) study which, in his opinion, invalidates the Nelson and Phelps approach, replicates the former study for the sample of OECD countries and performs a sensitivity analysis of the results to the use of alternative human capital data sets and the presence of outliers. He starts by replicating (Benhabib & Spiegel, 1994) study with the (Kyriacou, 1991) human capital dataset for the 19 OECD countries of their sample using cross section data and concludes that neither the domestic innovation nor the technological diffusion components are significant. These results are however reversed with the use of either the (Barro & Lee, 2001) or the (De la Fuente & Doménech, 2002) human capital data sets. More importantly, the use of these alternative human capital data sets leads to a higher significance of the technology diffusion component, although the implied innovation coefficient is negative and significant.

The author also tests the (Benhabib & Spiegel, 1994) model but using only higher levels of schooling which yields much higher coefficients. He then goes on to test a hybrid model that considers both the influence of the accumulation and the level of human capital in economic growth due to the low values of the coefficients estimates. He does not however consider the separate influence of the level of human capital but only the interaction term since this is in his view a more correct interpretation of the (Nelson & Phelps, 1966) model and since the coefficient estimate of the first is insignificant.

Of interest to us are the results of the estimation of this hybrid model considering that higher levels of schooling determine the technology diffusion component while the accumulation component depends on total years of schooling. In this case both coefficients are positive and significant as expected. An important result of this study is thus that the importance of human capital for output growth is largest when specific categories of human capital are considered. It also has the merit of testing an encompassing growth regression that considers the predictions of both the exogenous and endogenous growth literature. The main shortcoming on the other hand is that it does not investigate in more detail the lack of significance of the level of human capital since for a sample of developed countries it is quite puzzling to dismiss the importance of innovation activities for technological change and growth. It also does not consider additional technological change determinants, alongside human capital, such as R&D efforts, and the respective interactions.

(Papageorgiou, 2003) also reviews the (Benhabib & Spiegel, 1994) study in order to include specific roles for primary and post-primary education. In his formulation total output growth is determined by the accumulation of human capital acquired through primary schooling and by the level of post-primary education. The innovation of his approach comes from the fact that he considers an aggregate production function where primary education enters directly as an input in final goods production while post-primary education enters indirectly by enhancing imitation and innovation.

The author tests this hypothesis using a cross-country regression finding that primary education contributes to the production of final output, whereas post-primary education contributes to the production of new knowledge and the adoption of technology from abroad. For the high-income countries sample[52] the evidence supports the (Benhabib & Spiegel, 1994) finding that human capital has a significant influence on economic growth mainly as an input in innovation activities while its influence due to imitation activities is much less strong. When however the influence of human capital is differentiated according to primary and post-primary education the results are just the opposite.

This is an interesting study since it tries to estimate the relationship between level-specific educational investments and growth based on a structural specification derived from an endogenous growth framework. Applied to the OECD countries we think it might make more sense to consider primary and secondary education as determining final goods production and only tertiary education influencing technological progress, as proposed by (Romer, 1990b). Also his sample of high-income countries includes countries like Algeria, Argentina, Uruguay, Venezuela or Iraq, not just OECD countries.

Another recent paper aimed specifically at investigating what educational levels matter most for growth is (Petrakis & Stamatakis, 2002). The main purpose

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[52] The countries in the sample were ranked according to their initial per capita GDP and then divided into three income classes: high-income, middle-income, and low-income.

is to link the impact of education on growth to levels of development by considering 3 groups of countries, advanced, developed and less developed (where OECD countries are included in the first two groups) and decomposing the information on the educational attainment of the labour force by level. The empirical approach is based on a growth regression derived from a growth model a la (Lucas, 1988) and the general conclusions are: a) in each sub-sample of more homogeneous countries each educational level has a different impact in economic growth, or as the authors put it "(…) each educational level has a unique growth role and, as a result, its growth contribution differs significantly with the other educational levels." p.518; and b) comparing the three sub-samples, it is also possible to conclude for different impacts of each level - primary education is more important in the less developed countries, while higher education dominates in the advanced countries. The case for the importance of higher education in OECD countries however is not very clear. Only the coefficient on primary education is found to be significant in both the advanced and the developed countries sample and in the former the coefficient on higher education is negative[53]. Also the equation tested can also be derived under an exogenous growth specification so it is not clear the channel through which education influences growth.

The studies reviewed until now only considered the complementarity between education and disembodied technological diffusion. We review now some studies that focus on a specific channel of technology diffusion, imports and/or FDI, emphasizing its complementarity with education.

Imports are widely recognized as an effective channel of technology diffusion (see e.g., Rivera-Batiz and Romer (1991), (G. Grossman & Helpman, 1995), (Eaton & Kortum, 1996), (Keller, 2004)), especially imports of goods that embody technology, i.e. imports of goods such as machinery and transport equipment that belong to industries classified as high technology industries[54].

(Mayer, 2001) analyses imports of machinery and transport equipment in a sample of developing countries and estimates cross-country growth regressions to evaluate its impact in association with human capital stocks on economic growth. Technology diffusion is measured as the average of the GDP ratios of machinery imports over the sample period, reflecting the idea that an increase in the stock of ideas requires a continuous stream of technology inflows. His first major conclusion is that human capital matters for growth as a requirement to adopt imported machinery. Second, when the GDP ratio of imports of general-purpose machinery is used the impact of human capital is stronger, a result explained by the author by the fact that the machines developed in advanced countries require skilled workers that are not available in developing countries, and this problem is greater for specialized machinery than for general-purpose ones. Finally, using imports of machinery and transport equipment lowers the

[53] The authors however found positive and significant coefficients for both secondary and higher education in the advanced countries sample when considering 10-years averages for output growth instead of 5-year averages, and also when only primary and higher education are introduced as explanatory variables.

[54] See the appendix to chapter 4 for the OECD classification of high technology industries.

economic growth impact of human capital and the author concludes that there is a hierarchy in the impact of the different measures of technology imports on economic growth, with general-purpose machinery having the highest impact, followed by imports of machinery and at last imports of machinery and transport equipment.

In a final specification, (Mayer, 2001) tests the hypothesis that domestic innovation requires workers with more skills than the adoption of technology from abroad. He thus includes in the specification as a proxy for the stock of human capital available for R&D activities the share of the population with some tertiary and completed secondary education, and uses the share of the population with some secondary education in the interaction term with general-purpose machinery imports. The results support the argument that in the analysis of the education-technological change link different categories of human capital should be used. The shortcomings of this analysis come from ignoring other determinants of technological change and its interactions with human capital. It also does not provide an analysis of developed countries where technology diffusion cannot be ignored.

(M. P. Connolly, 2003) tests the importance of high technology imports (defined as imports of goods from developed countries in Standard International Trade Classes 7, 86, and 89) for innovation and imitation activities and for output growth in a sample of eighty-six developed and developing countries between 1965 and 1995. The author first tests the importance of imports for imitation and innovation, concluding for its relevance and then introduces these variables as regressors in an output growth regression, alongside imports growth. Human capital, measured as quality adjusted researchers, is introduced as a control variable in the regressions, and is always positive and significant as expected. She concludes that less developed countries rely more heavily on high technology imports for productivity growth. This study ignores the possible interactions between human capital and imports as determinants of productivity growth.

(Crespo, Martín, & Velázquez, 2004) on the other hand focus on a sample of OECD countries to explore the role of imports as a vehicle of technology diffusion in economic growth, alongside human capital and R&D capital stocks. They modify the (Benhabib & Spiegel, 1994) growth specification in order to include additionally R&D capital stocks and a direct measure of international technology spillovers. The authors conclude that the impact of the own stock of technological knowledge is more than ten times greater than that of international technology spillovers. However the impact varies with the endowment of the stock of knowledge: countries with lower endowments such as Portugal, Poland and Greece, show elasticities that are a third of those of countries with greater endowments, such as the USA, Norway or Denmark. They also find evidence that the higher the technological capacity of the trading partners, the higher the positive influence of imports on growth. The authors do not consider specific types of imports as vehicles of technological diffusion nor do they attribute specific roles to the different educational sub-categories.

Another widely studied vehicle of technology diffusion is FDI, namely foreign direct investment by multinational corporations (MNCs).

(Borensztein, Gregorio, & Lee, 1998) examine empirically the role of FDI in economic growth through technology diffusion and its complementarity with human capital based on the predictions of the (Barro & Sala-i-Martin, 1997) model in a sample of developing countries using panel data. FDI is measured as inflows from industrial countries alone, since FDI from other developing countries responds to factors others than technology differences, and human capital as male secondary schooling. They confirm the hypothesis that FDI enhances economic growth due to its role in the transmission of technology and especially that this positive influence is due to its complementarity with human capital. Actually, they find that in countries with very low levels of human capital the FDI influence is negative. Again this analysis does not include OECD countries and is mainly worried with the role of FDI in economic growth not considering additional determinants of technological change, especially of the domestic innovation rate, more relevant for developed countries. It also restricts itself to using secondary schooling attainment as a proxy for human capital providing no comparison of the role of the different schooling levels.

(Li & Liu, 2005) use a sample of developed and developing countries to examine whether FDI inflows have a positive impact on economic growth of the host country, actively testing for endogeneity of FDI and output growth in order to select the appropriate econometric techniques. They conclude that FDI has both a direct and an indirect influence on economic growth in developing and developed countries, with FDI and economic growth forming an increasingly endogenous relationship in the period 1985-1999. As far as human capital is concerned, the authors confirm the necessity to promote human capital in order to fully exploit the growth benefits from FDI inflows. One shortcoming of the analysis comes from the fact that it does not consider the impact of different levels of education nor its interaction with FDI.

3.2.2. Education, technology, and TFP

Following Solow's (1957) conclusion, using a growth accounting framework, that between 1909 and 1949, 87.5% of output growth in the United States was explained by technological change or TFP growth, the growth residual, a vast amount of research was dedicated to the decomposition of the residual into economically meaningful changes such as changes in the quality of inputs, or changes in the national accounts statistics and statistical methodology. These studies however did not explain the causes of TFP growth, only quantified them.

It was the endogenous growth literature that provided researchers with explanations for productivity growth and lead the way to a striving empirical literature on the computation of rates of return to R&D (classical references include (Griliches, 1980), (Griliches & Lichtenberg, 1984), and (Griliches, 1992)). Few however were interested in analysing the importance of human capital for TFP, alongside R&D efforts. For this reason our review starts with the work of (Coe & Helpman, 1995) on international R&D spillovers that originated some interesting follow-up studies that emphasize the role of human capital in productivity growth. Assuming that a rise in the efficiency with which inputs are used has a positive influence on output growth, these empirical studies analyse the evidence on the education-technological change-economic growth link considering as dependent variable a measure of TFP (growth or level).

(Coe & Helpman, 1995) is the benchmark study that tries to assess the importance of both domestic and foreign R&D efforts for TFP. Focusing on a sample of OECD countries plus Israel they construct a measure of the domestic and foreign knowledge stocks based on R&D spending and analyse its influence on TFP levels using panel cointegration techniques. The foreign R&D capital stock measure is defined as the import-share-weighted domestic R&D stocks of a country's different trade partners. International trade is thus viewed as the preferential channel for technology diffusion. They confirm the hypothesis that TFP depends not only on domestic R&D efforts but also on foreign R&D stocks of the trade partners and this last influence is greater the larger the share of domestic imports on GDP and for smaller countries. This study lead the way to a vast number of other studies, many of which try to improve it in some respect, namely in what concerns the consideration in TFP regressions of human capital as an explanatory variable. Since the endogenous growth literature has also attributed from the start a fundamental role to human capital as a source of productivity growth this was the next logical step.

(Engelbrecht, 1997) extends the (Coe & Helpman, 1995) study to include human capital. Using the same sample of countries his main goal is to ascertain whether human capital influences TFP independently of R&D efforts, both in innovation and imitation activities. The main argument is that technological innovation is not confined to R&D so the inclusion of both variables allows the consideration of other ways in which human capital affects innovation, such as "on-the-job-learning" and "learning-by-doing"[55]. Based on the panel estimation of regressions for the level and growth rate of TFP, the author concludes that the introduction of human capital confirms the previous results from (Coe & Helpman, 1995) of a positive influence of both domestic and foreign R&D on TFP, although reducing the size of the relationship, and reveals an independent channel of influence for human capital both as a facilitator of domestic innovation and as a vehicle for international technology spillovers. The results for the TFP growth rate specification allow him to identify a role for human capital not only as an input in innovation activities in industrialised countries, as did (Benhabib & Spiegel, 1994), but also as a facilitator of technology transfers. The author then suggests: "Future research on economic growth should put more emphasis on modelling the different modes of human capital accumulation separately." (p.1487).

(Frantzen, 2000) is another study that tries to verify empirically the R&D growth models prediction of growth driven by research efforts and their

[55] "One cannot assume a-priori that innovation through formal R&D is more important than innovation associated with general human capital" p.1481.

complementarity with human capital[56]. Based on a sample of OECD countries and cross-section data he starts by estimating a regression for the growth rate of TFP. The results confirm the influence of human capital on TFP growth through all its roles. He then estimates panel cointegration equations for the TFP level and the corresponding Error Correction models (ECM) to allow for short-term dynamics including domestic and foreign R&D capital stocks and the level of human capital, confirming the importance of this last variable. He concludes that R&D efforts and human capital levels explain most of TFP growth. This study uses a longer time period than (Engelbrecht, 1997), a different method to compute the human capital missing observations in order to get annual data, and different estimation procedures.

None of the above mentioned studies is concerned with the different roles primary, secondary, and tertiary education might play in explaining TFP growth since the human capital proxy used refers to average years of total schooling. Recalling the quotation from (Engelbrecht, 1997) we can conclude that this is an important issue for this author and one that he will analyse in greater detail in a later study that follows from the work of (Coe, Helpman, & Hoffmaister, 1997). In this study, (Coe, Helpman, & Hoffmaister, 1997) depart from the industrialised countries sample of the previous work to analyse the importance of R&D spillovers for TFP in developing countries. This time they allow for the influence of the quality of the labour force, proxied by secondary school enrolment ratios, both directly and as a facilitator of technology diffusion. The main conclusions are that developing countries do reap important benefits from foreign R&D stocks and this impact is greater for more open economies, and that TFP growth is higher for higher secondary school enrolment ratios, although the evidence does not support the hypothesis that a better qualified labour force facilitates technology diffusion. However, as discussed in chapter 2 enrolment ratios are not the most adequate human capital proxy. Furthermore, since they only consider secondary school enrolment ratios it is not possible to uncover potential different roles for the different schooling levels in determining productivity growth.

(Engelbrecht, 2002) applies his own suggestion from the 1997 work about the need to distinguish the role of education sub-categories and tries to improve the results of the former study considering also a sample of developing countries. He confirms the need to distinguish the role of different types of human capital in the explanation of TFP[57]. (Coe, Helpman, & Hoffmaister, 1997) cannot provide supporting evidence for the importance of human capital as a facilitator of

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[56] According to the author "One shortcoming of innovation-driven growth models is that they do not adequately take into account the role of human capital, which is at most viewed as an input in the research process. These models fail to accord adequate consideration to the need for a sufficiently qualified labour force, capable of working with the new technologies created by innovation efforts. (…)" (p.58).

[57] "(…) While the impact of TYR may seem similar when human capital is modelled (a) as an additional input in an aggregate production function and (b) to capture domestic innovation and TFP catch-up, in case of the former the results seem to be driven by primary schooling, (…), while, not unreasonably, innovation and technology absorption seem to be driven by secondary schooling." p.839.

technology diffusion but only assign human capital a role as an input into production, a result that cannot be accepted lightly in view of the endogenous growth literature predictions. To overcome this conclusion the author suggests including a policy conditioned human capital variable and to consider that each role relates to different schooling levels. The evidence does not support the hypothesis that human capital is an input in final goods production when average years of schooling is used as a proxy for human capital instead of school enrolment ratios, but using the policy-conditioned human capital variable shows a positive influence of changes of these in TFP growth.

Using sub-categories of human capital, average years of primary schooling vs. average years of secondary schooling, suggests that the relevant variable is changes in average years of primary education for the female population. When only the level of human capital and an interaction term with the catch-up variable appear on the regression, it is average years of secondary schooling that explains the positive and significant influence of these variables on TFP growth. The author concludes by pointing out the need to distinguish between embodied and disembodied technology spillovers, as well as knowledge spillovers not related to R&D when analysing TFP growth. An interesting extension to this study would be to replicate it for OECD countries highlighting the roles of the different schooling levels.

(Crespo, Martín, & Velázquez, 2002) focus on a sample of OECD countries to analyse the importance of technology diffusion through imports. They build an aggregate measure of domestic innovation based on human capital and R&D data using the principal components method. In addition, they construct the human capital stock following the method of (Barro & Lee, 2001) but adjusting by public expenditure per student. Using panel data to estimate a TFP growth regression they conclude that domestic innovation is the most important TFP growth determinant and that R&D and human capital are fundamental to benefit from technology diffusion associated with imports. Due to this fact richer OECD countries benefit more from technology diffusion. There is however no specific analysis of the different roles each schooling level can play in innovation and imitation activities.

Concerned with the sensitivity of the results of the (Coe & Helpman, 1995) and the (Engelbrecht, 1997) studies to the quality of the human capital data used, (Barrio-Castro, López-Bazo, & Serrano-Domingo, 2002) replicate both studies using average years of total schooling from (De la Fuente & Doménech, 2000) for OECD countries. Using panel cointegration techniques they conclude that the impact of domestic and foreign R&D capital is less important, whereas human capital has a much larger estimated return when the more recent human capital data set is used: the elasticity of TFP to human capital is much larger than previously reported and more in line with the results from the microeconometric literature on rates of return to education. This is an interesting study since it deals with a problem common to empirical studies on the importance of human capital for growth, measurement error. It confirms the importance of human capital for TFP growth without however investigating the importance of differentiating between schooling levels.

The former studies consider the complementarity between human capital and both disembodied and embodied technology diffusion. In this last case however they focus on imports as the channel through which productivity levels across countries are interrelated. We turn now to studies that consider FDI as the sole vehicle for technology diffusion across countries or include it alongside international trade.

Although not analysing the role of human capital, we briefly review the study of (Potterie & Lichtenberg, 2001) a pioneer study of this relationship[58]. The authors analyse a sample of 13 industrialized over the 1971-1990 period using panel cointegration analysis. They build a proxy for the foreign R&D capital stock based on outward and inward FDI flows and compare the results with the ones obtained with a measure of the foreign R&D capital stock based only on import shares as in (Coe & Helpman, 1995). The most interesting result concerning the importance of FDI for knowledge transmission is that technology diffuses only through outward FDI, i.e., the evidence does not support the idea that the host countries benefit from investments of foreign R&D-intensive firms in terms of TFP but only if it invests in R&D-intensive foreign countries.

(Xu & Wang, 2000) test for the simultaneous influence of capital goods imports and FDI as channels of technology diffusion in a sample of OECD countries analysing at the same time the role of human capital in TFP growth. They conclude that capital goods imports are a major channel of technology diffusion, while only outward FDI, technology that Multi National Corporations (MNCs) transmit back to the home country, is important for TFP growth. Changes in human capital are also found to be positive and significant in explaining TFP growth. The authors consider only the importance of human capital accumulation for productivity growth ignoring its influence over the domestic innovation rate and as a determinant of the absorptive capacity of the economy, namely the ability of the host country to benefit from inward FDI. Additionally, there is no concern with the role of the different schooling levels.

(Lee, 2001) is specifically concerned with empirically assessing the importance of education for TFP growth considering different roles for different schooling levels on productivity growth. The sample refers to a cross-section of developing countries and the channels of technology diffusion considered are either machinery and transport equipment imports or FDI. The main conclusions are that the initial level of human capital (measured as average years of total schooling) is an important determinant of TFP growth and that either FDI or international trade influence TFP growth only if there is a sufficient level of human capital, i.e., when the interaction term between these variables and human capital (measured this time as average years of secondary and tertiary education) is included in the regressions the direct influence of FDI or international trade becomes insignificant. The study does not include however any comparison of the relative strength of the human capital effects, i.e. it does not analyse whether the results improve if specific schooling levels are

[58] This article is a revised version of a NBER working paper, (Lichtenberg & Potterie, 1996) and a chapter of the PhD thesis, (Potterie, 1998).

considered instead of average years of total schooling nor does it consider OECD countries.

(Xu, 2000) reviews the evidence on the importance of FDI as a channel for knowledge spillovers and concludes that it is mixed due to difficulties in measuring FDI but also due to the inability of previous studies to distinguish between the technology diffusion effects of MNCs and other productivity-enhancing effects. He proposes to use a measure of technology transfer from US MNCs based on their spending on royalties and licensing fees as a share of their value added. He considers a panel of developed countries but the human capital variable is not found to be significant. He concludes however for the importance of a minimum human capital level to benefit from this kind of technology diffusion based on the results from regressing the technology transfer variable on the technology gap and the human capital level. More specifically, the author concludes that technology transfer from US MNCs is important only for developed countries since these have the necessary human capital to benefit from this kind of transfers. Although considering a specific level of education as relevant to benefit from technology diffusion through FDI it is not clear why only average years of male secondary schooling should matter.

The lack of significance of FDI as a channel of technology diffusion lead (Crespo & Velázquez, 2003) to analyse the causes of these results in a sample OECD countries. The estimation of twelve different specifications of the TFP growth rate, differing on the domestic innovation and technology diffusion indicators used, lead to the conclusion that the evidence does not support FDI inflows as a channel of technology diffusion. When, however, the TFP growth equation is estimated with each indicator alone the results show a positive and significant coefficient for the technology transfer indicators. The authors suggest that the puzzling results are due to an overlap of the variables considered that does not allow for a proper detection of the effects of FDI. To confirm this hypothesis they regress the technological knowledge stock variable on the technology transfer variable and confirm that there is a positive influence. The next step is thus to run the previous regressions with the residual from this regression instead of the original technology knowledge stock variable. The results show that defining domestic innovation in this way allows finding evidence to support the predicted positive influence of FDI on TFP growth. As for human capital it has a direct influence on TFP growth but there is no evidence that it speeds up technology diffusion through FDI.

(Savvides & Zachariadis, 2005) investigate the importance of three channels of technology diffusion, foreign R&D, FDI and imports of machinery and transport equipment, for productivity growth of the manufacturing sector of a sample thirty-two low and middle-income countries from 1965 to 1992. They also consider the direct role of human capital (measured as the secondary school enrolment ratio) and its interaction with the three channels of technology diffusion as additional determinants of productivity growth. Human capital is found to have a positive direct effect and to interact with foreign R&D and FDI in determining productivity growth. In this last case countries need a threshold level of human capital, corresponding to a 7% secondary schooling enrolment rate, to benefit from a positive effect of FDI. As for its interaction with the imports variables, it has a positive effect when interacted with imports of machinery (but not statistically significant) but negative when interacted with imports of transportation equipment. A possible explanation for these findings according to the authors is that transportation equipment needs lower levels of skills to be utilized while certain types of machinery need a more qualified workforce. The human capital proxy used in this study however is a flow variable, which might explain the lack of significance of the results. Additionally, the authors do not take into account possible different impacts associated with different educational sub-categories.

3.2.3. Comments

Empirical results on the importance of education for output and productivity growth based on the predictions of new growth theory suggest that human capital acquired through formal education is an important source of growth having both a direct influence on the domestic innovation rate, alongside R&D efforts, and facilitating the absorption of technology from abroad, disembodied as well as embodied in trade and FDI. The results however often do not allow for an identification of the relative importance of each channel, although imitation activities seem to have a stronger role even in OECD countries.

Additionally, most studies concentrate on finding evidence for the importance of human capital proxied by overall educational attainment or a particular education sub-category and do not assess the relative importance of each schooling level, an important insight from endogenous growth theory, although a major conclusion that stems from these studies is that when more disaggregated measures of human capital are considered results on the education-growth link improve and are quantitatively stronger.

The comparability of these attempts to measure empirically the impact of education on growth is hindered by four aspects. First, the diversity of growth regression specifications estimated, especially the fact that most analyses focus on only one particular channel of influence. Second, the different education measures used which can be problematic due to the measurement error problem associated with human capital proxies. Third, the derivation of implications for OECD countries as to the preferential channel through which the influence of education is felt is not easy as many studies use evidence for both developed and developing countries together. And, finally, the use of different econometric approaches and estimation procedures.

In light of these comments, we suggest that there is room for a more systematic approach to the study of the importance of education for growth in OECD countries that addresses this comparability issues while emphasizing the need to assess empirically the importance of the different schooling levels.

3.3. The empirical specification and data overview

In this section we start by presenting the empirical specification that we will use to investigate the importance of education for productivity growth in our sample of twenty-three OECD countries from 1960 to 2000. The derivation of this specification from a formal model in the spirit of (Benhabib & Spiegel, 1994) was carried out in chapter 2 so our objective here is just to present the final expression and explain which control variables, the additional technological change determinants, are included in this chapter based on the literature review from the previous section. We proceed with an overview of the data used to test the hypothesized relationships.

3.3.1. The empirical specification

In chapter 2 we presented a testable empirical specification based on the predictions of new growth theory on the role of education in productivity growth that included also a vector of additional innovation determinants, Z, and a vector of additional imitation determinants, W. According to the empirical growth studies reviewed in this chapter the main additional technological change determinants are R&D efforts, international trade and FDI. We can thus now clarify which variables are included in each vector.

Recalling the productivity growth specification from the previous chapter:

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + nZ_{it} + \omega W_{it} + \varepsilon_{it} \qquad (3.1)$$

in the aggregate cross-country analysis of this chapter we consider that the growth rate of technology (equation (3.1)) of country i at time t depends on: **i)** a country-specific component, c_i, that represents changes in the efficiency with which inputs are used associated with the country characteristics that remain constant over time (e.g., climate, geography, language); **ii)** a time-specific component, c_t, common to all countries (e.g., common macroeconomic shocks); **iii)** the level of human capital translating its influence on the domestic rate of innovation, H_{it-1}; **iv)** an interaction term between the level of human capital and disembodied technology diffusion, $H_{it-1}\log(A_{maxt-1}/A_{it-1})$; **v)** a vector Z_{it} that includes the influences of R&D efforts on productivity growth both through the domestic rate of innovation, a direct influence, as well as the possible influence of interaction terms between human capital and R&D representing the fact that R&D efforts might require a certain amount of human capital to be fully exploited, and the transfer of technology that translates into the introduction of an interaction term between R&D efforts and disembodied technology diffusion so that R&D also exerts a positive influence on the absorptive capacity of the economy; **vi)** a vector W_{it} that includes the influences of embodied technology diffusion both through international trade and FDI. It includes a measure of imports of capital goods and a measure of FDI, and also interaction terms of these variables with human capital due to the above-explained relationship with the absorptive capacity; and **vii)** an i.i.d. error term, ε_{it}.

As we will explain later on, our baseline growth specification corresponds to the (Benhabib & Spiegel, 1994) specification where human capital is the sole determinant of technological change. To this basic specification we add the other technological change determinants gradually in order to identify an encompassing technological change regression that includes the statistically significant growth influences. The additional explanatory variables are first introduced alternatively due to data availability that implies different country and period coverage for the study of each influence. After identifying the statistically significant influences and taking into account data availability across the different data sets we analyse the robustness of the education results to the consideration of the joint influences.

If all the above-hypothesized influences were confirmed our final technological change specification would correspond to the one outlined above (equation 3.1). As we will see however this is not the case.

3.3.2. Overview of data

Before proceeding to the estimation of the empirical model presented above we will give a brief overview of the data used. We will focus on the time trend and cross-country differences of the different variables used, highlighting also the changes in the relative position of OECD countries.

3.3.2.1. TFP growth and levels

To compute TFP growth and levels we use PPP-adjusted GDP and physical capital stocks from the Annual Macroeconomic Database (AMECO), Spring 2005 version of the European Commission's Directorate for Economic and Financial Affairs[59]. Labour input is measured as total annual hours worked from the Groningen Growth and Development Centre and The Conference Board, Total Economy Database, January 2005[60]. Our sample consists of twenty-three OECD countries[61] with data for the period 1960-2000.

We measure TFP growth as the difference between aggregate GDP growth and the rates of growth of physical capital and labour weighed by their shares in country GDP (see chapter 2 for details on the methodology used to compute TFP growth and levels). We test the robustness of the results to the use of two production function specifications, the Cobb-Douglas and the translog specification, in the computation of TFP growth and levels. TFP growth refers to the average growth rate for each 5-year period between 1960 and 2000. Relative TFP measures the distance to the technological leader at the beginning of each 5-year period.

[59] Downloaded from http://ec.europa.eu/economy_finance/index_pt.htm

[60] Downloaded from: http://www.ggdc.net

[61] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, UK, USA.

The Cobb-Douglas specification is the most widely used in the literature, assuming constant income shares across countries and time. As is common in the literature we use the average capital income share of 1/3 and the average labour income share of 2/3 percent to compute TFP growth and levels with this production function specification.

Table 3.1 reports the values of the exponential of relative TFP[62], computed assuming a Cobb-Douglas specification, at the beginning of each 5-year period for the twenty-three OECD countries in our sample. In 1960, the USA was the technological leader followed by New Zealand and Switzerland. Turkey, Portugal, and Japan occupied the last positions. In 1995, the technological leader was Belgium (it occupied the tenth position in 1960) followed by France and Ireland. The USA occupied the fifth position. Ireland showed the most remarkable recovery: in 1960 it occupied the nineteenth and in 2000 the third. Turkey, Greece and Portugal occupied the last three positions. The mean value of relative TFP fell during the period a sign that there was technological convergence in the sample between 1960 and 2000. This decline however was mildly reversed in the last decade.

Table 3.2 presents the average growth rate of TFP in each country for the whole period and for each 5-year period. On average, TFP grew 1.99% during this forty-year period but TFP growth slowed down towards the end of the period reaching its lowest value in the beginning of the nineties (1990-95). Relating this information to the one in the previous table, the countries further away from the leader at the beginning of each 5-year period are on average the ones that grew the most, a sign that there was technological catch up.

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62 Relative TFP is the proxy used to measure the technological distance to the leader country as

$$\log(\frac{A_{\max t}}{A_{it}}) = RTFP_{it} = \log TFP_{\max t} - \log TFP_{it} = \log\left(\frac{Y_{\max t}}{Y_{it}}\right) - \frac{1}{3}\log\left(\frac{K_{\max t}}{K_{it}}\right) - \frac{2}{3}\log\left(\frac{L_{\max t}}{L_{it}}\right)$$

where $\log TFP_{maxt}$ is the TFP level of the technological leader, i.e. the country with the highest TFP level at time t.

	1960-65	rank	1965-70	rank	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank
Australia	1.165	**5**	1.194	**6**	1.128	**6**	1.140	**10**	1.164	**10**	1.162	**12**	1.285	**15**	1.251	**14**
Austria	1.544	**15**	1.480	**16**	1.253	**13**	1.135	**9**	1.103	**8**	1.148	**11**	1.129	**7**	1.147	**7**
Belgium	1.487	**14**	1.364	**10**	1.163	**7**	1.061	**5**	1.000	**1**	1.000	**1**	1.000	**1**	1.000	**1**
Canada	1.074	**4**	1.074	**4**	1.045	**3**	1.020	**3**	1.080	**6**	1.087	**6**	1.195	**10**	1.216	**10**
Denmark	1.235	**7**	1.303	**8**	1.234	**11**	1.233	**13**	1.217	**14**	1.137	**10**	1.205	**11**	1.161	**8**
Finland	1.682	**17**	1.702	**18**	1.517	**19**	1.372	**18**	1.360	**18**	1.323	**18**	1.302	**17**	1.290	**17**
France	1.387	**9**	1.320	**9**	1.185	**9**	1.106	**7**	1.061	**5**	1.006	**2**	1.002	**2**	1.035	**2**
Germany	1.413	**11**	1.390	**11**	1.250	**12**	1.176	**11**	1.135	**9**	1.129	**8**	1.090	**5**	1.170	**9**
Greece	2.132	**20**	1.817	**19**	1.551	**20**	1.449	**20**	1.403	**19**	1.593	**21**	1.730	**22**	1.844	**22**
Iceland	1.463	**13**	1.391	**12**	1.481	**17**	1.338	**17**	1.179	**12**	1.285	**17**	1.292	**16**	1.507	**20**
Ireland	1.958	**19**	1.963	**21**	1.765	**21**	1.574	**21**	1.498	**21**	1.428	**19**	1.349	**18**	1.231	**11**
Italy	1.582	**16**	1.427	**14**	1.234	**10**	1.180	**12**	1.101	**7**	1.103	**7**	1.126	**6**	1.124	**6**
Japan	2.336	**21**	1.936	**20**	1.482	**18**	1.413	**19**	1.437	**20**	1.451	**20**	1.400	**19**	1.453	**18**
Netherlands	1.169	**6**	1.182	**5**	1.098	**5**	1.010	**2**	1.038	**3**	1.038	**4**	1.040	**3**	1.053	**4**
New Zealand	1.033	**2**	1.030	**2**	1.092	**4**	1.068	**6**	1.254	**15**	1.217	**15**	1.423	**20**	1.458	**19**
Norway	1.402	**10**	1.404	**13**	1.334	**14**	1.261	**14**	1.174	**11**	1.131	**9**	1.154	**8**	1.045	**3**
Portugal	2.610	**22**	2.175	**22**	1.796	**22**	1.727	**22**	1.602	**22**	1.722	**22**	1.656	**21**	1.613	**21**
Spain	1.923	**18**	1.609	**17**	1.476	**16**	1.332	**15**	1.288	**16**	1.188	**13**	1.221	**12**	1.246	**13**
Sweden	1.314	**8**	1.250	**7**	1.167	**8**	1.130	**8**	1.181	**13**	1.198	**14**	1.260	**13**	1.269	**15**
Switzerland	1.044	**3**	1.049	**3**	1.000	**1**	1.039	**4**	1.050	**4**	1.085	**5**	1.154	**9**	1.286	**16**
Turkey	3.570	**23**	3.445	**23**	2.972	**23**	2.727	**23**	2.955	**23**	2.691	**23**	2.595	**23**	2.807	**23**
United Kingdom	1.424	**12**	1.464	**15**	1.407	**15**	1.338	**16**	1.322	**17**	1.263	**16**	1.281	**14**	1.240	**12**
United States	1.000	**1**	1.000	**1**	1.014	**2**	1.000	**1**	1.028	**2**	1.020	**3**	1.057	**4**	1.081	**5**
Mean	*1.606*		*1.520*		*1.376*		*1.297*		*1.288*		*1.278*		*1.302*		*1.327*	
St. Dev.	*0.603*		*0.524*		*0.413*		*0.365*		*0.398*		*0.359*		*0.337*		*0.380*	

Notes: $TFP_{leader}/TFP_{countryi}$ is computed as the exponential of RTFP as defined in the main text. The technological leader presents a value equal to one. The further from the leader a country is, the higher this value. The first position in the rank is thus occupied by the leader and countries with higher RTFP values occupy the last positions.

Table 3.1. $TFP_{leader}/TFP_{countryi}$, Cobb-Douglas ($\alpha$=2/3) specification adjusted for hours worked, OECD countries

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	1960-65	rank	1965-70	rank	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank	Average Growth 1960-2000
Australia	2.18	21	2.68	15	0.82	22	1.04	17	1.07	13	-0.28	22	1.79	5	1.71	11	1.39
Austria	3.52	10	4.88	3	3.00	5	2.02	11	0.26	20	2.05	6	0.96	12	2.23	3	2.38
Belgium	4.41	6	4.74	4	2.85	6	2.63	5	1.07	12	1.73	9	1.27	9	2.03	6	2.60
Canada	2.69	14	2.10	20	1.51	18	0.31	21	0.93	16	-0.16	21	0.91	13	1.59	14	1.24
Denmark	1.61	23	2.62	16	1.04	21	1.70	13	2.41	3	0.57	18	2.02	3	1.77	10	1.73
Finland	2.46	19	3.83	8	3.02	3	1.60	14	1.64	9	2.04	7	1.44	7	3.32	2	2.44
France	3.68	8	3.71	9	2.40	9	2.30	7	2.12	4	1.81	8	0.62	17	1.90	7	2.32
Germany	3.02	12	3.68	10	2.26	10	2.17	8	1.18	11	2.41	4	-0.23	20	1.45	15	2.01
Greece	5.80	4	4.71	5	2.24	11	2.09	10	-1.51	23	0.07	20	-0.04	19	1.82	8	1.95
Iceland	3.66	9	0.21	23	3.02	4	3.98	1	-0.67	22	1.62	11	-1.88	23	2.15	4	1.55
Ireland	2.63	17	3.66	11	3.31	1	2.43	6	2.03	5	2.84	1	3.09	2	5.28	1	3.18
Italy	4.75	5	4.46	7	1.90	15	2.83	4	1.03	15	1.33	13	1.29	8	0.79	22	2.31
Japan	6.43	1	6.90	1	1.96	14	1.13	16	0.88	17	2.44	3	0.53	18	1.02	20	2.67
Netherlands	2.45	20	3.03	13	2.69	8	0.91	19	1.06	14	1.68	10	1.02	11	0.90	21	1.73
New Zealand	2.74	13	0.26	22	1.44	19	-1.76	23	1.65	8	-1.47	23	0.79	16	1.05	19	0.63
Norway	2.66	16	2.56	17	2.16	12	2.89	3	1.81	7	1.33	14	3.26	1	1.80	9	2.32
Portugal	6.33	2	5.37	2	1.56	17	2.96	2	-0.40	21	2.50	2	1.76	6	1.44	16	2.74
Spain	6.23	3	3.27	12	3.07	2	2.15	9	2.69	2	1.17	15	0.87	14	-0.07	23	2.43
Sweden	3.70	7	2.93	14	1.67	16	0.57	20	0.77	18	0.72	17	1.13	10	2.07	5	1.70
Switzerland	2.60	18	2.50	18	0.23	23	1.26	15	0.40	19	0.49	19	-0.91	22	1.30	17	1.00
Turkey	3.38	11	4.49	6	2.74	7	-0.21	22	2.93	1	2.37	5	-0.53	21	1.20	18	2.12
United Kingdom	2.14	22	2.34	19	2.02	13	1.71	12	1.99	6	1.44	12	1.91	4	1.64	13	1.91
United States	2.69	15	1.28	21	1.29	20	0.92	18	1.21	10	1.02	16	0.83	15	1.65	12	1.37
Mean	*3.56*		*3.31*		*2.10*		*1.64*		*1.15*		*1.29*		*0.95*		*1.74*		*1.99*
St. Dev.	*1.44*		*1.58*		*0.82*		*1.22*		*1.06*		*1.06*		*1.17*		*1.01*		*0.61*

Table 3.2. Average (5-year) TFP growth rate for the Cobb-Douglas (α=2/3) specification adjusted for hours worked, OECD countries 1960-2000 (%)

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The translog specification on the other hand allows us to consider that factor shares vary across countries and time. Table 3.3 reports the values of the exponential of relative TFP, computed assuming a translog specification, at the beginning of each 5-year period between 1960 and 2000 for the twenty-three OECD countries in our sample. As we can see there are no major differences relative to the values computed using the Cobb-Douglas specification. In the period 1960-65, the USA was also the technological leader followed by New Zealand and now Canada. The same countries as before occupy the last three positions. In the period 1995-2000, Belgium was again the technological leader followed by France and Norway. Turkey, Greece and Portugal occupied the last three positions. Table 3.4 presents the average growth rate of TFP compute based on the translog specification in each country for the whole period and for each 5-year period. On average, TFP grew 1.88% during this forty-year period but again TFP growth slowed down towards the end of the period reaching its lowest value in the beginning of the nineties (1990-95).

	1960-65	rank	1965-70	rank	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank
Australia	1.18	5	1.193	6	1.11	6	1.133	10	1.16	10	1.152	11	1.262	13	1.218	11
Austria	1.515	15	1.446	16	1.221	12	1.121	8	1.097	7	1.145	9	1.128	6	1.145	7
Belgium	1.462	14	1.339	10	1.143	7	1.056	4	1	1	1	1	1	1	1	1
Canada	1.073	3	1.066	3	1.031	3	1.017	3	1.079	6	1.081	5	1.184	10	1.199	10
Denmark	1.233	7	1.283	8	1.212	11	1.229	13	1.22	14	1.143	8	1.21	12	1.162	8
Finland	1.647	17	1.663	18	1.479	19	1.364	18	1.36	18	1.318	18	1.299	16	1.292	16
France	1.369	9	1.297	9	1.162	9	1.101	7	1.062	4	1.012	2	1.014	2	1.051	2
Germany	1.395	11	1.376	12	1.238	13	1.174	12	1.142	9	1.145	10	1.109	5	1.182	9
Greece	2.189	20	1.785	19	1.506	20	1.437	20	1.403	19	1.588	21	1.725	22	1.836	22
Iceland	1.441	13	1.365	11	1.454	18	1.341	17	1.192	12	1.29	17	1.299	17	1.495	20
Ireland	1.913	19	1.91	21	1.715	22	1.57	21	1.499	21	1.425	19	1.344	18	1.218	12
Italy	1.55	16	1.399	14	1.209	10	1.169	11	1.102	8	1.106	6	1.13	7	1.138	6
Japan	2.304	21	1.887	20	1.42	16	1.424	19	1.443	20	1.44	20	1.388	19	1.441	19
Netherlands	1.18	6	1.178	5	1.087	5	1	1	1.04	3	1.058	4	1.059	4	1.07	4
New Zealand	1.021	2	1.02	2	1.077	4	1.065	6	1.252	15	1.209	15	1.4	20	1.396	18
Norway	1.386	10	1.389	13	1.319	14	1.262	14	1.197	13	1.16	12	1.183	9	1.069	3
Portugal	2.452	22	2.018	22	1.68	21	1.843	22	1.592	22	1.646	22	1.55	21	1.54	21
Spain	1.859	18	1.555	17	1.421	17	1.325	15	1.285	16	1.179	13	1.209	11	1.235	14
Sweden	1.301	8	1.233	7	1.149	8	1.129	9	1.183	11	1.206	14	1.265	14	1.281	15
Switzerland	1.09	4	1.083	4	1.019	2	1.058	5	1.074	5	1.109	7	1.169	8	1.299	17
Turkey	2.706	23	2.634	23	2.298	23	2.251	23	2.51	23	2.32	23	2.544	23	2.533	23
United Kingdom	1.402	12	1.434	15	1.375	15	1.33	16	1.32	17	1.255	16	1.271	15	1.225	13
United States	1	1	1	1	1	1	1.001	2	1.03	2	1.019	3	1.053	3	1.07	5
Mean	*1.551*		*1.459*		*1.319*		*1.278*		*1.271*		*1.261*		*1.295*		*1.309*	
St. Dev.	*0.474*		*0.383*		*0.294*		*0.294*		*0.314*		*0.288*		*0.32*		*0.327*	

Notes: $TFP_{leader}/TFP_{countryi}$ is computed as the exponential of RTFP as defined in the main text. The technological leader presents a value equal to one. The further from the leader a country is, the higher this value.
The first position in the rank is thus occupied by the leader and countries with higher RTFP values occupy the last positions.

Table 3.3. $TFP_{leader}/TFP_{countryi}$, translog specification adjusted for hours worked, OECD countries 1960-2000

	1960-65	rank	1965-70	rank	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank	Average growth 1960-2000
Australia	2.06	22	2.53	15	0.70	22	0.94	18	0.94	16	-0.25	22	1.68	5	1.54	14	1.26
Austria	3.93	7	5.28	2	3.38	2	2.42	7	0.40	19	2.12	5	0.99	11	2.18	3	2.58
Belgium	4.05	6	4.25	6	2.64	7	2.64	4	1.09	12	1.67	9	1.19	8	1.94	6	2.43
Canada	2.68	14	2.03	20	1.44	18	0.26	21	0.82	17	-0.21	21	0.83	14	1.60	11	1.18
Denmark	1.60	23	2.48	16	0.90	21	1.65	13	2.34	2	0.49	18	1.95	3	1.69	8	1.63
Finland	2.55	16	3.95	7	2.98	4	1.63	14	1.59	7	1.96	6	1.46	7	3.40	2	2.43
France	3.58	9	3.50	9	2.21	9	2.29	8	2.13	4	1.72	8	0.46	18	1.77	7	2.20
Germany	2.71	13	3.36	11	2.13	10	2.12	10	1.11	11	2.34	4	-0.23	20	1.29	16	1.85
Greece	6.69	1	5.14	3	1.99	12	1.90	11	-1.48	23	0.02	20	-0.16	19	1.67	9	1.94
Iceland	3.42	10	-0.14	23	2.67	6	3.51	1	-0.83	22	1.44	11	-1.81	23	2.08	4	1.27
Ireland	2.76	11	3.77	8	3.43	1	2.54	6	2.09	5	2.80	1	3.04	2	5.13	1	3.19
Italy	4.78	5	4.42	5	1.99	13	2.93	3	1.08	13	1.28	13	1.17	9	0.67	22	2.28
Japan	6.58	2	6.86	1	2.25	8	1.53	15	1.06	14	2.42	3	0.46	17	0.95	20	2.74
Netherlands	2.23	19	2.86	13	2.69	5	0.95	17	1.03	15	1.66	10	0.98	12	0.95	19	1.67
New Zealand	2.75	12	0.25	22	1.36	19	-1.92	23	1.39	9	-1.52	23	1.02	10	0.77	21	0.50
Norway	2.32	18	2.28	17	1.88	14	2.62	5	1.46	8	1.08	15	3.17	1	1.63	10	2.05
Portugal	6.16	4	5.14	4	1.54	17	3.33	2	-0.38	21	2.44	2	1.49	6	1.39	15	2.62
Spain	6.19	3	3.28	12	3.08	3	2.29	9	2.68	1	1.13	14	0.75	16	-0.03	23	2.40
Sweden	3.60	8	2.85	14	1.56	16	0.60	20	0.74	18	0.64	17	0.96	13	2.02	5	1.62
Switzerland	2.14	20	2.07	19	-0.33	23	1.02	16	0.26	20	0.46	19	-0.95	22	1.25	17	0.73
Turkey	2.49	17	3.38	10	1.64	15	-1.22	22	2.24	3	1.91	7	-0.23	21	1.05	18	1.40
United Kingdom	2.11	21	2.24	18	2.02	11	1.71	12	1.97	6	1.42	12	1.91	4	1.59	12	1.87
United States	2.66	15	1.24	21	1.25	20	0.91	19	1.20	10	0.99	16	0.80	15	1.59	13	1.33
Mean	*3.48*		*3.18*		*1.97*		*1.59*		*1.08*		*1.22*		*0.91*		*1.66*		*1.88*
St. Dev.	*1.56*		*1.63*		*0.90*		*1.32*		*1.01*		*1.04*		*1.13*		*1.00*		*0.67*

Table 3.4. Average (5-year) TFP growth rate for the translog specification adjusted for hours worked, OECD countries 1960-2000 (%)

3.3.2.2. Education

The education variable used is average years of schooling of the population measured at the beginning of each 5-year period, as discussed in chapter 2. In this chapter we use data on average years of schooling of the population aged 15 and over, total and for secondary and tertiary education from (Barro & Lee, 2001)[63]. Since measurement error in the construction of the education data can influence the results on the impact of education on productivity growth we use

[63] Downloaded from http://www.cid.harvard.edu/ciddata/ciddata.html.

also data on average years of schooling from (De la Fuente & Doménech, 2002)[64] to check for the robustness of the results[65].

To recall the main conclusions from the analysis of these two data sets carried out in chapter 2, we can say that the different figures have risen significantly in OECD countries especially due to the increase in average years of secondary and tertiary education, since educational attainment at the primary level was already high in 1960.

Another important result from the analysis of the data is that the dispersion in average years of schooling has fallen: in this case the (Barro & Lee, 2001) data set attributes the result to tertiary education, while the (De la Fuente & Doménech, 2002) data set shows a more pronounced reduction at the secondary level.

Concerning the time trends of the different average years of schooling measures the two data sets give similar patterns with the (De la Fuente & Doménech, 2002) data set showing a smoother evolution. As for the cross-country differences, the USA position is roughly the same in the two data sets, at the top of the table, while Greece, Italy, Portugal, Spain and Turkey also occupy the last places in both data sets. A higher number of differences arise in the middle positions although not very significant.

3.3.2.3. R&D

R&D data refers to R&D expenditures as a percentage of GDP from the OECD Main Science and Technology Indicators ((OECD, 2003b)). In Table 3.5 we give some summary statistics concerning R&D expenditures as a percentage of GDP measured as 5-year averages between 1970 and 2000.

There are significant cross-country differences on the share of GDP spent in R&D activities: for instance in the period 1970-1975, Greece spent 0.18% of its GDP in R&D, while the United States spent 2.43%, around thirteen times more. In the period 1995-2000, R&D expenditures range from 0.52% in Turkey to 3.64% in Sweden.

As for the time trend of this variable, OECD countries average R&D expenditure rose steadily between 1970 and 2000. The United States looses ground (from first to fifth), Japan, Finland and Sweden show impressive performances, while Portugal, Greece, Spain and Turkey positions remain relatively unchanged at the bottom of the table.

[64] Downloaded from http://iei.uv.es/~rdomenec/human/human.html.

[65] For a more thorough discussion of the two data sets please refer to chapter 2.

	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank
Australia	1.15	11	0.96	15	1.02	15	1.23	15	1.50	14	1.57	16
Austria	0.75	17	1.00	12	1.18	13	1.31	14	1.48	15	1.72	14
Belgium	1.38	9	1.36	9	1.52	9	1.63	10	1.67	12	1.88	11
Canada	1.18	10	1.08	11	1.33	10	1.46	12	1.66	13	1.76	13
Denmark	0.95	13	0.96	14	1.12	14	1.40	13	1.71	10	2.05	9
Finland	0.87	14	0.99	13	1.31	11	1.72	9	2.13	7	2.84	3
France	1.82	7	1.74	8	2.03	7	2.26	6	2.36	6	2.23	7
Germany	2.16	3	2.26	1	2.50	2	2.74	4	2.41	5	2.34	6
Greece	0.18	22	0.16	22	0.20	22	0.31	23	0.43	22	0.57	22
Iceland	0.54	19	0.67	19	0.68	19	0.86	18	1.31	16	2.07	8
Ireland	0.75	16	0.72	18	0.69	18	0.81	19	1.09	18	1.25	17
Italy	0.83	15	0.77	17	0.94	17	1.20	16	1.15	17	1.04	19
Japan	1.95	6	2.03	5	2.45	3	2.80	1	2.87	2	2.89	2
Netherlands	1.98	5	1.89	6	1.89	8	2.09	8	1.97	9	1.99	10
New Zealand	0.66	18	0.89	16	0.94	16	0.90	17	0.99	19	1.06	18
Norway	1.09	12	1.21	10	1.29	12	1.62	11	1.68	11	1.65	15
Portugal	0.30	20	0.27	21	0.32	21	0.42	21	0.57	21	0.67	21
Spain	0.29	21	0.37	20	0.46	20	0.66	20	0.84	20	0.86	20
Sweden	1.59	8	1.88	7	2.36	4	2.75	3	3.02	1	3.64	1
Switzerland	2.17	2	2.26	2	2.31	5	2.78	2	2.71	3	2.69	4
Turkey							0.32	22	0.42	23	0.52	23
United Kingdom	2.09	4	2.13	4	2.27	6	2.19	7	2.04	8	1.86	12
United States	2.43	1	2.25	3	2.53	1	2.68	5	2.58	4	2.60	5
Mean	*1.23*		*1.27*		*1.42*		*1.57*		*1.68*		*1.82*	
St. Dev.	*0.69*		*0.68*		*0.75*		*0.84*		*0.77*		*0.81*	

Table 3.5. R&D expenditures as a % of GDP in OECD countries, 1970-2000

3.3.2.4. International trade

Table 3.6 presents the data for technology diffusion measured as imports of machinery from the other 22 OECD countries as a percentage of GDP computed as 5-year averages between 1965 and 2000, from the OECD International Trade by Commodity Statistics database ((OECD, 2002d) and (OECD, 2005)).

The average value for this variable rose during the period and, as expected, smaller countries present higher imports ratios. Ireland occupies the first position in all periods, Belgium is also always at the top of the rank and the same applies to the Netherlands. The USA, Japan and Germany, big less open countries are always at the bottom of the rank.

	1965-70	rank	1970-75	rank	1975-80	rank	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank
Australia	2.67	15	2.32	17	2.63	16	3.01	15	3.32	17	3.26	20	3.51	20
Austria	5.31	3	5.87	3	6.02	3	6.43	3			6.38	4	6.86	6
Belgium	5.58	2	6.91	2	6.64	2	7.19	2	8.56	2	7.68	2	10.13	2
Canada	3.94	9	4.25	12	4.79	7	5.01	7	5.31	8	5.97	6	8.10	4
Denmark	4.25	6	4.59	7	4.36	10	4.50	12	5.17	9	5.04	9	5.89	10
Finland	3.91	10	5.16	4	4.83	6	4.92	9	4.96	10	4.86	10	6.61	7
France	1.77	17	2.30	18	2.42	17	2.90	17	3.40	16	3.37	19	3.96	17
Germany	1.48	20	1.79	21	2.15	19	2.91	16	3.62	14	3.76	15	3.67	19
Greece	3.16	14	3.44	14	2.91	15	2.67	18	3.14	19	3.46	18	3.81	18
Iceland	4.01	8	4.42	8	4.39	9	4.42	13	4.68	12	4.15	14	5.59	11
Ireland	6.01	1	7.00	1	9.25	1	10.82	1	11.62	1	12.03	1	14.01	1
Italy	1.49	19	2.01	19	2.19	18	2.23	21	2.55	20	2.57	21	3.19	21
Japan	0.64	22	0.60	22	0.44	23	0.47	23	0.46	22	0.51	23	0.73	23
Netherlands	4.85	4	5.00	5	4.92	5	5.76	4	7.45	3	7.33	3	8.25	3
New Zealand	3.42	13	3.88	13	4.23	12	4.81	11	4.74	11	4.65	12	4.67	15
Norway	4.43	5	4.81	6	5.29	4	4.95	8	5.38	7	4.73	11	5.12	13
Portugal	3.83	11	4.30	11	4.29	11	5.18	6	6.45	4	6.17	5	6.59	8
Spain	2.58	16	2.50	16	2.14	20	2.38	20	3.51	15	3.54	16	4.56	16
Sweden	3.67	12	4.37	10	4.74	8	5.42	5	5.97	5	5.88	7	7.89	5
Switzerland	4.10	7	4.42	9	4.06	13	4.90	10	5.90	6	5.32	8	6.02	9
Turkey	1.33	21	1.95	20	1.91	21	2.45	19	3.27	18	3.47	17	4.97	14
United Kingdom	1.69	18	2.57	15	3.24	14	3.73	14	4.64	13	4.56	13	5.17	12
United States	0.38	23	0.57	23	0.76	22	1.02	22	1.47	21	1.56	22	1.67	22
Mean	*3.24*		*3.70*		*3.85*		*4.26*		*4.80*		*4.79*		*5.69*	
St. Dev.	*1.59*		*1.78*		*1.99*		*2.20*		*2.40*		*2.33*		*2.82*	

Table 3.6. Imports of machinery as a % of GDP in OECD countries, 1965-2000

3.3.2.5. FDI

Finally, Table 3.7 presents the data for technology diffusion measured as FDI inflows as a percentage of GDP computed as 5-year averages between 1980 and 2000. The data was taken from the OECD International Direct Investment Statistics database ((OECD, 2004a)).

The average value of this ratio rose over the period. Belgium, the Netherlands and the UK occupy the top rank positions in all years, while Japan occupies the bottom positions. The remaining countries change positions quite often during the period.

	1980-85	rank	1985-90	rank	1990-95	rank	1995-2000	rank
Australia	0.92	2	1.90	4	1.68	7	1.86	17
Austria	0.30	10	0.33	16	0.52	17	2.08	14
Belgium	1.18	1	2.44	1	4.23	1	12.91	1
Canada	0.18	14	1.09	8	1.08	10	3.51	9
Denmark	0.18	15	0.47	14	1.57	8	4.08	6
Finland	0.05	18	0.31	18	0.74	13	3.96	7
France	0.39	8	0.80	10	1.30	9	2.05	15
Germany	0.10	16	0.21	21	0.24	20	0.47	21
Greece			0.24	20	0.30	19		
Iceland	0.06	17	0.33	17	0.10	21	1.28	18
Ireland	0.52	7	0.75	11	0.64	14	8.99	3
Italy	0.23	13	0.41	15	0.35	18	0.52	20
Japan	0.05	19	0.08	22	0.09	23	0.01	22
Netherlands	0.71	4	1.64	5	2.24	4	6.99	4
New Zealand	0.25	12	1.36	6	4.20	2	3.52	8
Norway			0.73	12	0.92	12	2.99	11
Portugal					0.10	22	2.33	13
Spain	0.75	3	1.92	3	2.01	5	2.41	12
Sweden	0.29	11	0.69	13	2.41	3	9.33	2
Switzerland	0.32	9	1.24	7	0.95	11	3.23	10
Turkey			0.27	19	0.52	16	0.55	19
United Kingdom	0.60	5	2.24	2	1.69	6	4.31	5
United States	0.56	6	0.97	9	0.62	15	1.87	16
Mean	*0.40*		*0.93*		*1.24*		*3.60*	
St. Dev.	*0.32*		*0.71*		*1.17*		*3.25*	

Table 3.7. FDI inflows as a % of GDP in OECD countries, 1980-2000

3.4. Empirical Findings

In light of the discussion on the use of panel data econometrics in growth empirics from chapter 2, we estimate our productivity growth regressions using the within groups (WG) estimator to account for omitted country characteristics, while maintaining the exogeneity assumption concerning all the regressors in the analysis. To correct for heteroscedasticity in the data we use the Huber-White sandwich estimator of variance (see e.g., (Huber, 1967), (White, 1980), (White, 1982)). We also conduct a sensitivity analysis of the results to the possible endogeneity of the regressors using the first differenced GMM (Diff-GMM) estimator that considers lagged values of the endogenous variables as instruments (see chapter 2 and the notes on each table for details).

Our baseline growth specification corresponds to the (Benhabib & Spiegel, 1994) specification. To test the robustness of the education results to the introduction of alternative technological change and growth determinants we first introduce the additional variables gradually due to data availability that implies different country and period coverage for the study of each influence.

In order to define an encompassing growth regression that includes the relevant technological change and growth influences, after identifying the statistically significant influences and taking into account data availability across the different data sets, we analyse the robustness of the education results to the consideration of the joint influences.

3.4.1. The basic specification: (Benhabib & Spiegel, 1994)

Our basic productivity growth specification corresponds to the (Benhabib & Spiegel, 1994) specification with education as the sole growth determinant (equation (3.2)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \varepsilon_{it} \qquad (3.2)$$

Table 3.8 presents the results of estimating this basic specification[66]. (Romer, 1990b) argues that technological advance requires more than the basic skills provided by the earlier stages of education, so H, human capital allocated to the R&D sector would correspond to tertiary education, and not aggregate education. We do not want to adopt such a definite distinction for the roles of the different schooling levels in the sense that, for instance, if innovation activities do require "scientific talent" which is only possible to acquire in higher education, the adoption of technologies originally developed in another country might only require skills at the secondary level.

We thus compare the results of estimating the basic specification with an aggregate education variable with the ones from considering the influence over innovation and imitation activities of different education sub-categories, secondary and tertiary education. Our main purpose is to select the relevant schooling level for each activity, before testing the robustness of the education results to the introduction of alternative technological change determinants.

Columns (1) to (10) present the results of estimating the (Benhabib & Spiegel, 1994) specification with the different education variables using within groups. We first introduce the direct impact alone of each education variable on TFP growth through the rate of innovation (columns (1), (3), (5), and (7)). The estimated coefficients are positive but only statistically significant at conventional levels when we consider higher schooling levels, SHYR and HYR.

[66] In this and the following chapters when presenting the results of the estimation of the different regressions in the respective tables we substitute the notation for the theoretical concept of technological efficiency, A, used when presenting the equations for the notation corresponding to the proxy used, TFP. Following the same reasoning, the distance to the leader is represented by RTFP in the tables and $\log(A_{max}/A_i)$ in the equations.

When we additionally consider a role for each education variable through the rate of technology diffusion (columns (2), (4), (6), and (8)), the former estimated coefficients are no longer statistically significant but the estimated coefficients on the interaction terms between the education variables and relative TFP are positive and statistically significant as expected confirming the role of education as a determinant of the absorptive capacity of OECD countries.

In column (9) we test a specification where SHYR influences productivity growth through the rate of innovation, since for the specifications that consider the direct influence of education alone it presents the highest R-squared, and where TYR influences productivity growth through technology diffusion since for the specifications that consider both influences of education it presents the highest R-squared. However, the results only support the influence of education through technology diffusion: the estimated coefficient on SHYR is positive as expected but not statistically significant.

Our preferred specification is (10) where we consider the only statistically significant influence, TYRxRTFP. The estimated coefficient is again positive and statistically significant. This result is contrary to that of (Benhabib & Spiegel, 1994) that find that, for their rich-countries sample, education matters for growth only as a determinant of the domestic rate of innovation[67].

67 Notice however that our OECD sample is not the same as (Benhabib & Spiegel, 1994) wealthiest-third sample. On the one hand they do not consider OECD countries like Austria, Belgium, Iceland, the Netherlands, Finland, or Switzerland, and on the other hand they include countries like Argentina, Chile, Iraq, or Venezuela in the "rich" countries sample, determined by the initial GDP per capita levels. For instance, (Engelbrecht, 2003) reports cross-section results for the 19 OECD countries in the (Benhabib & Spiegel, 1994) sample using their original human capital data set and gets insignificant coefficients on both the domestic innovation and the technology diffusion component. Estimating the same equation for a sample of 25 OECD countries with the Barro and Lee (2001) and the De la Fuente and Domenéch (2002) human capital data sets, (Engelbrecht, 2003) also reports a positive and significant coefficient for the technology diffusion component, and a negative and sometimes significant coefficient for the domestic innovation component.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TYR_{t-1}	0.0012	0.00005								
	(0.536)	(0.0203)								
$TYRxRTFP_{t-1}$		**0.0045**							**0.0043**	**0.0045**
		(2.59)							**(2.61)**	**(2.64)**
SYR_{t-1}			0.0032	0.0013						
			(1.15)	(0.489)						
$SYRxRTFP_{t-1}$				**0.0099**						
				(1.86)						
$SHYR_{t-1}$					**0.0037**	0.002			0.0029	
					(1.45)	(0.741)			(1.13)	
$SHYRxRTFP_{t-1}$						**0.009**				
						(1.92)				
HYR_{t-1}							**0.0150**	0.0024		
							(1.95)	(0.196)		
$HYRxRTFP_{t-1}$								**0.0632**		
								(2.31)		
$\bar{R}$-squared	0.444	0.488	0.449	0.473	0.453	0.477	0.452	0.469	0.495	0.488
No. Countries	23	23	23	23	23	23	23	23	23	23
Time coverage	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000	1960-2000
No. Obs.	184	184	184	184	184	184	184	184	184	184

Notes: Dependent variable is the 5-year average growth rate of TFP computed assuming a translog production function specification and adjusted for total hours worked. The results are robust to the use of alternative production function specifications (Cobb-Douglas) and employment as the labour input. TYR is average years of total schooling, SYR is average years of secondary schooling, SHYR is average years of secondary and tertiary schooling, HYR is average years of tertiary schooling, for the population aged 15 and over from the Barro and Lee (2001) data set measured at the beginning of each 5-year period. RTFP is the log of the coefficient of the TFP level of the leader over that of the country under analysis measured at the beginning of each 5-year period. All regressions include a full set of time dummies and country fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 3.8. The basic specification, OECD countries

For our sample of OECD countries education is important for productivity growth since it allows to fully exploit the benefits from technological spillovers. Additionally, it is overall educational attainment that has the highest explanatory power. The results presented above do not support any direct role for education as a determinant of domestic innovation activities. It can be the case nevertheless that education matters for the production of new knowledge through its interaction with R&D efforts.

We proceed with our empirical analysis of the importance of education for productivity growth by adding to our basic specification the additional technological change determinants identified in the theoretical and empirical growth literature in order to clarify the different channels through which education exerts its influence and to check the robustness of the education results to the introduction of these variables.

3.4.2. The basic specification with additional technological change determinants

In the following sections we try to shed some additional light on the mechanisms through which education influences productivity growth and check the robustness of the education results for the basic specification to the introduction of additional technological change determinants identified by the theoretical and empirical growth literature. These additional influences are R&D efforts, international trade and FDI. Since data availability varies for the proxies used to test each of these influences we introduce each of them separately.

3.4.2.1. Adding R&D intensity to the basic specification

The specification resulting from adding only the influence of R&D intensity to the basic specification is (equation (3.3)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + nZ_{it} + \varepsilon_{it} \tag{3.3}$$

where the vector Z_{it} includes the variables that reflect the different influences of R&D efforts on technological change: a direct influence and an interaction term with education, that test the influence of R&D on the domestic rate of innovation, and an interaction term between R&D and the technological gap that tests the hypothesis that R&D speeds technology diffusion, as can be seen on the second and third lines of the RHS of equation (3.4):

$$\begin{aligned}\Delta \log A_{it} = {} & c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \\ & + n_1(R\ \&\ D)_{it} + n_2 R\ \&\ D_{it} H_{it-1} + n_3 (R\ \&\ D)_{it} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \varepsilon_{it}\end{aligned} \tag{3.4}$$

Table 3.9 reports the results of the estimation of the growth specification considering the different influences of R&D efforts proxied by R&D expenses as a percentage of GDP. The sample period was reduced to 30 years from 1970 to 2000 and the number of countries is now twenty-two (Turkey is not included) due to R&D data availability. We replicated the selected specification from the previous section in column (1) confirming the positive influence of average years of total schooling through technology diffusion.

Regarding the results when R&D expenses are introduced as an additional explanatory variable, the estimated coefficient of the interaction term between relative TFP and TYR do not change, i.e. it is always positive and statistically significant whatever the specification considered.

When the influence of R&D expenses is considered alone (column (2)) the estimated coefficient is positive and statistically significant as expected. In column (3) we introduce additionally the influence of R&D as a facilitator of technology diffusion but the estimated coefficient is negative although not statistically significant so we drop it from the analysis.

In columns (4)-(7) we test additionally the hypothesis that education enhances productivity growth benefits from R&D efforts by introducing interaction terms between R&D and the different education variables. The results confirm this hypothesis since the estimated coefficients of all interaction terms are positive and statistically significant as expected. When the interaction term between R&D and TYR (column (4)) is considered the direct impact of R&D becomes negative and statistically significant, in columns (5) and (6) it is negative but not statistically significant, and in column (7) it is positive and significant. We retain specification (6) that considers the interaction between R&D and SHYR as our preferred specification since it presents the highest R-squared. In column (8) we estimate the selected specification considering only the statistically significant influences. The results confirm the positive influence of both variables, TYRxRTFP and R&DxSHYR.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(TYRxRTFP)_{t-1}$	**0.0055**	**0.0053**	**0.0061**	**0.0051**	**0.0054**	**0.0053**	**0.005**	**0.0052**
	(2.57)	**(2.46)**	**(1.61)**	**(2.39)**	**(2.43)**	**(2.42)**	**(2.39)**	**(2.43)**
$(R\&D)_t$		**0.0051**	**0.0068**	**-0.0088**	-0.003	-0.003	**0.0036**	
		(2.09)	**(1.94)**	**(-1.45)**	(-0.75)	(-0.77)	**(1.37)**	
$(R\&D)_t$ $xRTFP_{t-1}$			-0.006					
			(-0.46)					
$(R\&D)_t$ $xTYR_{t-1}$				**0.0014**				
				(2.38)				
$(R\&D)_t$ $xSYR_{t-1}$					**0.0019**			
					(2.30)			
$(R\&D)_t$ $xSHYR_{t-1}$						**0.0018**		**0.0014**
						(2.34)		**(2.98)**
$(R\&D)_t$ $xHYR_{t-1}$							**0.0048**	
							(1.61)	
$\bar{R}$ -squared	0.277	0.291	0.292	0.316	0.316	0.318	0.3	0.316
No. Countries	22	22	22	22	22	22	22	22
Time coverage	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000
No. Obs.	132	132	132	132	132	132	132	132

Notes: Dependent variable is the 5-year average growth rate of TFP computed assuming a translog production function specification and adjusted for total hours worked. The results are robust to the use of alternative production function specifications (Cobb-Douglas) and employment as the labour input. TYR is average years of total schooling, SYR is average years of secondary schooling, SHYR is average years of secondary and tertiary schooling, HYR is average years of tertiary schooling, for the population aged 15 and over from the Barro and Lee (2001) data set measured at the beginning of each 5-year period. RTFP is the log of the coefficient of the TFP level of the leader over that of the country under analysis measured at the beginning of each 5-year period. R&D is the GDP ratio of R&D expenditures measured as 5-year averages. All regressions include a full set of time dummies and country fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 3.9. The basic specification with R&D expenditures, OECD countries

According to our results, education influences positively productivity growth through innovation activities due to its complementarity with R&D efforts. Additionally, it is not overall educational attainment that matters the most but only education at higher levels, secondary and tertiary. These results are in line with the predictions of (Romer, 1990b), (Bailey & Eicher, 1994), and (Storesletten & Zilibotti, 2000), i.e. they support the argument of endogenous growth theory that only that part of the labour force with advanced education will be able to conduct domestic R&D activities. We will consider the influence of R&D interacted with average years of secondary and tertiary schooling in our joint specification.

3.4.2.2. Adding international trade to the basic specification

The specification resulting from adding only the influence of international trade to the basic specification is (equation (3.5)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \omega W_{it} + \varepsilon_{it} \tag{3.5}$$

where the vector W_{it} includes the variables that test the influence of international trade on productivity growth through technological diffusion - a direct influence and an interaction term with education (equation (3.6)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \omega_1 IMPS_{it} + \omega_2 IMPS_{it} H_{it-1} + \varepsilon_{it} \quad (3.6)$$

Table 3.10 reports the results for the basic specification considering additionally the GDP ratio of imports of machinery (IMPS)[68] and its interaction with education as determinants of technology diffusion. The sample was reduced to twenty-two countries since Austria did not report imports data for the period 1980-1990. Column (1) replicates the selected specification for the baseline specification confirming the positive influence of TYR through technology diffusion.

Regarding the importance of imports of machinery for productivity growth, the results concerning the interaction term between relative TFP and TYR do not change. In column (2) we introduce the influence of IMPS alone confirming its positive influence. However, when the interaction term with the education variables is considered simultaneously (columns (3)-(6)) the estimated coefficient on the direct impact is not statistically significant (except in column (6)).

We select as our preferred specification (3) that considers the interaction term between imports and overall educational attainment since it presents the highest R-squared. In column (7) we drop the direct influence of IMPS from the regression since it was not statistically significant confirming the importance of education to benefit from technology diffusion incorporated in imports of machinery.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(TYRxRTFP)_{t-1}$	**0.0051**	**0.0058**	**0.0059**	**0.0062**	**0.0060**	**0.0055**	**0.0059**
	(2.42)	**(3.46)**	**(4.08)**	**(4.05)**	**(4.09)**	**(3.34)**	**(4.10)**
$IMPS_t$		**0.0038**	-0.001	0.0012	0.0009	**0.0025**	
		(2.60)	(-0.48)	(0.616)	(0.483)	**(1.38)**	
$IMPS_t$ x$(TYR)_{t-1}$			**0.0006**				**0.0005**
			(2.10)				**(3.96)**
$IMPS_t$ x$(SYR)_{t-1}$				**0.0008**			
				(1.91)			
$IMPS_t$ x$(SHYR)_{t-1}$					**0.0007**		
					(1.95)		
$IMPS_t$ x$(HYR)_{t-1}$						0.0020	
						(1.11)	
$\bar{R}$ -squared	0.406	0.448	0.474	0.472	0.472	0.456	0.473
No. Countries	22	22	22	22	22	22	22
Time coverage	1965-2000	1965-2000	1965-2000	1965-2000	1965-2000	1965-2000	1965-2000
No. Obs.	154	154	154	154	154	154	154

Notes: Dependent variable is the 5-year average growth rate of TFP computed assuming a translog production function specification and adjusted for total hours worked. The results are robust to the use of alternative production function specifications (Cobb-Douglas) and employment as the labour input. TYR is average years of total schooling, SYR is average years of secondary schooling, SHYR is average years of secondary and tertiary schooling, HYR is average years of tertiary schooling, for the population aged 15 and over from the Barro and Lee (2001) data set measured at the beginning of each 5-year period. RTFP is the log of the coefficient of the TFP level of the leader over that of the country under analysis measured at the beginning of each 5-year period. IMPS is the GDP ratio of imports of machinery measured as 5-year averages. All regressions include a full set of time dummies and country fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 3.10. The basic specification with imports of machinery, OECD countries

[68] We also run regressions considering the GDP ratios of imports of machinery and transportation equipment together and imports of transportation equipment alone. We concluded that the results in the first case were driven by the results relative to imports of machinery alone since the estimated coefficients when considering imports of transportation equipment separately were never statistically significant.

The results achieved in this section reveal that potential productivity growth improvements associated with technology spillovers incorporated in machinery imports are enhanced by education investments, as defended by among others (Bartel & Lichtenberg, 1987) and tested by (Mayer, 2001). Our joint specification of the importance of the different technological change determinants for TFP growth will thus include the interaction term between international trade and average years of total schooling.

3.4.2.3. Adding FDI to the basic specification

The specification resulting from adding only the influence of FDI to the basic specification is (equation (3.7)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \omega W_{it} + \varepsilon_{it} \qquad (3.7)$$

where now the vector W_{it} includes only the variables that test the influence of FDI on productivity growth through technological diffusion, again a direct influence and an interaction term with education (equation (3.8)):

$$\Delta \log A_{it} = c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \omega_3 FDI_{it} + \omega_4 FDI_{it} x H_{it-1} + \varepsilon_{it} \qquad (3.8)$$

Table 3.11 reports the results for the basic specification considering now the GDP ratio of FDI inflows and its interaction with education as determinants of embodied technology diffusion. The sample was reduced to just nineteen countries since Greece, Norway, Portugal and Turkey did not report data for most of the period. We also had to reduce the period coverage to twenty years from 1980 to 2000.

Column (1) again replicates the selected specification from the baseline specification confirming the positive influence of TYR through technology diffusion. This result does not change when we introduce the different influences of FDI on productivity growth.

Regarding the importance of FDI inflows for TFP growth, when we consider its direct influence alone (column (2)) the respective estimated coefficient is positive and statistically significant as expected. When we additionally consider the interaction of FDI with the different education variables (columns (3)-(6)), the estimated coefficients on the interaction terms are all negative contrary to what expected and statistically significant when the interaction between FDI and TYR and FDI and HYR are considered, a result hard to reconcile with economic theory. The direct impact of FDI is still positive and statistically significant.

We retain specification (3) that considers the direct influence of FDI and the influence of FDI interacted with TYR on TFP growth as our preferred specification since it presents the highest R-squared.

	(1)	(2)	(3)	(4)	(5)	(6)
$(TYRxRTFP)_{t-1}$	**0.0085**	**0.0097**	**0.0114**	**0.0098**	**0.0100**	**0.0109**
	(1.76)	(2.47)	(2.73)	(2.41)	(2.42)	(2.59)
FDI_t		**0.0016**	**0.0073**	0.0019	**0.0023**	**0.0036**
		(2.39)	(1.61)	(1.24)	(1.30)	(2.36)
FDI_t x$(TYR)_{t-1}$			**-.0006**			
			(-1.33)			
FDI_t x$(SYR)_{t-1}$				-.00005		
				(-0.209)		
FDI_t x$(SHYR)_{t-1}$					-.0002	
					(-0.43)	
FDI_t x$(HYR)_{t-1}$						**-0.003**
						(-1.43)
$\bar{R}$ -squared	0.274	0.348	0.362	0.348	0.349	0.360
No. Countries	19	19	19	19	19	19
Time coverage	1980-2000	1980-2000	1980-2000	1980-2000	1980-2000	1980-2000
No. Obs.	76	76	76	76	76	76

Notes: Dependent variable is the 5-year average growth rate of TFP computed assuming a translog production function specification and adjusted for total hours worked. The results are robust to the use of alternative production function specifications (Cobb-Douglas) and employment as the labour input. TYR is average years of total schooling, SYR is average years of secondary schooling, SHYR is average years of secondary and tertiary schooling, HYR is average years of tertiary schooling, for the population aged 15 and over from the Barro and Lee (2001) data set measured at the beginning of each 5-year period. RTFP is the log of the coefficient of the TFP level of the leader over that of the country under analysis measured at the beginning of each 5-year period. FDI is the GDP ratio of FDI inflows measured as 5-year averages. All regressions include a full set of time dummies and country fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 3.11. The basic specification with FDI inflows, OECD countries

Contrary to what expected, the results achieved in this section reveal that potential productivity growth improvements associated with technology spillovers incorporated in FDI are hindered by investments in education, a result difficult to interpret in economic terms. Our joint specification will nevertheless include the direct influence of FDI and its interaction with total years of schooling.

3.4.3. The joint specification

In this section we test a joint productivity growth specification that retains the statistically significant influences identified in the previous sections. From the empirical analysis of the basic specification we retain the influence of average years of total schooling in the absorptive capacity of the economies. The statistical significant influences retained from the previous sections concerning the additional technological change determinants are the interaction term between R&D efforts and average years of secondary and tertiary education, the interaction term between imports of machinery and average years of total schooling, the direct influence of FDI, and the interaction term between FDI and average years of total schooling. The joint specification is thus (equation (3.9)):

$$\begin{aligned} \Delta \log A_{it} &= c_i + c_t + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{\max t-1}}{A_{it-1}}\right) + \\ &+ n_2 R\&D_{it} xH_{it-1} + \omega_2 IMPS_{it} xH_{it-1} + \\ &+ \omega_3 FDI_{it} + \omega_4 FDI_{it} xH_{it-1} + \varepsilon_{it} \end{aligned} \tag{3.9}$$

Table 3.12 reports the results of the estimation of the joint specification using the within groups and the first differenced GMM estimators and the Barro and Lee (2001) and the (De la Fuente & Doménech, 2002) education data sets.

Data availability across R&D, imports and FDI data sets implied reducing the sample to just eighteen countries for the 1980-2000 period with the Barro and Lee (2001) education data set and to seventeen countries with the (De la Fuente & Doménech, 2002) education data set. Since the results for FDI reveal not to be robust we also test a specification without its influence for a sample of twenty-one countries for the period 1970-2000 with the Barro and Lee (2001) education data set and for a sample of twenty countries with the (De la Fuente & Doménech, 2002) education data set.

The results using the within groups (WG) estimator (columns (1)-(4)) confirm the positive and statistically significant influence of overall educational attainment through both disembodied and embodied technology diffusion and the influence of average years of secondary and tertiary education through its interaction with R&D efforts using either of the education data sets, and the direct influence of FDI and its interaction with average years of total schooling with the BL data set but not with the DD data set (columns (1) and (3)). In columns (2) and (4) we thus ignore the FDI influences and confirm the remaining ones with both data sets.

In columns (5)-(8) we present the results using the first differenced GMM (Diff-GMM) estimator. We consider all the regressors as potentially endogenous and use the adequate lagged values as instruments. Since education is measured at the beginning of each period we consider it as predetermined. The remaining explanatory variables are measured as period averages so we consider them as weakly exogenous. The results with the Diff-GMM estimator confirm most of the previous results using the BL data set (the exception is the IMPS coefficient negative and statistically significant). In this case only the FDI influences reveal not to be statistically significant (column (5)). When we consider all influences and the DD data set however none of the influences is confirmed (column (7)). In columns (6) and (8) we ignore the FDI influences and the results support the remaining influences. The employed specification tests support the GMM estimation of our model: the Sargan test and second-order serial correlation tests p-values are within the acceptable values (although the latter is not very high) and cannot reject the null hypothesis of correct specification of the different models.

	(1) BL WG	(2) BL WG	(3) DD WG	(4) DD WG	(5) BL Diff-GMM	(6) BL Diff-GMM	(7) DD Diff-GMM	(8) DD Diff-GMM
$TYRxRTFP_{t-1}$	**0.0125**	**0.0058**	**0.0072**	**0.0043**	**0.0157**	**0.0085**	0.0073	**0.0052**
	(4.09)	**(3.83)**	**(2.80)**	**(3.05)**	**(2.26)**	**(2.05)**	(1.28)	**(1.60)**
$(R\&D)_t xSHYR_{t-1}$	**0.0010**	**0.0009**	**0.0002**	**0.0009**	**0.0047**	**0.0020**	0.0003	**0.0027**
	(1.58)	**(1.57)**	**(1.50)**	**(1.83)**	**(1.61)**	**(1.64)**	(1.08)	**(3.25)**
$(IMPS)_t xTYR_{t-1}$	**0.0005**	**0.0003**	**0.0004**	**0.0003**	**-0.0007**	**0.0007**	-0.0004	**0.0006**
	(1.92)	**(2.31)**	**(1.78)**	**(1.82)**	**(-1.31)**	**(2.51)**	(-0.876)	**(2.46)**
FDI_t	**0.0104**		0.0086		0.0110		0.0054	
	(2.70)		(1.05)		(0.920)		(0.618)	
FDI_t $x(TYR)_{t-1}$	**-0.001**		-0.0007		-0.0008		-0.0002	
	(-2.72)		(-0.94)		(-0.62)		(-0.232)	
$\bar{R}$ -squared	0.475	0.344	0.369	0.279				
Sargan test					15.68	16.14	17.46	23.43
[*p-value*]					[0.267]	[0.849]	[0.179]	[0.436]
AR(2)					0.4006	2.388	0.1388	2.021
[*p-value*]					[0.689]	[0.017]	[0.890]	[0.043]
No. Countries	18	21	17	20	18	21	17	20
Time period	1980-2000	1970-2000	1980-2000	1970-2000	1980-2000	1970-2000	1980-2000	1970-2000
No. Obs.	72	126	68	120	54	105	51	100

Notes: Dependent variable is the 5-year average growth rate of TFP computed assuming a translog production function specification and adjusted for total hours worked. The results are robust to the use of alternative production function specifications (Cobb-Douglas) and employment as the labour input. TYR is average years of total schooling, SYR is average years of secondary schooling, SHYR is average years of secondary and tertiary schooling, HYR is average years of tertiary schooling, for the population aged 15 and over from the Barro and Lee (2001) data set in columns (1), (2), (5), and (6) and from the De la Fuente and Doménech (2002) data set in columns (3), (4), (7) and (8), measured at the beginning of each 5-year period. RTFP is the log of the coefficient of the TFP level of the leader over that of the country under analysis measured at the beginning of each 5-year period. R&D is the GDP ratio of R&D expenditures measured as 5-year averages. IMPS is the GDP ratio of imports of machinery measured as 5-year averages. FDI is the GDP ratio of FDI inflows measured as 5-year averages. All regressions include a full set of time dummies. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Instruments used in Diff-GMM are values of all variables included in the respective specification lagged two to four periods. Since the cross-sectional dimension of our data set is small to avoid over-fitting problems we work with a reduced number of instrumental variables so we only use the first acceptable lag and lags up to the fourth as instruments for the endogenous variables (weakly exogenous and predetermined). Results for the one-step GMM estimator with standard errors robust to heteroscedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards.

Table 3.12. The joint specification, OECD countries

In conclusion, the results of the estimation of the joint specification endorse the ones from the previous sections regarding the importance of education for productivity growth.

As far as innovation activities are concerned, the direct role of education emphasized by endogenous growth literature is not confirmed but its influence in the production of new knowledge is still felt due to its association with R&D efforts, supporting in this respect the argument of endogenous growth theory that only that part of the labour force with advanced education will be able to conduct domestic R&D activities.

The productivity growth benefits from education are not exhausted in innovation activities, as predicted by (Nelson & Phelps, 1966). Overall educational attainment that includes primary, secondary and tertiary schooling can accurately assess the importance of education to absorb both disembodied and embodied technology developed abroad. However, the results do not support any influence for FDI, neither direct nor through its interaction with the education variables.

3.4.4. Quantifying the contribution of education to TFP growth

Based on the results from the previous section we can quantify the contribution of education for TFP growth in each OECD country highlighting the relative importance of its contribution through innovation and imitation activities.

We use the estimated coefficients from column (6), Table 3.12 concerning: (i) the interaction term between R&D and average years of secondary and tertiary education to quantify the impact of education through innovation activities ($\hat{n}_2$=0.002); (ii) the interaction term between relative TFP and average years of total education to quantify the impact through disembodied technology diffusion ($\hat{m}$=0.0085); and (iii) the interaction term between imports of machinery and average years of total schooling to quantify the impact through embodied technology diffusion ($\hat{\omega}_2$=0.0007).

This quantification is possible for the twenty-one countries that constitute the sample used to estimate our joint specification over the period 1970-2000 with the BL schooling data. For each country the contribution of education to productivity will depend positively on the respective average R&D expenditures, distance to the technological frontier, and GDP ratio of imports of machinery.

Country	Av. R&D	Av. RTFP	Av. IMPS	Innovation ($\hat{n}_2$=0.002)	Disembodied Technology Diffusion ($\hat{m}$=0.0085)	Embodied Technology Diffusion ($\hat{\omega}_2$=0.0007)
Australia	1.24	0.1677	2.98	0.0025	0.0014	0.0021
Belgium	1.58	0.0218	7.89	0.0032	0.0002	0.0055
Canada	1.41	0.1100	5.57	0.0028	0.0009	0.0039
Denmark	1.37	0.1748	4.93	0.0027	0.0015	0.0034
Finland	1.66	0.2934	5.21	0.0033	0.0025	0.0036
France	2.07	0.0595	3.07	0.0041	0.0005	0.0021
Germany	2.39	0.1623	2.88	0.0048	0.0014	0.0020
Greece	0.31	0.4737	3.25	0.0006	0.0040	0.0023
Iceland	1.03	0.2932	4.61	0.0021	0.0025	0.0032
Ireland	0.89	0.3377	10.76	0.0018	0.0029	0.0075
Italy	0.98	0.1371	2.45	0.0020	0.0012	0.0017
Japan	2.49	0.3661	0.54	0.0050	0.0031	0.0004
Netherlands	1.97	0.0572	6.45	0.0039	0.0005	0.0045
New Zealand	0.90	0.2352	4.42	0.0018	0.0020	0.0031
Norway	1.42	0.1716	5.02	0.0028	0.0015	0.0035
Portugal	0.43	0.4664	5.53	0.0009	0.0040	0.0039
Spain	0.58	0.2420	3.12	0.0012	0.0021	0.0022
Sweden	2.55	0.2001	5.68	0.0051	0.0017	0.0040
Switzerland	2.48	0.1448	5.11	0.0050	0.0012	0.0036
United Kingdom	2.09	0.2471	3.97	0.0042	0.0021	0.0028
United States	2.51	0.0341	1.17	0.0050	0.0003	0.0008

Notes: the parameters used in the computations were taken from column (6), Table 3.12.
Av. R&D is the average of R&D expenditures as a percentage of GDP for the period.
Av. RTFP is the average of relative TFP for the period.
Av. IMPS is the average of imports of machinery as a percentage of GDP for the period.

Table 3.13. Contribution of education to TFP growth in 21 OECD countries, 1970-2000

Table 3.13 reports the results of the contribution of education to TFP in twenty-one OECD countries over the period 1970-2000. Regarding the impact of education through innovation activities it is higher in Sweden, the US, Japan, and Switzerland countries that spent on average more than 2.5% of its GDP in R&D. On the contrary it is lower in Greece, Portugal, Spain, and Ireland that spent on average less than 1% of its GDP in R&D.

The impact through disembodied technology diffusion was higher in the countries on average further away from the technological frontier Greece, Portugal, Japan, and Ireland, and lower in the leaders, Belgium, the US, France, and the Netherlands.

The impact through technology diffusion embodied in imports of machinery was higher in Belgium, Ireland, the Netherlands, and Sweden, smaller more open countries that present higher imports ratios, and lower in Japan, the US, Italy, and Germany, bigger less open countries.

In most countries the quantitative impact from imitation activities is higher than that of innovation activities. In the US, France, Japan, Germany, and Switzerland the impact of education through domestic innovation is quantitatively more important. In Sweden, the United Kingdom and the Netherlands it is roughly the same as through imitation activities. In Greece, Portugal, Ireland, Spain, New Zealand and Iceland the impact through the adoption of technology developed abroad is distinctively higher.

3.5. Summary and Conclusions

The aim of this chapter was to conduct a systematic econometric search of the different ways through which education influences productivity growth at the aggregate cross-country level in twenty-three OECD countries between 1960 and 2000, highlighting possible interactions with other technological change determinants and specific roles for educational sub-categories since according to endogenous growth theory, while a university education is generally viewed as necessary condition for the domestic production of new knowledge, technology diffusion may only require skills provided by a broader educational category that includes primary, secondary and tertiary education.

The econometric analysis of the importance of education for productivity growth took the (Benhabib & Spiegel, 1994) specification as the benchmark regression but tried to improve it by conducting a systematic search of productivity growth determinants ignored by the authors but highlighted by the theoretical and empirical growth literature reviewed earlier on, R&D efforts, international trade and FDI, in a panel data framework.

In our overall specification search we checked for the robustness of education results for our basic specification to the inclusion of these additional technological change determinants, that were first analysed separately due to different country and time coverage of the data, in order to identify the statistically significant growth influences and define a joint growth specification.

In each specification we first tested the importance of education as a whole for economic growth using average years of total education, for comparison purposes, but our main goal was always to identify the schooling level responsible for the link, according to the predictions of the endogenous growth literature and the evidence from previous empirical growth studies.

The estimation of the basic specification revealed that education speeds technology diffusion among OECD countries with overall educational attainment as the relevant schooling variable to benefit from disembodied technology transfers. This result is opposite to that of (Benhabib & Spiegel, 1994) for their rich countries sample according to which education matters for innovation but not for imitation activities. This result is robust to the introduction of the additional determinants of technological change and growth. The estimated coefficient associated with the domestic innovation term, on the other hand, is never statistically significant.

Regarding the influence of the additional determinants of technological change, the results reveal that to fully exploit the benefits from R&D expenses in terms of productivity growth, OECD countries need a sufficient level of secondary and tertiary education, thus confirming the argument of endogenous growth theory that innovation is the engine of growth which in turn requires advanced skills.

Concerning the introduction of imports of machinery as the vehicle through which technology is transferred from the leader to the followers, the empirical findings endorsed the hypothesis that its productivity growth benefits are enhanced when interacted with the educational attainment of the population, with overall educational attainment as the relevant education variable to fully take advantage of this kind of embodied technology diffusion. Finally, the results regarding the introduction of FDI do not support the hypothesis of a positive direct influence neither its complementarity with education.

The confirmation that education has positive and statistically significant effects on productivity growth through both innovation and the absorption of technology from abroad allowed us to quantify its relative importance through these different channels for technological change in each country. This exercise revealed that the influence through the adoption of technology developed abroad is quantitatively more important in most countries. Since these benefits from technology diffusion are bound to be exhausted as countries close the technology gap, sustained productivity growth demands a change of focus from imitation to innovation activities. As expected, the countries responsible for most of the R&D efforts in the World economy, the US, France, Japan, and Germany, are the ones where the impact of education through innovation activities is quantitatively more important.

Some immediate policy implications follow from these findings. The main policy implication from our point of view is that policy reforms aimed at improving productivity growth cannot be undertaken separately – educational policy reforms should be outlined at the same time as R&D and trade policy reforms. These results imply a need for government policy to sustain incentives for human capital formation, R&D activities and a reduction of the costs associated with the adoption of technology incorporated in international trade. The coordination of such efforts is crucial for productivity growth.

Moreover, as far as educational policies are concerned, the composition of human capital is also important to fully exploit the growth benefits of the different technological change determinants, i.e. policy on education cannot focus solely on a quantity dimension. While education at the secondary and tertiary levels allows benefiting from growth due to domestic innovation, overall educational attainment is especially important to achieve productivity and growth improvements through technology spillovers embodied in imports of machinery. As OECD countries close the technology gap, only education at higher levels will allow them to sustain productivity improvements since this is the relevant schooling level to benefit from R&D efforts.

The evidence that we have presented is reassuring in the sense that it endorses investments in education as a means of improving the growth performance of OECD countries. It is nevertheless open to improvements, some of which will be dealt with in the next chapter while others are avenues for future work. Interesting extensions of our work would be to determine the threshold level of the distance to the frontier for which tertiary education becomes more growth enhancing than primary/secondary education and to evaluate if the complementarity of the levels of education with the other technological change determinants is still supported by the data. The incorporation of the study of the impact of high quality tertiary educational capital (e.g. scientists and engineers), for instance, could also provide an answer to the puzzling results regarding the direct role of education through the domestic rate of innovation. The importance of the different schooling levels and the several potential channels through which they exert their growth influence should also be explored in the context of other data sets covering wider country samples that include both developed and developing countries.

In the next chapter we explore different issues continuing to focus on OECD countries but from a more disaggregate perspective. The key questions we want to explore are to what extent are the aggregate results on the role of education in productivity growth supported by the industry-level evidence and whether this influence is related to industry technological characteristics. The industry-level analysis sheds further light on issues that the macro-level analysis may fail to capture such as the differential growth impact of education according to technological characteristics. Differences at the industry level may point to variations in the extent to which countries are benefiting from broader economic changes, or from the potential offered by new technologies.

3.6. Appendix - Data sources

Output: GDP in 1995 constant international USD. We converted data on real GDP at constant 1995 prices in local currency from the AMECO database, Spring 2005 edition into constant international USD using AMECO's GDP PPPs.

Physical capital: real capital stock expressed in 1995 constant international USD. We converted data on real physical capital stock at constant 1995 prices in local currency from the AMECO database, Spring 2005 edition into constant international USD using AMECO's GDP PPPs.

Labour input: annual hours worked from the Groningen Growth and Development Centre and The Conference Board, Total Economy Database, January 2005.

Education: average years of education, total and by schooling level, from (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002).

R&D: Gross Domestic Expenditure on R&D (GERD) as a percentage of GDP from the OECD Main Science and Technology Indicators, (OECD, 2003b).

International trade: imports of machinery from the other 22 OECD countries as a percentage of GDP.

$$IMPS_{it} = \frac{IMPSMACH_{22t}}{GDP_{it}} x100 \qquad (3.10)$$

where $IMPSMACH_{it}$ is imports of machinery from the other 22 OECD countries of country i at time t in thousands of current USD and GDP_{it} is Gross Domestic Product at current market prices in thousands of USD. Imports data was taken from the OECD International Trade by Commodity Statistics database, (OECD, 2002d) and (OECD, 2005).

FDI: FDI inflows as a percentage of GDP. FDI data comes from the OECD International Direct Investment Statistics, (OECD, 2004a), and covers the period 1980 to 2000 expressed in millions of USD. We used data on GDP at current prices in USD from the AMECO database to compute the FDI GDP ratio as:

$$FDI_{it} = \frac{FDIinflows_{it}}{GDP_{it}} x100 \qquad (3.11)$$

where $FDIinflows_{it}$ is the amount of FDI received by country i at time t in millions of current USD and and GDP_{it} is Gross Domestic Product at current market prices in millions of USD.

Chapter 4

Levels of education, technology and growth: An industry-level analysis of the manufacturing sector in eleven OECD countries

4.1. Introduction

In the previous chapter we used aggregate cross-country data in our empirical analysis of the role of education as a determinant of technological change and economic growth. In this chapter we want to examine this relationship from a more disaggregate perspective by assessing the contribution of education for productivity growth in a panel of fifteen manufacturing industries in eleven OECD countries over the last two decades of the twentieth century.

The investigation of the importance of education for productivity growth at the industry level can shed additional light on the factors that drive growth especially if there are persistent differences in the determinants of growth across industries, so that the evidence at the country level may result from the aggregation of different sectoral patterns. This issue is an important one since e.g. (Scarpetta, Bassanini, Pilat, & Schreyer, 2000) show that around half of the productivity growth over 1990-1997 in the non-farm business sector of countries like Australia, Canada, Finland, France, Italy, Japan, the United States and Western Germany was due to the manufacturing sector and, "Within manufacturing, non-electrical machinery (which includes computers in some countries) and electrical machinery (which includes telecommunications equipment and semiconductors) have been an important source of productivity growth, especially in the United States as well as Finland and Sweden." p.49.

In order to understand better the process of growth and convergence at the aggregate level, a number of studies has analysed this issue at the more disaggregated sectoral or industry level based on the idea that differences in convergence rates across industries can improve our knowledge on why productivity gaps between countries exist and how they disappear.

For instance, (Dollar & Wolff, 1988) and (Dollar & Wolff, 1993), chapter 3, investigate the convergence of labour productivity levels in twenty-eight manufacturing industries of thirteen industrial countries over the period 1963-1982(86) by analysing measures of the dispersion in labour productivity. They conclude that convergence at the aggregate level is rooted in industry level convergence, although convergence for manufacturing as a whole is stronger than within individual industries, especially within heavy and high-tech industries. (Englander & Gurney, 1994) also confirm the evidence that productivity convergence was interrupted in the early 1970's in the machinery and equipment sector that contains the high-tech industries.

(Bernard & Jones, 1996a) and (Bernard & Jones, 1996b) examine whether multifactor productivity (MFP) levels have converged in six sectors (agriculture, mining, manufacturing, utilities, construction, services) of fourteen OECD countries in the 1970-1987 period by regressing relative MFP on its past levels. They conclude that aggregate convergence is due to convergence in the services sector but it does not hold in the manufacturing sector.

(Carree, Klomp, & Thurik, 2000) also adopt an econometric methodology to analyse the spread of the extent of labour productivity convergence across twenty-eight manufacturing industries in eighteen OECD countries over the 1972–1992 period. They find no evidence of convergence in the manufacturing sector as a whole and at the same time large inter-industry differences. They attribute the lack of catching-up in some industries to high knowledge and capital barriers that prevent a quick catch-up.

(García-Pascual & Westermann, 2002) analyse TFP convergence separately in eleven sub-sectors of aggregate manufacturing in order to isolate the influence of the use of different technologies in productivity convergence. They argue that the higher the level of aggregation of the analysis the less likely it is that the evidence supports the existence of convergence. Their results show that some sub-sectors converge while others and aggregate manufacturing do not. The lack of convergence is found in sub-sectors with more than ten industries a result that suggests that it is the heterogeneity in the technologies used that prevents convergence.

Other studies that we briefly review in the next section have focused on the analysis of the causes of productivity growth and catch-up, namely the interplay between R&D, education and international trade as determinants of productivity growth through their role in imitation and innovation activities. The evidence regarding education is however mixed, either supporting or dismissing its importance. The focus of the different studies is quite different as far as the countries included in the sample are concerned. We review studies that focus on a sample of OECD countries, studies that focus on a sole country, and studies that focus on a sample of developing countries. In any case, at the OECD industry-level the existing studies are not conclusive as to the importance of education for productivity growth so we propose to empirically investigate in more detail its role as a determinant of TFP growth in a group of manufacturing industries from eleven OECD countries over the last two decades of the twentieth century, highlighting the importance of each educational sub-category and of technological characteristics.

The empirical specification outlined in chapter 2 is the baseline specification for our industry level analyses slightly modified in order to estimate a regression closer to the ones of the industry level studies that we review in the next section. Again we analyse the relationship between education and productivity growth through innovation activities and the adoption of technology from abroad and the interplay between education and other determinants of technological change, this time R&D efforts and international trade due to the lack of FDI data at the industry level, comparing the influence of overall educational attainment vs. the influence played by specific educational sub-categories. We also divide the manufacturing industries according to their R&D intensity into high technology and low technology industries and investigate whether the impact of educational sub-categories differs across these two groups.

Regarding our main results they can be summarized in the following way. First, when the analysis is carried out for the fifteen industries together as well as when we distinguish the analysis for low technology and high technology industries, TFP growth of the leader exerts a positive influence in productivity growth, confirming that there is a long-run relationship between TFP levels in the followers and in the leaders.

Second, the existence of technological catch-up, although confirmed when we consider the fifteen industries together masks quite distinct situations in low-tech and high-tech industries: in the first case, low-tech industries that are further away from the low-tech frontier experience higher rates of productivity growth as predicted by the theory, while for high-tech industries there is only evidence of technological catch-up if they operate in countries with sufficient education levels, otherwise technological catch-up is not automatic.

Third, education influences the rate of innovation and technology diffusion in any of the three samples considered although the relevant schooling level for each activity differs across technology groups. When all the fifteen industries are considered, overall educational attainment influences the rate of innovation but only tertiary education determines the absorptive capacity to benefit from technological backwardness. In low-tech industries, on the other hand, tertiary education has an indirect impact through its complementary with disembodied and embodied technological diffusion, while overall educational attainment interacts with R&D. In high-tech industries secondary and tertiary education together influence the rate of innovation but overall educational attainment influences technology diffusion. These results are robust to the use of the first-differenced GMM estimator but the results concerning the direct impact of education on productivity growth do not survive the use of an alternative education data set, (De la Fuente & Doménech, 2002) instead of (Barro & Lee, 2001): not only the estimated coefficients have the wrong sign but they are also statistically significant, a result hard to reconcile with economic theory.

Fourth, the dominant effect of R&D on productivity growth is felt through the rate of innovation in the whole sample and in the sample of high-tech industries, and through its interaction with education in the low-tech industries sample.

Fifth, the way international trade influences productivity growth differs across samples and does not survive the use of the Diff-GMM estimator for the high-tech industries. In low-tech industries, increased international trade only affects positively productivity growth if the countries have a sufficient level of tertiary education.

This chapter is structured as follows. In Section 2 we review some studies of the relationship between productivity growth and education at the industry level. Section 3 is dedicated to the description of the empirical specification and data, and Section 4 concerns the description and analysis of the empirical findings. Section 5 concludes highlighting policy implications.

4.2. Selective review of the empirical literature

Most empirical studies of the relationship between education and growth that followed the theoretical growth analysis of the late 1980's early 1990's focused on the aggregate country level but there are some interesting examples of industry-level analysis that can help shed an additional light on the factors that drive growth. We review a selection of these studies using as main criterion the inclusion in the analysis of the importance of education for industry productivity growth.

(Griffith, Redding, & Van Reenen, 2004) focus on a sample of fourteen industries across twelve OECD countries over the 1974-1990 period to determine the quantitative importance of R&D for TFP growth going beyond the usual studies that compute the social rate of return to R&D by considering not only the direct impact of R&D but also its role in speeding up technology transfer, the "two-faces of R&D" hypothesis proposed by (W. Cohen & Levinthal, 1989). The evidence supports the "two-faces of R&D" hypothesis and to check the robustness of these results they additionally include education and international trade in their baseline specification. The introduction of the education variables in the TFP growth regression does not change the results concerning R&D and confirms the positive influence of education on productivity growth both directly and through technology diffusion.

(Scarpetta & Tressel, 2002) analyse the impact of innovation activities and product and labour market institutions in TFP growth in a panel of twenty-three manufacturing industries and business services in eighteen OECD countries from 1984 to 1998. The impact of market conditions and institutions on TFP growth is analysed both directly and through its interaction with innovative activities and the process of adoption of existing technologies. They classify industries according to their market structure in high-tech, low-concentration; high-tech, high-concentration; and low-tech industries and use as control variables TFP growth of the leader, relative TFP and education distinguishing also the impact between manufacturing and services industries. The evidence supports the technological catch-up hypothesis and the prediction of a positive influence of education on productivity growth when an industry-specific education measure is used but not when a countrywide measure is considered so the authors dropped the education variable in the remaining regressions.

(Scarpetta & Tressel, 2004) follow the same line of research focusing on seventeen manufacturing industries in eighteen OECD countries from 1988 until 1994 to analyse how important are education and R&D in fostering productivity (directly and indirectly), whether their impact varies according to the technological characteristics of each industry, and assess the importance of labour adjustment costs and bargaining regimes for productivity growth. Again, using a countrywide measure of education they could not find evidence of a positive association between education and productivity growth, only when using an industry-specific education measure. There are also no significant differences in the estimated effect of education depending on the industry technology level. In this study only the impact of secondary education is considered.

(Cameron, 2000) analyses how the returns to R&D vary across industries in line with a number of industry characteristics, including an education variable computed as the industry ratio of medium and highly educated workers to total workers. Using data for nineteen UK manufacturing industries between 1972 and 1992, he finds evidence that the level of TFP is positively influenced by education through its effect on the R&D elasticity rather than individually, i.e., industries with more educated workers have higher R&D responses.

(Cameron, 2005) tests the hypothesis that the process of TFP growth in a follower country is different from that of a leader country, since the follower is able to benefit from technology transfers and thus grow faster than the leader, using data for eleven Japanese manufacturing industries between 1963 and 1989 and taking the USA as the technological leader. TFP growth is modelled as a function of R&D efforts, education levels in each industry, and a productivity gap. The impact of education in both levels and first differences is found to be insignificant. In this study education is measured indirectly as the ratio of non-production to total workers.

(Cameron, Proudman, & Redding, 2005) are especially concerned with the role technology transfer (alongside innovation) has played in explaining TFP growth in fourteen UK manufacturing industries during the 1970-1992 period considering the roles played by R&D and education as determinants of absorptive capacity, on one hand, and international trade as a vehicle of technological diffusion, on the other hand. The results suggest that the influence of education through positive externalities is non-existent since both the estimated coefficients on education alone and on the interaction term are insignificant[69]. However this study focus on a single country and considers only tertiary education as a productivity growth determinant.

(Schiff & Wang, 2006) analyse the importance for TFP levels of North-South and South-South trade-related R&D spillovers in sixteen manufacturing industries of twenty-four developing countries from 1976 to 1998 dividing the industries into two groups according to their R&D intensity and including education as a control variable. The conclusion is that education has a positive and significant effect on TFP across specifications with the coefficient implying that, if the share of the population of age 25 and above that completed a high-school education increases by 1 percentage point, TFP will rise by more than 6%.

[69] Since TFP is computed using a quality-adjusted labour input measure the authors conclude that "once one controls for the direct effect of human capital on output through private rates of return, there is no evidence of an additional effect through externalities."p.22.

A similar analysis is carried out by (Schiff & Wang, 2004) this time focusing on the importance of education and governance for the level of TFP. An interesting conclusion is that education raises the level of TFP directly in all industries and through its interaction with foreign R&D in R&D-intensive industries. Again only one educational sub-category is considered and the focus is on developing countries.

From the studies reviewed in this section it is not possible to get a consistent picture on the importance of education for productivity growth at the industry level, which can be due to differences in country samples, time coverage, education variables, and/or estimation procedures used. Even the studies that focus on a sample of OECD industries reach quite different results: (Griffith, Redding, & Van Reenen, 2004) conclude that higher education at the countrywide level is an important determinant of productivity growth both directly and through technology diffusion, while (Scarpetta & Tressel, 2002) and (Scarpetta & Tressel, 2004) dismiss any influence of aggregate measures finding that industry-specific education is an important determinant of the domestic rate of innovation but bears no influence over technology diffusion.

It is thus our opinion there is still room for improvements on the study of the importance of education, and especially the relative importance of the different schooling levels, for productivity growth at the industry level in OECD countries. As in the previous chapter we propose to conduct a more systematic search of the role of education in productivity growth at the industry level and how it relates to other technological change determinants and industry technological characteristics.

4.3. Empirical specification and data overview

In this section we present the empirical specification that will be used to evaluate the importance of education for productivity growth at the industry level, closely related to the general specification presented in chapter 2 but including the specific variables for this level of analysis. We also highlight the main features of the data.

4.3.1. Empirical specification

The approach developed by (Benhabib & Spiegel, 1994) for the analysis of the role of human capital in economic development using aggregate cross country data is the starting point for the empirical analysis, as in the previous chapter, but we modify and augment it to become more suitable for the analysis of growth at the industry-level.

Recalling the testable empirical specification outlined in chapter 2, vector Z of additional innovation activities determinants includes as in the previous chapter R&D efforts, while vector W of additional imitation determinants now only includes international trade as a vehicle of embodied technological diffusion due to the lack of FDI data at the industry level. Additionally, it includes a direct influence of disembodied technological diffusion and the contemporaneous growth rate of productivity growth in the leader country in order to make our results more comparable with previous industry-level studies for the OECD following closely (Griffith, Redding, & Van Reenen, 2004), (Scarpetta & Tressel, 2002), (Scarpetta & Tressel, 2004), and (Cameron, Proudman, & Redding, 2005).

The econometric specification for the growth rate of productivity in each industry i of country c at time t, $\Delta \log A_{cit}$, that we estimate in the empirical analysis, augmented to include all the additional explanatory variables, is thus given by:

$$\begin{aligned}\Delta \log A_{cit} = \eta_{ci} + \eta_t + \beta \Delta \log A_{\max it} + \theta \log(\frac{A_{\max}}{A_c})_{it-1} + gH_{ct-1} + mH_{ct-1} \log(\frac{A_{\max}}{A_c})_{it-1} + \\ + \gamma_1 (R\,\&\,D)_{cit-1} + \gamma_2 (R\,\&\,D)_{cit-1} \log(\frac{A_{\max}}{A_c})_{it-1} + \gamma_3 (R\,\&\,D)_{cit-1} H_{ct-1} + \\ + \mu_1 IMPS_{cit-1} + \mu_2 IMPS_{cit-1} H_{ct-1} + \varepsilon_{cit}\end{aligned} \tag{4.1}$$

According to equation (4.1), the growth rate of productivity in industry i of each country c at time t is the result of: **i)** country-industry specific characteristics to control for unobserved heterogeneity that may be correlated with the explanatory variables, η_{ci}; **ii)** common macroeconomic shocks that affect all countries-industries, η_t; **iii)** the contemporaneous rate of productivity growth in the industry leader, $\Delta \log A_{maxit}$, a specification consistent with an ADL(1,1) and a long-run cointegrating relationship between productivity levels in frontier and non-frontier countries-industries[70], that we include for comparison purposes with previous studies, so that productivity growth is spurred by new technological innovations occurring at the frontier industry; **iv)** a direct influence of disembodied technology diffusion proxied by $\log(A_{max}/A_c)_{it-1}$, to capture the idea that countries-industries further away from the leader have a potential for faster growth by copying the existing technologies; **v)** the influence of education over the capacity to develop new ideas domestically, H_{ct-1}; **vi)** the influence of education over the successful adoption of ideas developed by the leader industry, $H_{ct-1}\log(A_{max}/A_c)_{it-1}$; **vii)** the influence of R&D efforts over the capacity to develop new ideas domestically, $R\&D_{cit-1}$; **viii)** the influence of R&D efforts over the successful adoption of ideas developed by the leader industry, $R\&D_{cit-1} \log(A_{max}/A_c)_{it-1}$; **ix)** an interaction term between R&D efforts and education, $R\&D_{cit-1}H_{ct-1}$, to capture the idea that education is important to fully exploit the benefits from R&D; **x)** the influence of international trade through embodied technology diffusion, $IMPS_{cit-1}$; **xi)** an interaction term between international trade and education, $IMPS_{cit-1}H_{ct-1}$, to capture the idea that education is important to fully exploit the benefits from embodied technology diffusion; **xii)** and a serially uncorrelated error term, ε_{cit}.

[70] See e.g. (Cameron, Proudman, & Redding, 2005).

4.3.2. Overview of data

The data used comes from different sources: the OECD STAN, ANBERD, and Bilateral Trade databases, (M. O'Mahony & B. van Ark, 2003) and the (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002) human capital data sets. Data availability across the different data sets made it impossible to replicate the country-level analysis from the previous chapter at the industry-level for the same twenty-three OECD countries. We had to restrict our analysis to eleven countries: Canada (CAN), Denmark (DNK), Finland (FIN), France (FR), Germany (GER), Italy (ITA), the Netherlands (NLD), Norway (NOR), Sweden (SWE), the United Kingdom (UK), and the USA[71].

Maximizing the two dimensions of the panel (time and countries-industries) while achieving a high level of disaggregation of the manufacturing sector[72], resulted in a sample of fifteen manufacturing industries at the two and three-digit of the International Standard Industrial Classification of all Economic Activities (ISIC) classification levels in eleven OECD countries over the period 1981-2000[73]. The fifteen industries covered are identified in Table 4.13 of the Appendix and can be divided into two groups: low technology and high technology industries. These two groups are based on the OECD classification of manufacturing industries according to their technology intensity in high-technology, medium-high-technology, medium-low-technology and low-technology industries using an ISIC, Revision 3 activity breakdown (see Table 4.14 in the Appendix) by evaluating the R&D intensities of thirteen OECD countries for the period 1991-97.

We restricted our classification to two groups due to the limited data availability at the four-digit industry level. Our low technology industries group includes the low technology and medium-low-technology industries from the OECD classification. Our high technology industries group includes the high technology and medium-high-technology industries from the OECD classification. For the 1991-1997 period the average R&D intensity in the thirteen OECD countries was 0.6% for the low R&D intensity industries and 6.5% for the

[71] This might in itself explain any major differences in the results. However, the estimation of the productivity growth regression at the country-level for the eleven countries considered in this chapter did not present any major differences relative to the whole country-level sample. For economy of space reasons we do not present the results.

[72] We focus on the manufacturing sector since productivity measurement in the services sector faces additional measurement problems: "An important point for the validity of productivity measures is that price and quantity indices of output should be constructed independently of price and quantity indices of inputs. Such dependence occurs, for example, when quantity indices of outputs are based on extrapolation of some input series. (…) Input-based extrapolation is more frequent and quantitatively more important for services industries than for other parts of the economy (…)." (OECD, 2001a), p.34.

[73] We focus on the last two decades following (Scarpetta & Tressel, 2002) suggestion of poor quality of R&D data for the 1970's and the high incidence of aggregate and sectoral shocks in this decade that might make it harder to disentangle short-run from long-run growth determinants and also for data availability reasons.

high R&D intensity industries[74]. This distinction will be used to examine how the impact of education varies with industries' R&D intensity.

4.3.2.1. TFP growth and levels

TFP growth and levels are computed from a translog production function specification that has the advantage over the Cobb-Douglas specification of allowing factor shares to vary across industries and time a necessity more acutely felt at the industry level (see Chapter 2)[75].

The computation of TFP growth and levels requires data on real value-added, real physical capital stock, labour input and labour shares. This data comes from the OECD STAN (STructural ANalysis) database, 2004 edition, for industrial analysis ((OECD, 2004b)) that covers twenty-seven countries from 1970 to 2002, classifying industries according to ISIC, Revision 3. Since we want to compare productivity levels across industries and countries several considerations are in order concerning the comparability of the data available.

The STAN database contains information on nominal value added at current prices in local currency and, to a lesser extent, information on real value added expressed as volume indices. The comparison of TFP levels across countries-industries requires the conversion of the data on value-added into a common currency taking into account the differences in purchasing power parities (PPP) across countries.

The conversion at the industry-level has been most commonly done using PPP exchange rates for GDP, as in (Dollar & Wolff, 1993) and (Bernard & Jones, 1996b), but it is problematic if the relative prices of given industries evolve differently across countries[76]. The alternative is to use industry-specific PPPs but the computation of these requires a vast amount of data on product prices, available only for a few countries and products[77]. Additionally, if one uses data

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[74] See below the average R&D intensities for the different industries in our sample between 1980 and 2000.

[75] We checked the robustness of the results to the use of the Cobb-Douglas specification but for economy of space reasons do not present them here.

[76] For instance, (Sorensen, 2001) and (Sorensen & Schjerning, 2003) show that the lack of convergence of the manufacturing sector found by (Bernard & Jones, 1996a) and (Bernard & Jones, 1996b) may be due to the PPP conversion factor used by the authors to compute TFP growth rates and relative TFP levels. If aggregate PPP were adequate conversion factors then the relative productivity levels should be invariant to the choice of a base year for PPP. However what the data shows is that these measures do depend on the choice of the base year and, furthermore, when early base years are chosen there is evidence of convergence in manufacturing productivity levels, while the opposite applies when later base years are chosen.

[77] (Harrigan, 1997) constructs price levels for ISIC codes industries 382, 383, and 384, using the component deflators of overall GDP PPPs reported by the OECD, and shows that there may be significant distortions when using aggregate PPPs since the ratio of industry price levels to the GDP price level are not close to unity. The Groningen Growth and Development Centre constructs industry level value-added deflators for EU countries by compiling unit value indexes from primary statistical sources (see (Mary O'Mahony & Bart van Ark, 2003)). (Scarpetta & Tressel, 2002) and (Scarpetta & Tressel, 2004) compute industry-specific expenditure PPPs to convert real value-added into a comparable currency using PPPs for detailed expenditure headings from the United Nations

on nominal value-added (more widely available) and convert it using PPPs we are faced with the additional problem of choosing the adequate price index to deflate these values. Since, PPPs are expressed in USD this means using the adequate US deflator, preferentially a value added deflator. In this paper, we use GDP PPPs from the OECD to convert nominal value added into current international USD and data on nominal and real value-added for the different US industries to compute the value-added deflators.

The information on physical capital stocks from the STAN database concerns the volume of existing physical capital assets available to producers expressed in local currency. To construct internationally comparable capital stocks we need to convert these local currency values using a capital stock PPP, which is an aggregate price level, i.e., it is the same for all industries. However for the Netherlands, Norway, Sweden, the UK, and the USA there is no data on capital stocks available, only on gross fixed capital formation (GFCF), at current prices expressed in local currency and, to a lesser extent, as volume indices.

If we use GFCF nominal data, the construction of comparable physical capital stocks requires three steps. First, we have to convert current prices GFCF into a comparable currency, usually the USD, which we did using data on investment price levels from (Heston, Summers, & Aten, 2002), PWT Mark 6.1. To compute real GFCF we need a US deflator for GFCF, obtained using the data on nominal and real GFCF for the US industries. Finally, the perpetual inventory method can be used to construct a proxy for the real physical capital stock as a distributed lag of past investment flows[78].

Having computed international comparable data on value-added and physical capital stocks we finally have to decide on which labour input measure to use. According to the (OECD, 2001a) manual on productivity measurement labour input is most appropriately measured as the total number of hours worked[79] because the simple headcount of persons employed can hide changes in average hours worked. The STAN database contains information on total employment, number of employees and hours worked. However, this last information is much more sparse, namely there is no data on hours worked for Germany, Italy, and the UK, and the US data covers a fewer number of industries, so we complemented this data with data from (M. O'Mahony & B. van Ark, 2003).

Finally, we need data on labour shares, α, to be able to compute TFP growth and levels. Following (Harrigan, 1997) and (Harrigan, 1999) we smooth the relatively volatile labour income shares using the fitted values from a regression of labour shares on capital-labour ratios[80].

Comparisons Project (ICP), correcting also for the impact of indirect taxes and trade on the differential between expenditure and production prices.

78 See the Appendix for further details on the construction of this variable.

79 "(…) it is recommended that hours actually worked be the statistical variable used to measure labour input, as opposed to simple head counts of employed persons. Hnours paid and full-time equivalent persons can provide reasonable alternatives. Significant differences in country practices for calculating hours worked and full-time equivalent persons persist, and raise issues of international comparability." (OECD, 2001a), p.39.

80 Under the perfect competition assumption the labour shares can be proxied by the share of labour compensation in total costs. However the share of labour in value added is quite volatile,

Table 4.1 reports average annual TFP growth rates derived from the translog production technology by country-industry for the 1981-2000 period. Considering TFP growth in Total Manufacturing, it was positive in all countries and in excess of 2%, except for Italy. The Scandinavian countries (with the exception of Denmark) and the Netherlands registered the highest growth rates followed by Canada and the UK.

When we consider the different sub-sectors we can find some similarities but also considerable heterogeneity in TFP growth rates across both countries and industries. For instance, in nine out of eleven countries TFP growth in Food, Beverages and Tobacco (FOOD) as well as Paper, Publishing and Printing (PAP) industries was negative. In general however TFP growth was positive but taking quite different values across countries and industries. On average, Rubbers and Plastics (RUB) was the industry that grew the most, followed by Electrical Goods and Machinery and Equipment (MEL) industries. In Canada and Finland it was MEL's TFP that grew the most; in Denmark, Germany, the Netherlands and Norway it was RUB, in France and the USA it was Petroleum Products (PETRO), in Italy Basic Metals (BMI), and in Sweden and the UK Machinery and Equipment (MAI).

	CAN*	DNK	FIN	FR	GER**	ITA	NLD***	NOR	SWE****	UK	USA
FOOD	-0.60	-2.59	-1.45	-0.41	-1.15	-2.30	0.08	1.12	0.67	-1.14	-1.49
TEX	3.03	1.84	1.85		2.60	1.60	4.39	3.71	3.24	3.28	2.60
WOOD	1.40	0.57	0.03	2.08	1.33	1.61	2.97	1.68	-0.78	-0.39	0.14
PAP	-1.26	-1.05	0.21	-0.72	-0.73	-1.94	-0.19	0.87	-0.34	-0.49	-1.20
CHE	1.22	2.64	1.23	1.54	1.28	1.95	2.78		1.68	1.35	2.17
PETRO	6.45	-1.76	-9.47	8.94	0.79	-5.91	-9.46		-2.24	-2.36	3.64
RUB	4.41	4.12	4.45	1.01	5.97	2.17	6.96	4.98	3.84	3.31	3.64
ONMP	1.71	1.82	1.75	3.26	1.97	0.01	2.61	3.10	2.37	2.69	1.05
BMI	3.10		4.82		4.39	2.13	1.93	3.16	3.61	2.45	1.09
FMP	1.48		2.50		0.44	0.43	2.39	3.32	0.87	1.40	1.33
MAI	5.90		3.39		2.55	1.50	-0.58	3.59	3.01	4.23	1.83
MEL	9.55		7.33		1.75	1.00	-1.67	4.56	0.18	2.41	3.34
MTR	1.99	-0.96	-0.48	2.30	-0.10	-0.56	2.83	1.71	0.85	1.31	1.20
MED			0.75		-0.35	-1.93	-6.33	1.00	-3.99	0.21	-1.38
OMAN	2.17	1.09	1.19	0.98	0.96	-0.43	1.19	2.43	2.65	2.80	2.28
TOTAL MAN	**2.93**	**2.45**	**3.84**	**2.85**	**2.30**	**1.28**	**3.72**	**4.00**	**3.25**	**2.83**	**2.48**

*Canada:1997-2000 averages for MAI and MEL; **Germany: 1993-2000 averages for BMI.
***Netherlands: 1988-2000 averages for MAI, MEL and MED; ****Sweden: 1991-2000 averages for MAI, MEL and MED.
FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products; PETRO - Coke, refined petroleum products and nuclear fuel; RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment; MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery; MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c.

Table 4.1. Average annual TFP growth rate in 15 OECD manufacturing industries, 1981-2000 (%)

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which is suggestive of measurement error. Given perfect competition and a translog production function the labour share can be expressed as a function of the capital-labour ratio as in, $\alpha_{cit}=\psi_{ci}+\varphi_i \log(K_{cit}/L_{cit})$ and this functional form can be used to estimate the labour share in order to obtain smoother, less volatile values for the translog production function specification. See e.g. (Griffith, Redding, & Van Reenen, 2004), (Scarpetta & Tressel, 2002), and (Scarpetta & Tressel, 2004).

Table 4.2 reports the countries with the three highest levels of relative TFP (exponential) and some basic statistics for this variable in 1981, 1991 and 2000. A value of the mean closer to unity (lower values of the exponential of RTFP) corresponds to a higher average level of relative TFP, i.e. on average the followers are technologically closer to the leader (whose RTFP exponential value equals unity). There is some variation in the identity of the leader across manufacturing industries, with the European countries standing relatively close to the frontier or even becoming leaders. In 1981, the USA is the leader in only seven industries and by 2000 it maintains its leadership in only three industries. In most industries and years however it occupied one of the first three places. In eight industries average RTFP was lower in 2000 than in 1981, and in thirteen industries the standard deviation fell between 1981 and 2000.

	rank	1981	1991	2000
FOOD	1st	**USA**	**USA**	**FR**
	2nd	FR	FR	USA
	3rd	CAN	CAN	CAN
	Mean	1.73	1.66	1.58
	St. Dev.	0.58	0.46	0.46
TEX	1st	**ITA**	**USA**	**NLD**
	2nd	CAN	ITA	CAN
	3rd	USA	NLD	USA
	Mean	1.49	1.39	1.37
	St. Dev.	0.53	0.44	0.36
WOOD	1st	**UK**	**USA**	**CAN**
	2nd	USA	GER	NLD
	3rd	SWE	UK	USA
	Mean	1.55	1.61	1.59
	St. Dev.	0.46	0.40	0.44
PAP	1st	**USA**	**UK**	**FIN**
	2nd	UK	USA	USA
	3rd	ITA	NLD	UK
	Mean	1.38	1.40	1.21
	St. Dev.	0.42	0.29	0.17
CHE	1st	**USA**	**USA**	**USA**
	2nd	FR	FR	FR
	3rd	CAN	SWE	SWE
	Mean	1.44	1.55	1.40
	St. Dev.	0.42	0.43	0.37
PETRO	1st	**FR**	**SWE**	**FR**
	2nd	DNK	USA	USA
	3rd	NLD	ITA	SWE
	Mean	3.96	2.94	4.12
	St. Dev.	5.05	3.13	4.64
RUB	1st	**FR**	**GER**	**GER**
	2nd	ITA	FR	CAN
	3rd	USA	UK	FR
	Mean	2.02	1.32	1.85
	St. Dev.	1.07	0.21	0.49
ONMP	1st	**ITA**	**UK**	**SWE**
	2nd	USA	ITA	UK
	3rd	CAN	NLD	NLD
	Mean	1.29	1.71	1.43
	St. Dev.	0.51	0.41	0.30

	rank	1981	1991	2000
BMI	1st	**USA**	**UK**	**NOR**
	2nd	NLD	NLD	NLD
	3rd	CAN	USA	CAN
	Mean	1.85	1.57	1.39
	St. Dev.	0.85	0.36	0.37
FMP	1st	**USA**	**USA**	**USA**
	2nd	CAN	GER	CAN
	3rd	GER	UK	UK
	Mean	1.42	1.36	1.38
	St. Dev.	0.34	0.25	0.29
MAI	1st	**CAN**	**NLD**	**UK**
	2nd	USA	CAN	CAN
	3rd	ITA	UK	NLD
	Mean	2.21	1.58	1.37
	St. Dev.	0.72	0.29	0.17
MEL	1st	**CAN**	**USA**	**FIN**
	2nd	USA	CAN	USA
	3rd	GER	GER	CAN
	Mean	1.60	1.43	1.90
	St. Dev.	0.44	0.34	0.62
MTR	1st	**USA**	**USA**	**CAN**
	2nd	CAN	CAN	USA
	3rd	SWE	GER	FR
	Mean	1.48	1.39	1.61
	St. Dev.	0.60	0.29	0.53
MED	1st	**USA**	**UK**	**NLD**
	2nd	FIN	USA	FIN
	3rd	ITA	NOR	UK
	Mean	1.21	1.24	1.34
	St. Dev.	0.22	0.07	0.24
OMAN	1st	**CAN**	**USA**	**USA**
	2nd	USA	GER	CAN
	3rd	ITA	FR	UK
	Mean	1.30	1.39	1.46
	St. Dev.	0.39	0.36	0.30
TOTAL MAN	1st	**ITA**	**UK**	**SWE**
	2nd	UK	ITA	UK
	3rd	SWE	NLD	NLD
	Mean	1.72	1.71	1.43
	St. Dev.	0.51	0.41	0.30

Notes: FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products; PETRO - Coke, refined petroleum products and nuclear fuel; RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment; MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery; MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c..

Table 4.2. Relative TFP levels and the technology leaders in 15 OECD manufacturing industries, 1981, 1991 and 2000

4.3.2.2. Education

We use aggregate education data to analyse the importance of education for TFP growth at the industry level, as in (Griffith, Redding, & Van Reenen, 2004), (Cameron, Proudman, & Redding, 2005), (Scarpetta & Tressel, 2004), and (Schiff & Wang, 2004). By using a country-level educational attainment measure we want to capture the technological externalities from human capital accumulation, as analysed in chapter 2.

As in the previous chapter, we use average years of total schooling as our benchmark educational measure not distinguishing the impact of the different schooling levels. We next examine several combinations of influences of each schooling level or different schooling levels combined in determining productivity growth through technology diffusion or the domestic innovation rate. We also investigate if the impact of the different schooling levels on productivity growth varies according to the R&D intensity of industries. To test these hypotheses we use the education stock series from (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002) described in chapter 2, so we do not go into great details about their times series cross country behaviour here.

Notice that some of the studies reviewed in this chapter also use an industry-specific human capital proxy (e.g., (Griffith, Redding, & Van Reenen, 2004), (Scarpetta & Tressel, 2002), and (Scarpetta & Tressel, 2004)). These industry-specific human capital proxies have limited country-industry coverage and are based on skill data not education data. Although (Cameron, Proudman, & Redding, 2005) call our attention to the fact that skill-based human capital proxies also reflect the impact of education on industry productivity growth (there is evidence of a high time-series correlation between the share of non-production workers and the share of high-education workers in employment) and are more widely available than industry-specific education attainment data, the fact is that the use of these proxies implies making quite strong assumptions across industries and countries.

Due to the limited data availability of industry-specific education measures and the strong implied assumptions necessary to obtain this variable, we restrict our analysis to the use of countrywide education data. In any case, our main goal is to assess the importance of education for productivity growth according to endogenous growth theory that emphasizes externalities associated with innovation efforts as the engine of growth so this measure seems appropriate to our objective.

4.3.2.3. R&D

R&D data comes from the OECD ANBERD (Analytical Business Enterprise Research and Development) database, (OECD, 2002a) and (OECD, 2003a). This database provides internationally comparable business enterprise R&D expenditures across industries, in national currencies as well as PPP USD, and includes all R&D performed by the business sector regardless of the origin of funding. The goal of the ANBERD database is to use official BERD data to construct continuous time series data on business R&D comparable across OECD countries, relying on estimation techniques to fill in missing observations[81].

In the introduction to this section we discussed the classification of industries according to the respective R&D intensity based on the OECD classification of high, medium-high, medium-low and low technology industries. For our sample, the average R&D intensity of the "High Technology" industries in the 1980-2000 period is 11.66% and that of the "Low Technology" industries is 1.8%, so the cluster with high R&D intensities is on average 6.5 times more R&D intensive than the cluster comprising the industries with low R&D intensities. Table 4.3 reports some summary information on R&D intensities across industries and countries in the 1980-2000 period.

[81] See http://www.oecd.org/document/17/0,2340,en_2649_34409_1822033_1_1_1_1,00.html for a discussion of the methodology used to collect international comparable business R&D data and its major shortcomings.

	CAN	DNK	FIN	FR	GER	ITA	NLD	NOR	SWE	UK	USA
Low Technology											
FOOD	0.54	1.32	2.03	0.83	0.65	0.26	1.98	1.19	1.83	1.09	1.21
TEX	0.85	0.33	1.07	0.66	1.05	0.04	0.73	1.06	1.25	0.35	0.56
WOOD	0.48	0.52	0.89	0.33	1.16	0.07	0.27	0.75	0.33	0.25	0.75
PAP	0.69	0.18	1.44	0.28	0.29	0.04	0.21	0.77	1.96	0.24	1.06
PETRO	11.30		5.21	4.17	2.93	1.50	5.77		2.55	8.97	7.66
RUB	0.72	1.50	3.61	3.78	1.94	1.45	1.83	1.99	3.31	0.91	3.10
ONMP	0.46	1.35	2.44	1.74	1.67	0.18	0.57	1.47	1.78	1.25	2.49
BMI	2.13	1.37	3.34	3.80		1.06	2.41	5.17	3.52	1.41	1.77
FMP	0.80	0.89	2.17	0.77	1.98	0.44	0.92	1.69	2.28	0.75	1.45
OMAN	0.71	5.62	0.74	0.34	0.38	0.05	0.02	0.31	0.48	1.50	1.55
Mean	*1.87*	*1.45*	*2.29*	*1.67*	*1.34*	*0.51*	*1.47*	*1.60*	*1.93*	*1.67*	*2.16*
St. Dev.	*3.35*	*1.64*	*1.42*	*1.61*	*0.87*	*0.60*	*1.72*	*1.43*	*1.06*	*2.61*	*2.08*
High Technology											
CHE	4.28	13.89	10.62	12.60	13.52	6.12	11.60		17.61	14.80	12.04
MAI	5.06	5.18	6.77	5.58	6.13	2.43	9.78	8.84	9.88	4.73	11.37
MEL	18.90	9.07	18.44	17.19	14.72	8.13	18.56	18.63	33.03	16.39	16.29
MTR	4.70	3.44	3.66	14.48	15.50	11.37	7.21	2.05	17.68	13.69	24.50
MED		12.62	13.88	18.13	5.72	1.90	6.15	12.46	14.12	6.40	18.46
Mean	*8.24*	*8.84*	*10.67*	*13.60*	*11.12*	*5.99*	*10.66*	*10.50*	*18.46*	*11.20*	*16.53*
St. Dev.	*7.12*	*4.54*	*5.81*	*4.99*	*4.79*	*3.97*	*4.91*	*6.93*	*8.75*	*5.27*	*5.34*

Notes: FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear;
WOOD - Wood and products of wood and cork;
PAP - Pulp, paper, paper products, printing and publishing;
CHE - Chemicals and chemical products; PETRO - Coke, refined petroleum products and nuclear fuel;
RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries;
FMP - Fabricated metal products, except machinery and equipment;
MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery;
MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment;
MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c..

Table 4.3. Average R&D intensity by country and industry in 15 OECD manufacturing industries, 1980-2000 (%)

There are some differences in R&D intensities across countries for the same industry. For instance, Denmark has an R&D intensity of 5.62% in Other Manufacturing Industries (OMAN), almost 4 times as much as that of the US, the country with the second highest value. Sweden has an R&D intensity of 33.03% in Electrical Machinery (MEL), almost the double of that of Canada, the country with the second highest value. Despite these differences there are clearly two clusters of industries based on R&D intensity for each country.

4.3.2.4. International trade

As extensively discussed in this and the previous chapter, both theoretical and empirical growth literature stress the importance of international trade as a vehicle of technology diffusion. The effectiveness of these technology transfers depends in turn on the absorptive capability of each country-industry, i.e. it may also depend on education.

International trade data comes from the OECD Bilateral Trade Database (BTD) database ((OECD, 2000), (OECD, 2002b)) that contains information for each industry in each country on trade flows from one country or geographical area to another in thousands of USD at current prices[82]. This data is the product of conversion of the data from the OECD's International Trade by Commodity Statistics database so it has been converted from product classification schemes to an activity classification scheme. We use the ratio of an industry's imports from the OECD countries to gross output as a proxy for technology transfer through international trade.

Table 4.4 reports the averages for each country-industry of the imports ratio for the 1980-2000 period. On average, high-tech industries present higher import ratios. Within the low-tech industries Textiles (TEX) and Basic Metal Industries (BMI) also present relatively high imports ratios. The countries that import the most relative to its output are the small countries like the Netherlands and the Scandinavian countries, as expected.

[82] Unlike in the previous chapter it was not possible to have access to industry imports data by product type, such as imports of machinery and transport equipment, a better proxy for embodied technology diffusion.

	CAN	DNK	FIN	FR	GER	ITA	NLD	NOR	SWE	UK	USA
Low Technology											
FOOD	10.51	13.73	8.15	12.19	14.33	15.36	19.58	8.76	9.31	12.24	3.8
TEX	31.3	80.69	50.34	27.34	53.73	7.19	128.05	185.82	81.79	27.59	6.63
WOOD	7	51.66	3.24	21.79	20.85	11.72	82.48	24.94	25.91	17.34	6.32
PAP	13.04	30.32	3.44	17.25	14.98	11.97	30.11	17.98	25.57	12.5	4.1
PETRO	6.99	59.23	9.49	11.05	27.99	6.77	18.33		44.69	17.09	3.06
RUB	31.42	43.93	35.15	20.4	17.24	11.11	71.81	82.97	41.81	19.07	6.35
ONMP	27.81	21.28	15.39	13.85	13.26	5.74	37.83	28	20.94	12.54	5.11
BMI	21.38	158.19	21.51	35.77	26.54	28.97	85.69	43.72	41.34	28.33	9.71
FMP	25.41	31.65	23.02	10.99	11.12	4.37	32.24	58.65	23.35	11.01	4.18
OMAN	28.5	17.48	20.61	17.06	18.17	4.71	29.81	45.07	26.9	17.13	7.56
Mean	*20.34*	*50.82*	*19.03*	*18.77*	*21.82*	*10.79*	*53.59*	*55.10*	*34.16*	*17.48*	*5.68*
St. Dev.	*9.99*	*43.06*	*14.83*	*7.94*	*12.49*	*7.35*	*36.46*	*53.94*	*19.98*	*6.16*	*2.03*
High Technology											
CHE	43.63	86.6	60.59	33.87	28.55	35.21	49.73		53.71	35.71	9.56
MAI	122.1	63.85	45.65	44.99	21.74	23.73	142.42	120.39	46.95	45.77	16.07
MEL	75.96	79.1	48.15	31.35	24.77	28.93	66.93	89.98	48.63	39.55	28.32
MTR	69.65	125.33	82.06	27.6	24.67	40.89	107.39	74.07	41.84	36.11	18.13
MED		61.26	86.18	30.4	30.79	51.68	128.55	145.54	67.64	43.97	11.09
Mean	*77.84*	*83.23*	*64.53*	*33.64*	*26.10*	*36.09*	*99.00*	*107.50*	*51.75*	*40.22*	*16.63*
St. Dev.	*32.66*	*25.78*	*18.82*	*6.73*	*3.56*	*10.85*	*39.64*	*31.82*	*9.84*	*4.54*	*7.41*

Notes: FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork; PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products; PETRO - Coke, refined petroleum products and nuclear fuel; RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment; MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery; MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c.

Table 4.4. Ratio of imports from the OECD to gross output in 15 OECD manufacturing industries, average 1980-2000 (%)

4.4. Empirical findings

Our basic econometric specification is equation (4.1). Since our key concern is the role of human capital acquired through the different schooling levels in driving productivity growth, we start by including only this variable as a determinant of productivity growth alongside TFP growth of the leader and relative TFP. Our aim is to select the relevant schooling level for innovation and imitation activities.

We next analyse the additional role of R&D, first separately, then interacted with the education variables, considering the previous results on the relevant education variables for innovation and technology diffusion. We next repeat these regressions but considering also international trade to select our preferred specification that includes all the relevant influences from the previous regressions. We run these regressions first considering all fifteen manufacturing industries together. Next we present the results for the low and high technology industries separately.

The results presented refer to TFP computed based on the translog production function using total hours worked as the labour input. The conclusions are robust to changes in the computation of TFP in what concerns the use of total employment instead of total hours worked as the labour input and a Cobb-Douglas production function instead of a translog specification. We thus abstain from presenting these results here.

Since there may be omitted determinants of TFP growth correlated with the explanatory variables we estimate the different specifications considering country-industry fixed effects. We also include a full set of time dummies to account for the influence of common aggregate shocks that affect TFP growth in all countries-industries. To correct for heteroscedasticity in the data we use the Huber-White sandwich estimator of variance. Finally, we check the robustness of the results to the use of the first differenced GMM estimator.

4.4.1. Results for the fifteen OECD manufacturing industries

Table 4.5 contains the results for the whole sample for the specification with TFP growth of the leader ($\Delta logTFP_L$), the distance from the technological frontier (RTFP), and the influence of the different education variables on the domestic rate of innovation and technology diffusion. In columns (1) to (9) the estimated coefficients on $\Delta logTFP_L$ and RTFP have the expected positive sign and are highly statistically significant (except for the coefficient on RTFP in column (2)), suggesting that technological leaders serve as locomotives for growth in the followers and that within each industry the further it lies behind the technological frontier the higher its rate of TFP growth.

In column (1) we consider the influence of overall educational attainment measured as average years of total schooling (TYR) to capture its influence on the rate of innovation. The estimated coefficient is positive and statistically significant at conventional levels. Column (2) considers both the level of education and its interaction with RTFP to capture the importance of education in determining an industry's absorptive capacity of technology from abroad. The results change dramatically: the coefficient on TYR is not significant, the same happens to the coefficient on RTFP and only the coefficients of TFP growth of the leader and the interaction term between TYR and RTFP are positive and statistically significant at conventional levels. This means that to benefit from its technological backwardness an industry must operate in a country with a sufficient education level but education is no longer relevant for innovation.

In columns (3) to (8) we test the role of the different schooling levels, secondary (SYR), secondary and tertiary together (SHYR), and tertiary (HYR) education, in innovation and technology diffusion to determine if the above results concerning TYR also apply. When ignoring the role of education in technology diffusion (columns (3), (5), and (7)) all coefficients are positive and statistically significant but the impact of average years of tertiary education is more than the double of that of SYR or SHYR.

When both roles are considered however the coefficient on the direct impact becomes statistically insignificant and only the coefficient on the interaction term between SYR and RTFP is not statistically significant. The coefficient on RTFP alone in all cases remains positive and significant.

When we compare the specifications that consider only the direct impact of education (columns (1), (3), (5), and (7)), the R-squared is higher when we estimate the regression with total schooling relative to the other schooling levels. For the specifications with both education influences (columns (2), (4), (6), and (8)) the R-squared is higher when we consider tertiary education although the respective direct influence is not statistically significant.

We thus decided to consider simultaneously a different role for the schooling levels in TFP growth in column (9): total schooling is the relevant education variable for innovation activities while tertiary education is important to absorb technology produced in the leader industry. Now both coefficients are positive and highly statistically significant as expected and the coefficient of determination is higher than for the other regressions. Innovation requires all levels of education but the absorption of technology from the leader industry is determined by tertiary education. This is our preferred specification of the relationship between TFP growth and education that we will use to analyse the importance of R&D and international trade for productivity growth.

	1	2	3	4	5	6	7	8	9
$\Delta logTFP_{Lit}$	**.4241**	**.4261**	**.4240**	**.4256**	**.4243**	**.4259**	**.4234**	**.4242**	**.4248**
	(7.93)	**(7.90)**	**(7.92)**	**(7.90)**	**(7.93)**	**(7.91)**	**(7.92)**	**(7.96)**	**(7.96)**
$RTFP_{cit-1}$	**.1884**	.0086	**.1866**	**.1142**	**.1879**	**.1034**	**.1832**	**.0987**	**.1104**
	(5.26)	(0.08)	**(5.20)**	**(1.69)**	**(5.24)**	**(1.55)**	**(5.19)**	**(2.22)**	**(2.42)**
TYR_{cit-1}	**.0191**	.0081							**.0156**
	(4.35)	(1.14)							**(3.56)**
$(TYRxRTFP)_{cit-1}$		**.02**							
		(1.56)							
SYR_{cit-1}			**.0184**	.0079					
			(3.61)	(0.88)					
$(SYRxRTFP)_{cit-1}$				.0218					
				(1.17)					
$SHYR_{cit-1}$					**.0215**	.0097			
					(4.02)	(1.11)			
$(SHYRxRTFP)_{cit-1}$						**.0223**			
						(1.38)			
HYR_{cit-1}							**.0503**	.0295	
							(1.55)	(0.87)	
$(HYRxRTFP)_{cit-1}$								**.1878**	**.1717**
								(2.82)	**(2.58)**
$\bar{R}$ -squared	.2123	.2148	.2110	.2123	.2117	.2135	.2086	.2148	.2173
Root MSE	.10508	.10491	.10516	.10508	.10512	.10499	.10532	.10491	.10474

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. $\Delta logTFP_L$ is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001). The sample includes 2881 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 4.5. Roles of the different schooling levels in TFP growth, 15 OECD manufacturing industries

In Table 4.6 we test the importance of R&D and international trade as additional factors in generating innovation and technology transfer and its interaction with education, checking the robustness of the above education results to the introduction of these control variables. We confirm the results regarding the positive influences of $\Delta \log TFP_L$ and RTFP in all regressions.

In column (1) we introduce the lagged level of R&D intensity, which enters positively and is statistically significant at conventional levels and does not change the results concerning the education variables. Column (2) considers both the level and the interaction term between R&D and relative TFP. Both coefficients are positive as expected but neither is statistically significant at conventional levels so we excluded the interaction term in the following regressions considering that these results suggest that the dominant effect of R&D is on rates of innovation[83]. In columns (3) to (6) we also test for a possible interaction between education and R&D but none of the interaction terms is statistically significant and all have the wrong sign, negative.

In columns (7) to (11) we drop the interaction terms between R&D and the education variables and consider additionally a role for international trade in TFP growth (IMPS). The magnitude and statistical significance of the coefficients of the education variables and R&D remain basically unchanged. When IMPS is introduced on its own its coefficient is positive as expected but not significant (column (7)).

In columns (8) to (11) we test the hypothesis that education is fundamental to benefit from technology incorporated in imports. We ignored the direct effect of IMPS since the coefficients were always not statistically significant when included. The coefficients on the interaction terms between each education variable and IMPS are all not statistically significant contrary to our hypothesis. Our preferred specification is thus (1).

In column (12) we estimate our selected specification using the Diff-GMM estimator. We consider all the regressors but TFP growth of the leader as potentially endogenous and use the adequate lagged values as instruments (see the notes on each table for details). Since explanatory variables are measured at the beginning of each period we consider them as predetermined. The results confirm all previous influences. The second-order serial correlation test p-value supports the GMM estimation of our model[84].

Finally, in column (13) we check the robustness of the results to the use of the (De la Fuente & Doménech, 2002) education data set. All the coefficients remain significant but now the estimated coefficient on average years of total schooling is negative, meaning that industries that operate in countries with higher levels of total schooling have lower TFP growth, a result hard to reconcile with economic theory.

[83] Comparing these results with the ones from (Griffith, Redding, & Van Reenen, 2004) and (Scarpetta & Tressel, 2004), the first finds a role for R&D both in innovation and technology transfers while the second finds evidence of an influence only through the domestic rate of innovation.

[84] We have to rely on this test only since the Sargan statistic could not be computed due to the near singularity of the variance-covariance matrix of moment conditions. This arises when the cross-sectional dimension is small relative to the number of instruments.

	1	2	3	4	5	6	7	8	9	10	11	12 Diff-GMM	13 DD
$\Delta \log TFP_{Lit}$	.4484	.4473	.4486	.4485	.4486	.4488	.4496	.4494	.4495	.4494	.4491	0.3803	.44903
	(9.61)	(9.57)	(9.60)	(9.60)	(9.60)	(9.61)	(9.60)	(9.60)	(9.61)	(9.61)	(9.59)	(7.15)	(9.66)
$RTFP_{cit-1}$	.1044	.0898	.1040	.1044	.1042	.1026	.1143	.1142	.1141	.1142	.116	0.1393	.0930
	(2.93)	(2.36)	(2.92)	(2.93)	(2.92)	(2.86)	(3.10)	(3.10)	(3.10)	(3.10)	(3.11)	(1.69)	(2.57)
TYR_{cit-1}	.0121	.0122	.0126	.0122	.0125	.0117	.0122	.0117	.0113	.0112	.1246	0.0149	-.0256
	(2.87)	(2.91)	(2.74)	(2.63)	(2.73)	(2.76)	(2.88)	(2.68)	(2.38)	(2.41)	(1.84)	(1.55)	(-3.56)
$(HYRxRTFP)_{cit-1}$	.1401	.1128	.1413	.1402	.1410	.1464	.1292	.1287	.129	.1286	.1246	0.456	.1094
	(2.17)	(1.84)	(2.18)	(2.17)	(2.18)	(2.24)	(1.97)	(1.95)	(1.96)	(1.95)	(1.84)	(4.72)	(2.20)
$R\&D_{cit-1}$	.3195	.0778	.4166	.3314	.363	.3866	.3272	.3262	.3262	.326	.3255	0.2689	.3476
	(2.75)	(0.63)	(1.01)	(1.48)	(1.59)	(2.97)	(2.80)	(2.79)	(2.79)	(2.78)	(2.78)	(1.33)	(2.98)
$(R\&DxRTFP)_{cit-1}$		.4563											
		(1.22)											
$(R\&DxTYR)_{cit-1}$			-.0098										
			(-0.25)										
$(R\&DxSYR)_{cit-1}$				-.0032									
				(-0.06)									
$(R\&DxSHYR)_{cit-1}$					-.0102								
					(-0.21)								
$(R\&DxHYR)_{cit-1}$						-.1166							
						(-0.55)							
$IMPS_{cit-1}$							.0034						
							(0.22)						
$(IMPSxTYR)_{cit-1}$								.0008					
								(0.50)					
$(IMPSxSYR)_{cit-1}$									.0020				
									(0.44)				
$(IMPSxSHYR)_{cit-1}$										.0021			
										(0.53)			
$(IMPSxHYR)_{cit-1}$											.0305		
											(1.01)		
$\bar{R}$ -squared	.2575	.2614	.2572	.2572	.2572	.2573	.2585	.2585	.2585	.2586	.2587		.2584
Root MSE	.09305	.0928	.09306	.09307	.09306	.09306	.09338	.09338	.09338	.09338	.09337	0.1	.09299
Sargan test [*p-value*]													
AR(2)												0.02945	
[*p-value*]												[0.977]	

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. $\Delta \log TFP_L$ is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001); R&D is the ratio of Business R&D expenditure to value-added; IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 2881 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (12) estimates the specification in column (1) through Diff-GMM considering all variables except TFP growth of the leader as endogenous (predetermined). Instruments used are all values of $\Delta \log TFP_L$ and values of RTFP, TYR, (HYRxRTFP), and R&D lagged 2 to 5 periods. Results for the one-step GMM estimator with standard errors robust to heteroskedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards. Column (13) estimates the specification in column (1) with average years of schooling for the population aged 25 and over from (De la Fuente & Doménech, 2002).

Table 4.6. Roles of the different schooling levels, R&D and international trade in TFP growth, 15 OECD manufacturing industries

We proceed with our analysis testing for a differentiated impact of technological catch-up, education, R&D and international trade on productivity growth depending on the underlying technology level characterizing each industry, i.e. considering a sample of low technology and a sample of high technology industries according to the respective R&D intensities.

4.4.2. Results for the ten OECD low technology industries

Table 4.7 reports the results of estimating equation (4.1) for the group of ten low-technology industries. In columns (1) to (8) we repeat the analysis concerning the selection of the relevant education variable for productivity growth but this time for low-tech industries.

The results in columns (1) to (8) confirm the results for the whole sample regarding $\Delta logTFP_L$ and RTFP with both coefficients positive and statistically significant. Now, only when average years of tertiary education is considered do we confirm that education influences both the rate of innovation and technology diffusion and this is the specification with the highest R-squared so we retain HYR as the relevant schooling level for productivity growth in low-tech industries.

	1	2	3	4	5	6	7	8
$\Delta logTFP(LT)_{Lit}$	**.4459**	**.4478**	**.4456**	**.4476**	**.4459**	**.4478**	**.4458**	**.4466**
	(7.69)	**(7.66)**	**(7.68)**	**(7.65)**	**(7.69)**	**(7.66)**	**(7.71)**	**(7.75)**
$RTFP(LT)_{cit-1}$	**.2133**	.0368	**.2098**	**.1236**	**.2114**	**.1153**	**.2112**	**.1157**
	(4.81)	(0.28)	**(4.74)**	**(1.51)**	**(4.78)**	**(1.43)**	**(4.83)**	**(2.08)**
TYR_{cit-1}	**.0210**	.0092						
	(3.69)	(0.99)						
$(TYRxRTFP(LT))_{cit-1}$		**.0195**						
		(1.30)						
SYR_{cit-1}			**.0171**	.0024				
			(2.61)	(0.19)				
$(SYRxRTFP(LT))_{cit-1}$				.0260				
				(1.14)				
$SHYR_{cit-1}$					**.0213**	.0058		
					(3.12)	(0.48)		
$(SHYRxRTFP(LT))_{cit-1}$						**.0253**		
						(1.30)		
HYR_{cit-1}							**.1033**	**.0860**
							(2.50)	**(2.04)**
$(HYRxRTFP(LT))_{cit-1}$								**.2088**
								(2.68)
$\bar{R}$ -squared	.2242	.2262	.2222	.2238	.223	.2251	.2219	.2289
Root MSE	.11625	.1161	.11641	.11629	.11635	.11619	.11643	.1159

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. $log\Delta TFP_L$ is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001). The sample includes 1993 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 4.7. Roles of the different schooling levels in TFP growth, 10 OECD low technology (LT) industries

In Table 4.8 we check the robustness of the results to the introduction of R&D and international trade as additional technological change determinants.

In column (1), the estimated coefficient on R&D is positive and statistically significant at conventional levels although a little high implying a rate of return to R&D in excess of a hundred per cent. It was also the case for low-tech industries that the interaction term between R&D and relative TFP was not significant (column (2)).

As for the estimated coefficients on the interaction terms between R&D and the different education variables (columns (3)-(6)), only the one relative to the interaction term between R&D and overall educational attainment is positive and statistically significant as expected and renders the coefficient on the direct impact of R&D negative but not statistically significant (column(3)).

We retain the specification in column (7), where we dropped the direct influence of R&D, as our preferred specification and we introduce the influence of international trade in productivity growth in columns (8)-(12).

International trade has no direct impact on productivity growth (column (8)). As for the interaction terms with the different education variables (columns (9)-(12)) the only estimated coefficient that is positive and significant is IMPSxHYR (column (12)) so that productivity growth in low-tech industries benefits from increased international trade if the country's population possesses qualifications at the tertiary level.

The specification in column (12) is our preferred specification for low-tech industries and differs from the specification for the whole sample in the way education influences productivity growth. In low-technology industries tertiary education exerts a direct influence on the rate of innovation while overall educational attainment interacts with R&D. Tertiary education is also the relevant schooling level to benefit from technology diffusion. This might be explained by the fact that low-tech industries operate with relatively stable technologies that require a highly-skilled workforce to generate new production processes and product designs or to reverse engineering technology developed abroad.

Column (13) estimates the selected specification using the Diff-GMM estimator considering all regressors but TFP growth of the leader as potentially endogenous (predetermined) and use the adequate lagged values as instruments (see the notes on each table for details). The results confirm all influences expect for the direct influence of education: the estimated coefficient although positive is not statistically significant. In column (14) we drop this influence from the analysis and confirm the remaining influences. The second-order serial correlation test p-value supports the GMM estimation of our model[85]. Column (15) tests the robustness of the results to the use of the (De la Fuente & Doménech, 2002) data set: the estimated coefficient on HYRxIMPS is not significant and the estimated coefficient on the direct impact of HYR has the wrong sign although it is not statistically significant.

[85] We have to rely on this test only since the Sargan statistic could not be computed due to the near singularity of the variance-covariance matrix of moment conditions.

	1	2	3	4	5	6	7	8	9	10	11	12	13 Diff-GMM	14 Diff-GMM	15 DD
$\Delta logTFP(LT)_{Lit}$	.4721	.4711	.4699	.4709	.4704	.4703	.4715	.4717	.471	.4710	.4709	.4706	.4293	.4313	.4717
	(9.46)	(9.41)	(9.38)	(9.41)	(9.40)	(9.44)	(9.45)	(9.44)	(9.43)	(9.43)	(9.43)	(9.42)	(10.2)	(10.3	(9.48)
$RTFP(LT)_{cit-1}$	.1147	.1113	.1387	.1230	.1265	.1259	.1215	.1219	.1217	.1226	.1227	.1241	.1394	.1445	.1276
	(2.61)	(2.52)	(3.09)	(2.79)	(2.87)	(2.86)	(2.76)	(2.76)	(2.76)	(2.78)	(2.78)	(2.79)	(1.81)	(1.77)	(2.62)
HYR_{cit-1}	.0564	.0499	.0745	.0727	.0691	.0331	.0630	.062	.0662	.0685	.0682	.0622	.0083		-.032
	(1.59)	(1.45)	(1.95)	(1.88)	(1.81)	(0.83)	(1.73)	(1.70)	(1.82)	(1.89)	(1.88)	(1.71)	(0.11)		(-.73)
$(HYRxRTFP(LT))_{cit-1}$	.1349	.1227	.0959	.12	.1133	.1130	.1212	.1216	.1192	.1183	.1179	.1155	.3120	.3269	.0748
	(1.85)	(1.67)	(1.28)	(1.64)	(1.54)	(1.52)	(1.65)	(1.66)	(1.62)	(1.60)	(1.59)	(1.55)	(2.40)	(2.50)	(1.20)
$R\&D(LT)_{cit-1}$	1.127	.2372	-2.84	.0643	-.277	.1615									
	(1.80)	(0.30)	(-.90)	(0.04)	(-.17)	(0.14)									
$(R\&DxRTFP(LT))_{cit-1}$		.5501													
		(0.81)													
$(R\&D(LT)xTYR)_{cit-1}$			.3925				.1162	.1160	.1161	.1155	.1154	.1152	.0694	.0623	.0912
			(1.27)				(1.88)	(1.87)	(1.88)	(1.86)	(1.86)	(1.86)	(1.92)	(1.72)	(1.70)
$(R\&D(LT)xSYR)_{cit-1}$				.2786											
				(0.79)											
$(R\&D(LT)xSHYR)_{cit-1}$					.3096										
					(0.90)										
$(R\&D(LT)xHYR)_{cit-1}$						1.34									
						(0.76)									
$IMPS(LT)_{cit-1}$								-.007							
								(-.30)							
$(IMPS(LT)xTYR)_{cit-1}$									.0017						
									(0.83)						
$(IMPS(LT)xSYR)_{cit-1}$										.0053					
										(1.06)					
$(IMPS(LT)xSHYR)_{cit-1}$											.0051				
											(1.14)				
$(IMPS(LT)xHYR)_{cit-1}$												.058	.2707	.317	.0234
												(1.53)	(1.94)	(1.94)	(0.81)
$\bar{R}$ -squared	.2827	.2843	.2846	.283	.2833	.2836	.2838	.2835	.2836	.2837	.2837	.284			.2806
Root MSE	.1008	.10068	.10066	.10078	.10075	.10073	.10072	.10074	.10073	.10073	.10072	.10071	0.0959	0.0956	.10094
Sargan test															
[*p-value*]															
AR(2)													0.3601	0.3538	
[*p-value*]													[0.719]	[0.724]	

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. Δ log TFP_L is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001); R&D is the ratio of Business R&D expenditure to value-added; IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 1993 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (13) estimates the specification in column (12) through Diff-GMM considering all variables except TFP growth of the leader as endogenous (predetermined). Instruments used are all values of $\Delta logTFP_L$ and values of RTFP(LT), HYR, (HYRxRTFP(LT)), (TYRxR&D(LT)), and (IMPS(LT)xHYR) lagged 2 to 5 periods. Column (14) estimates the specification in column (13) without HYR through Diff-GMM considering all variables except TFP growth of the leader as endogenous (predetermined). Instruments used are all values of $\Delta logTFP_L$ and values of RTFP(LT), (HYRxRTFP(LT)), (TYRxR&D(LT)), and (IMPS(LT)xHYR) lagged 2 to 5 periods. Results for the one-step GMM estimator with standard errors robust to heteroskedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards. Column (15) estimates the specification in column (12) with average years of schooling for the population aged 25 and over from (De la Fuente & Doménech, 2002).

Table 4.8. Roles of the different schooling levels, R&D and international trade in TFP growth, 10 OECD low-tech (LT) manufacturing industries

4.4.3. Results for the five OECD high technology industries

Table 4.9 reports the results of estimating equation (4.1) for the five high-technology industries with the aim of selecting the relevant educational sub-categories for innovation and imitation activities.

From the results presented in columns (1) to (10) we conclude that overall educational attainment is the relevant education variable for high-tech industries to benefit from technological backwardness but that the rate of innovation in these industries depends on the more qualified, proxied by education at the secondary and tertiary levels. This conclusion draws from the fact that the interaction term between TYR and relative TFP is the only statistically significant interaction term between human capital and technological backwardness (column (2)) and that the direct effect of SHYR is the one with the highest t-statistic and the specification in column (5) has the highest R-squared when compared with the specifications in columns (1), (3) and (7).

High-tech industries incorporate both industries with rapidly changing technologies, such as Medical and Optical instruments and Machinery and Equipment, where product differentiation is high and there is always demand for new products, and relatively stable technologies, such as Chemicals or Transport Equipment, that present high sunk costs (see (Scarpetta & Tressel, 2002)). This might be the cause for the different results concerning the relevant schooling level for innovation and imitation activities relative to low-tech industries. Creative destruction, a characteristic of high-tech industries with rapidly changing technologies, probably demands both medium and high skilled workers to discover new products and production processes. Creative accumulation, on the other hand, a characteristic of high-tech industries with relatively stable technologies, probably implies the availability of a highly skilled workforce to add to the existing technology.

We test a specification with these two influences, SHYR and TYRxRTFP, in column (9) that reveals that both estimated coefficients are positive and statistically significant as expected. Notice however that the estimated coefficient on relative TFP is negative although not statistically significant (as was the case also in columns (2), (6) and (8)) meaning that technological catch-up will only occur in high-tech industries if the countries where they operate possess the necessary absorptive capacity in the form of education. We retain specification (10), where we drop RTFP, as our preferred specification to explain productivity growth in high-tech industries before analysing the additional roles of R&D and international trade in Table 4.10.

	1	2	3	4	5	6	7	8	9	10
ΔlogTFP(HT)$_{Lit}$	**.2410**	**.245**	**.2415**	**.2434**	**.2416**	**.2436**	**.2389**	**.2408**	**.2454**	**.2451**
	(4.9)	**(4.9)**	**(4.9)**	**(4.9)**	**(4.9)**	**(4.9)**	**(4.9)**	**(4.9)**	**(4.95)**	**(4.96)**
RTFP(HT)$_{cit-1}$	**.0938**	-.0254	**.0964**	.0483	**.0967**	.0493	**.0874**	**.0649**	-.0199	
	(4.73)	(-.31)	**(4.79)**	(0.98)	**(4.80)**	(0.98)	**(4.51)**	**(2.08)**	(-.26)	
TYR$_{cit-1}$	**.0127**	.0070								
	(2.19)	(1.04)								
(TYRxRTFP(HT))$_{cit-1}$		**.0136**							**.0133**	**.0111**
		(1.48)							**(1.57)**	**(5.01)**
SYR$_{cit-1}$			**.0152**	**.0108**						
			(2.28)	**(1.47)**						
(SYRxRTFP(HT))$_{cit-1}$				.0147						
				(1.09)						
SHYR$_{cit-1}$					**.0164**	**.0122**			**.0107**	**.0117**
					(2.29)	**(1.54)**			**(1.39)**	**(1.69)**
(SHYRxRTFP(HT))$_{cit-1}$						.0128				
						(1.05)				
HYR$_{cit-1}$							-.0188	-.0300		
							(-.45)	(-.69)		
(HYRxRTFP(HT))$_{cit-1}$								.0550		
								(0.98)		
$\bar{R}$ -squared	.2028	.2036	.2031	.2032	.2034	.2034	.1981	.1979	.2044	.2054
Root MSE	.0672	.0671	.0671	.0671	.0671	.0671	.0674	.0674	.0671	.0670

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. ΔlogTFP$_L$ is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001). The sample includes 883 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 4.9. Roles of the different schooling levels in TFP growth,
5 OECD high technology (HT) industries

In column (1) of Table 4.10 we introduce the lagged level of R&D intensity as a determinant of the rate of innovation and the estimated coefficient reveals itself positive and statistically significant as expected. The remaining results do not change. Since the interaction term between R&D and relative TFP and all the interaction terms between R&D and the different education variables were not significant (columns (2)-(6)) we analyse the influence of international trade on productivity growth considering only the direct impact of R&D (columns (7)-(11)).

In this case, the results for TFP growth of the leader, education and R&D remain basically unchanged and only the estimated coefficient on the direct impact of international trade is positive and statistically significant as expected (column (7)). The estimated coefficients on the interaction terms between international trade and the different education variables are also not statistically significant and render the estimated coefficient on the direct impact of international trade also not statistically significant (columns (8)-(11)) so we retain specification (7) as our preferred specification.

In column (12) we estimate our selected specification using the Diff-GMM estimator. We consider all the regressors but TFP growth of the leader as potentially endogenous and use the adequate lagged values as instruments (see the notes on each table for details). Since explanatory variables are measured at the beginning of each period we consider them as predetermined. The results confirm all influences expect that of international trade: the estimated coefficient although positive is not statistically significant. In column (13) we drop this influence from the analysis and confirm the remaining influences using the Diff-GMM estimator. The employed specification tests support the GMM estimation of our model: the Sargan test and second-order serial correlation tests p-values are within the acceptable values and cannot reject the null hypothesis of correct specification of the different models.

Finally, in column (14) we check the robustness of the results to use of the (De la Fuente & Doménech, 2002) human capital data set that confirms all the results in specification (7) expect for the direct impact of secondary and tertiary education in the rate of innovation: the estimated coefficient is now negative and statistically significant.

	1	2	3	4	5	6	7	8	9	10	11	12 Diff-GMM	13 Diff-GMM	14 DD
ΔlogTFP(HT)$_{Lit}$	.2519	.2526	.2521	.2518	.2519	.2523	.2377	.2372	.2374	.2374	.2378	.2876	.2495	.2335
	(5.15)	(5.12)	(5.15)	(5.14)	(5.14)	(5.16)	(4.68)	(4.68)	(4.67)	(4.67)	(4.68)	(4.85)	(4.41)	(4.60)
SHYR$_{cit-1}$	.0123	.0128	.0131	.0118	.0127	.0116	.0162	.0210	.0198	.019	.016	.0272	.0243	-.0172
	(1.76)	(1.81)	(1.59)	(1.29)	(1.52)	(1.62)	(2.20)	(1.88)	(1.54)	(1.55)	(2.03)	(2.86)	(2.46)	(-2.01)
(TYRxRTFP(HT))$_{cit-1}$	.0101	.0084	.0102	.0101	.0101	.0102	.0102	.0103	.0103	.0103	.0102	.01653	.0168	.0072
	(4.57)	(2.17)	(4.58)	(4.56)	(4.57)	(4.61)	(4.51)	(4.52)	(4.49)	(4.49)	(4.51)	(4.14)	(4.05)	(3.92)
R&D(HT)$_{cit-1}$	.1774	.137	.2377	.1624	.1942	.2255	.1726	.1774	.1739	.1734	.1729	.2667	.2816	.1923
	(2.81)	(1.42)	(0.64)	(0.80)	(0.97)	(2.34)	(2.72)	(2.76)	(2.73)	(2.72)	(2.72)	(2.84)	(2.87)	(3.02)
(R&DxRTFP(HT))$_{cit-1}$		.1428												
		(0.52)												
(R&D(HT)xTYR)$_{cit-1}$			-.0061											
			(-0.17)											
(R&D(HT)xSYR)$_{cit-1}$				.0042										
				(0.08)										
(R&D(HT)xSHYR)$_{cit-1}$					-.0041									
					(-0.09)									
(R&D(HT)xHYR)$_{cit-1}$						-.0920								
						(-0.73)								
IMPS(HT)$_{cit-1}$							.04	.084	.0542	.0519	.0374	.0215		.0284
							(1.78)	(1.18)	(1.25)	(1.19)	(1.06)	(0.593)		(1.32)
(IMPS(HT)xTYR)$_{cit-1}$								-.005						
								(-.65)						
(IMPS(HT)xSYR)$_{cit-1}$									-.005					
									(-.36)					
(IMPS(HT)xSHYR)$_{cit-1}$										-.004				
										(-.31)				
(IMPS(HT)xHYR)$_{cit-1}$											.0060			
											(0.10)			
$\bar{R}$ -squared	.214	.213	.213	.2129	.2129	.2133	.2158	.2151	.2149	.2148	.2148			.2111
Root MSE	.06663	.06665	.06667	.06667	.06667	.06666	.06728	.06731	.06732	.06732	.06732	0.0625	0.0625	.06748
Sargan test [*p-value*]												433.2 [0.003]	305.8 [0.066]	
AR(2) [*p-value*]												-.3131 [0.754]	-.3252 [0.745]	

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked across countries and industries. ΔlogTFP$_L$ is TFP growth of the leader; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all for the population aged 15 and over from (Barro & Lee, 2001); R&D is the ratio of Business R&D expenditure to value-added; IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 883 observations between 1981 and 2000. All columns include a full set of time dummies and country-industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (12) estimates the specification in column (7) through Diff-GMM considering all variables except TFP growth of the leader as endogenous (predetermined). Instruments used are all values of ΔlogTFP(HT)$_L$ and values of SHYR, (TYRxRTFP(HT)), R&D(HT), and IMPS(HT) lagged 2 to 5 periods. Column (13) estimates the specification in column (12) without IMPS(HT) through Diff-GMM considering all variables except TFP growth of the leader as endogenous (predetermined). Instruments used are all values of ΔlogTFP(HT)$_L$ and all values of SHYR, (TYRxRTFP(HT)), and R&D(HT) lagged 2 to 5 periods. Results for the one-step GMM estimator with standard errors robust to heteroskedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards. Column (14) estimates the specification in column (7) with average years of schooling for the population aged 25 and over from (De la Fuente & Doménech, 2002).

Table 4.10. Roles of the different schooling levels, R&D and international trade in TFP growth, 5 OECD high-tech (HT) manufacturing industries

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4.4.4. Quantifying the contribution of education to TFP growth

The evidence from the previous sections supports the importance of human capital acquired in the formal education sector for TFP growth both through innovation and imitation activities. We use the estimated coefficients from the econometric analysis to quantify the importance of education for productivity growth in the average low-tech and high-tech industry in each country, highlighting the relative impact through the rate of domestic innovation and through technology diffusion.

The estimated impact of education through innovation activities in low-tech industries is given by $\hat{\gamma}_3$R&D, where $\hat{\gamma}_3$=0.0623, i.e. in low-tech industries overall educational attainment influences productivity through the rate of innovation due to its complementarity with R&D. In high-tech industries, the estimated impact of education through innovation activities is given by $\hat{g}$=0.0243. The estimated impact of education through imitation activities is given by $\hat{m}\log(A_{max}/A_c)$, in both low-tech and high-tech industries, where $\hat{m}$ is equal to 0.3269 and 0.0168, respectively. Additionally, in low-tech industries education also enhances productivity growth through its interaction with international trade. The impact through this mechanism is given by $\hat{\mu}_2$IMPS, where $\hat{\mu}_2$=0.317.

For each country, the total impact of education on TFP growth will differ according to its distance to the technological frontier so that countries further from the frontier will have higher growth returns to increased educational attainment. In low-tech industries the impact will also differ according to the respective R&D efforts and imports ratios. Table 4.11 reports the results of the contribution of education to TFP growth in OECD low-tech and high-tech manufacturing industries over the period 1981-2000.

country	Low-tech industries						High-tech industries		
					Technology Diffusion				
	Av. RTFP	Av. R&D	Av. IMPS	Innovation ($\hat{\gamma}_3$=0.0623)	Disembodied ($\hat{m}$=0.3269)	Embodied ($\hat{\mu}_2$=0.317)	Av. RTFP	Innovation ($\hat{g}$=0.0243)	Technology Diffusion ($\hat{m}$=0.0168)
Canada	0.304	1.36	0.2034	0.0844	0.0993	0.0645	0.197	0.0243	0.0033
Denmark	0.658	1.93	0.5081	0.1202	0.2150	0.1611	0.710	0.0243	0.0119
Finland	0.689	1.99	0.1903	0.1240	0.2251	0.0603	0.410	0.0243	0.0069
France	0.283	1.33	0.1877	0.0826	0.0924	0.0595	0.250	0.0243	0.0042
Germany	0.352	1.42	0.2182	0.0886	0.1150	0.0692	0.336	0.0243	0.0056
Italy	0.368	1.45	0.1079	0.0901	0.1204	0.0342	0.409	0.0243	0.0069
Netherlands	0.368	1.44	0.5359	0.0900	0.1202	0.1699	0.440	0.0243	0.0074
Norway	0.541	1.72	0.5510	0.1070	0.1769	0.1747	0.498	0.0243	0.0084
Sweden	0.459	1.58	0.3416	0.0986	0.1499	0.1083	0.382	0.0243	0.0064
UK	0.293	1.34	0.1748	0.0835	0.0957	0.0554	0.267	0.0243	0.0045
USA	0.115	1.12	0.0568	0.0699	0.0375	0.0180	0.085	0.0243	0.0014

Notes: The parameters used in the computations are those in column (14), Table 4.8 for low-tech industries and column (13), Table 4.10 for high-tech industries. Av. RTFP the average value of relative TFP for the period computed as described in the main text. Av. R&D the average value of R&D intensity for the period computed as described in the main text.
Av. IMPS the average value of the imports ratio for the period computed as described in the main text.

Table 4.11. Contribution of education to TFP growth in the OECD manufacturing industries (1981-2000)

The impact of education is higher in low-tech than in high-tech industries, both through innovation and imitation activities. In the average high-tech industry however, growth returns to education from innovation activities are higher than from imitation activities, in all countries. The USA presents the lowest contribution of education through technology diffusion and is the only country where the contribution of education through imitation activities in the average low-tech industry is lower than the contribution of education through innovation activities. Denmark, Norway, the Netherlands and Finland are the countries with higher returns to education from imitation activities since they are further from the high-tech industries technological leader.

4.5. Summary and Conclusions

Recent empirical studies on growth and convergence have highlighted the importance of industry-level analysis to shed additional light on the conclusions of the studies that have been undertaken at the aggregate level. This chapter followed this suggestion to examine the role of education, and of the different schooling levels, on productivity growth from a more disaggregate industry-level perspective based on the predictions of endogenous growth models and the benchmark study on human capital and growth of (Benhabib & Spiegel, 1994). We wanted to know whether the trends observed at the aggregate level, such as the complementarity between education and R&D efforts, are representative of movements at the industry level.

Our industry-level analysis consisted in fifteen manufacturing industries from eleven OECD countries over the last two decades of the twentieth century, also divided into two groups, low technology and high technology industries according to the respective R&D intensities, to test whether the role of education in productivity growth depends on technological characteristics. We also tested how two other variables proposed by the literature as determinants of productivity growth, R&D and international trade, influence TFP growth and whether they interact with education in determining productivity growth.

The results for the whole fifteen manufacturing industries taken together revealed that industries that are further behind the technological frontier tend to experience higher rates of productivity growth and that technological leaders serve as growth locomotives for the followers. Education boosts productivity growth both directly through the rate of innovation and indirectly by speeding technology diffusion but the relevant schooling levels for each activity are not the same: the rate of innovation is influenced by all the schooling levels together in the form of average years of total schooling, while the absorption of technologies from abroad is determined by tertiary education.

The disaggregated analysis for low-tech and high-tech industries reveals that technological characteristics are important in the sense that the role of education differs across the two groups. In low-tech industries it is human capital acquired in tertiary education that boosts productivity growth both directly through the rate of innovation and indirectly through technology diffusion, while in high-tech industries both secondary and tertiary education determine the rate of innovation and all schooling levels together influence the absorptive capacity of technologies from abroad. Technological catch-up will only take place if the countries where these industries operate possess a sufficient education level. Additionally, in low-tech industries overall educational attainment influences productivity growth through its complementarity with R&D efforts.

When we consider the whole sample and the high-tech industries sample the dominant role of R&D in productivity growth is through the rate of innovation. In the low-tech industries case however R&D influences productivity growth only if the countries possess a qualified workforce. International trade, on the other hand, influences productivity growth in quite distinct ways according to industries' technological characteristics: in low-tech industries international trade only affects productivity growth if the population of countries where these industries operate have a sufficient level of tertiary education, while in high-tech industries only the direct impact of increased international trade matters.

The results are robust to the use of different industry production function specifications, total employment as a measure of the labour input and the Diff-GMM estimator, except for the results concerning the direct impact of education in low-tech industries and international trade in high-tech industries. The use of an alternative human capital data set, (De la Fuente & Doménech, 2002) instead of (Barro & Lee, 2001), renders the results on the direct influence of education on productivity growth hard to interpret in light of economic theory: the level of education has a negative and statistically significant impact on productivity growth through the rate of innovation.

These results have interesting implications pointing to the fact that technological catch-up will be faster in industries that operate in countries with sufficient education levels and, more importantly, productivity convergence in high-tech industries cannot be taken for granted, depending on whether the workforce has the necessary skills, coming from all schooling levels, to adapt the new technologies. The specialisation of countries in industries with different technological characteristics, low-tech or high-tech, requires the education of a country's population on the appropriate schooling levels for industries to boost productivity growth through innovation and taking advantage of new technologies available in the technological leaders. The returns to investing in education also differ across industries and countries depending on whether they are technological leaders or not. For instance, follower countries specialised in low-tech industries will have greater returns to tertiary education while those specialised in high-tech industries will have greater returns to all schooling levels.

In the next chapter we use this same disaggregate industry level methodology to investigate the role of education in a particular country, Portugal. Portugal is clearly not on the technological frontier and can thus reap important growth benefits from its technological backwardness, especially since it specializes in low-tech manufacturing industries where we have seen there is potential for technological catch up. At the same time however Portugal is characterized by low levels of educational attainment, namely at the tertiary level which can constitute an obstacle to productivity growth and catch up.

4.6. Appendix

4.6.1. Data Sources

Output: value added expressed in 1995 constant international USD. We converted data on nominal value added expressed in local currency from the OECD, STAN database, 2004 into current international USD using OECD GDP PPPs. To get real value added in constant 1995 international USD we computed industry-specific USD value added deflators using data on nominal and real value added for US industries.

Physical capital: real capital stock expressed in 1995 constant international USD. The OECD, STAN database, 2004 only provides data for the real physical capital stock at constant prices expressed in local currency for Canada, Denmark, Finland, France, Germany and Italy, with limited availability across industries. Since the coverage of the Gross Fixed Capital Formation (GFCF) at current prices expressed in local currency data is wider we used this data and the perpetual inventory method to compute the physical capital stock data. We first converted data in local currency into international USD using the GFCF price levels and exchanges rates from the (Heston, Summers, & Aten, 2002) Penn World Table Mark 6.1., following the suggestion of (Harrigan, 1997) and (Harrigan, 1999). To compute real GFCF we used the US deflator for GFCF computed using the available data for each US industry on nominal and real GFCF. Finally, the perpetual inventory method was used to construct a proxy for the real physical capital stock, K, as a distributed lag of past investment flows, I, as:

$$K_{cit} = (1-d)K_{cit-1} + I_{cit-1} \tag{4.6}$$

$$K_{ci0} = \frac{I_{ci0}}{(g_{GFCFci} + d)} \tag{4.7}$$

where the capital stock in year t does not include investment in year t, but only investment up to t-1, and d is the common depreciation rate. (Nadiri & Prucha, 1996) estimate that d=0.059 for the US total manufacturing sector and this is the value we use for the depreciation rate, common across all countries and industries. K_0 is the initial real physical capital stock, and g_{GFCF} is the average annual growth rate of I over the period where data is available.

Labour input: we measure labour input as hours worked. Total hours worked data was missing from the OECD, STAN database, 2004 for Germany, Italy and the UK and had limited availability for France, the Netherlands, Sweden and the USA. Data on hours worked for these countries and different industries was taken from the Groningen Growth and Development Centre, Industry and Labour Productivity Database, (M. O'Mahony & B. van Ark, 2003), downloadable from http://www.ggdc.net/index-dseries.html#top.

These labour input measures do not take into account differences in the quality of raw labour when in fact the labour input resulting from one hour worked by one person does not have to be the same as the labour input resulting from another's person hour worked due to differences in education, skills, health, experience, etc.. A "perfect" labour input measure would be obtained through aggregation of different kinds of labour inputs. The data requirements to compute the quality adjusted aggregate labour input are quite severe. We need data on a country-industry-year basis for at least hours worked broken down by category and the corresponding average labour compensation. This is why usually some simplifying assumptions are considered, depending on data availability. For instance, (Harrigan, 1997) and (Harrigan, 1999) use average hours worked in manufacturing to adjust total employment; (Griffith, Redding, & Van Reenen, 2004) use country-industry data when available to compute h_{cit} and u_{cit} and mean values of these figures for the missing values for countries for which these data are not available; (Scarpetta & Tressel, 2002) and (Scarpetta & Tressel, 2004) use even more detailed occupational data available only for some industries and some points in time. Due to these severe data requirements we restrict our analysis to the use of total employment and total hours worked data, readily available.

Education: average years of education, total and by schooling level, from (Barro & Lee, 2001) and (De la Fuente & Doménech, 2002). The data are available at five-yearly intervals so we use linear interpolation to compute annual values. We also interpolated the missing values using WINRATS 6.0 DISTRIB non-linear interpolation procedure that changes the frequency of the original series into a higher one assuming that the series follows a random walk. The results are robust to the use of this alternative interpolation procedure.

R&D: ratio of Business Enterprise Research and Development (BERD) expenditure to value-added. The data was taken from the ANBERD OECD Database, 2002 Edition, for the 1980-1986 period and from the ANBERD OECD Database, 2003 Edition, for the 1987-2000 period. The 2002 edition covers 15 countries from 1973 to 1998 classifying industries according to ISIC, Revision 2. The 2003 edition covers 19 countries from 1987 to 2000 classifying industries according to ISIC, Revision 3. R&D intensity (R&D) in industry i of country c is defined as business R&D expenditures as a percentage of value added:

$$R\,\&\,D_{cit} = \frac{BERD_{cit}}{VALU_{cit}} \text{x}100 \tag{4.8}$$

where BERD is business R&D expenditures in industry i of country c and VALU is value added in industry i of country c.

International trade: ratio of imports from the OECD to gross output.

$$IMPS_{cit} = \frac{TIMPS_{cit}}{PROD_{cit}} x100 \qquad (4.9)$$

where TIMPS is total imports from the OECD of industry i of country c and PROD is gross output in industry i of country c. The data was taken from the OECD Bilateral Trade Database (BTD). The 2000 Edition includes data from 1980 to 1998 and is based on ISIC Revision 2, while the 2002 Edition includes data from 1988 to 2002 and is based on ISIC Revision 3.

4.6.2. Data Coverage

	Code	ISIC correspondence	
		ISIC Rev. 2	ISIC Rev. 3
Low Technology (LT)			
Food products, beverages and tobacco	FOOD	31	15+16
Textiles, textile products, leather and footwear	TEX	32	17-19
Wood and products of wood and cork	WOOD	33	20+361
Pulp, paper, paper products, printing and publishing	PAP	34	21+22
Coke, refined petroleum products and nuclear fuel	PETRO	353+354	23
Rubber and plastic products	RUB	355+356	25
Other non-metallic mineral products	ONMP	36	26
Basic Metals	BMI	37	27
Fabricated metal products, except machinery and equipment	FMP	381	28
Manufacturing n.e.c.	OMAN	39	369
High Technology (HT)			
Chemicals and chemical products	CHE	351+352	24
Machinery and equipment n.e.c. and Office, accounting and computing machinery	MAI	382	29+30
Electrical machinery and apparatus and Radio, television and communication equipment	MEL	383	31+32
Transport equipment	MTR	384	34-35
Medical, precision and optical instruments	MED	385	33

Table 4.12. Industry coverage, 15 OECD manufacturing industries

	ISIC Rev. 2	ISIC Rev. 3	R&D intensity 1991-1997 average (%)
High-technology industries			
Aircraft and spacecraft	3845	353	14.2
Pharmaceuticals	3522	2423	10.8
Office, accounting and computing machinery	3825	30	9.3
Radio, television and communication equipment	3832	32	8.0
Medical, precision and optical instruments	385	33	7.3
Medium-high-technology industries			
Electrical machinery and apparatus, n.e.c.	383*less*3832	31	3.9
Motor vehicles, trailers and semi-trailers	3843	34	3.5
Chemicals excluding pharmaceuticals	351+352*less*3522	24 excl. 2423	3.1
Railroad equipment and transport equipment, n.e.c.	3842+3844+3849	352 + 359	2.4
Machinery and equipment, n.e.c.	382*less*3825	29	1.9
Medium-low-technology industries			
Coke, refined petroleum products and nuclear fuel	353+354	23	1.0
Rubber and plastic products	355+356	25	0.9
Other non-metallic mineral products	36	26	0.9
Building and repairing of ships and boats	3841	351	0.9
Basic metals	37	27	0.8
Fabricated metal products, except machinery and equipment	381	28	0.6
Low-technology industries			
Manufacturing, n.e.c.	39	36-37	0.4
Wood, pulp, paper, paper products, printing and publishing	33+34	20-22	0.3
Food products, beverages and tobacco	31	15-16	0.3
Textiles, textile products, leather and footwear	32	17-19	0.3

Source: OECD Science, Technology and Industry Scoreboard 2001, Towards a knowledge-based economy, Annex I.

Table 4.13. OECD Classification of manufacturing industries based on technology

4.6.3. Panel unit root tests for the OECD industry-level data

The first panel unit root test we perform is that proposed by (Levin, Lin, & Chu, 2002) (henceforth LL). The LL test is basically an augmented Dickey-Fuller (ADF) test for pooled time series that assumes, in its most general form, that the series y_{it} is generated by the model:

$$\Delta y_{it} = \gamma_i + \alpha_i t + \theta_t + \delta_i y_{i,t-1} + \sum_{L=1}^{P_i} \theta_{iL} \Delta y_{it-L} + \varepsilon_{it} \qquad (4.10)$$

thus allowing for individual-specific intercepts (γ_i) and time trends ($\alpha_i t$) where ε_{it}~IID($0,\sigma^2$). LL test the null hypothesis of non-stationarity H0: $\delta_i=\delta=0$, $\forall$ i against the alternative H1: $\delta_i=\delta<0$, $\forall$ i, i.e. they impose homogeneity of the dynamics across individuals. To test for the presence of a unit root they derive, in three steps, the t-statistic associated with the pooled panel estimator of the autoregressive coefficient (δ) and the corresponding asymptotic distribution, that they show follows a limiting standard normal distribution after allowing for mean and variance adjustments (see (Levin, Lin, & Chu, 2002) for details).

(Im, Pesaran, & Shin, 2003) (henceforth IPS) relax LL's assumption of a common autoregressive coefficient testing H0: $\delta_i=\delta=0$, $\forall$ i against the alternative H1: $\delta_i<0$ for $i=1,2,\ldots,N_1$ and $\delta_i=0$ for $i=N_1+1,\ldots,N$. Instead of pooling the data, the IPS panel unit root test is based on the individual t-statistics, i.e. they perform ADF tests on each individual and then compute a group-mean t-statistic based on the ADF statistics averaged across groups and show that it also has a limiting standard normal distribution after adjustments for mean and variance.

Table 4.14 presents the results of the panel unit root tests for the cross country-industry-level series. As we can see the null hypothesis of non-stationarity for the whole panel can be rejected applying either the LL or the IPS tests for all series except the ones involving R&D when using the LL test. Since (Im, Pesaran, & Shin, 2003) show that their test generally performs better than the LL test in the Monte Carlo simulations that they carry out it is not problematic that the LL test does not allows us to reject the null hypothesis of non-stationarity for the R&D series.

Variables	LL	IPS
ΔlogTFP	**-26.32**	**-32.53**
ΔlogTFP$_L$	**-29.07**	**-35.41**
RTFP	**-5.01**	**-8.86**
TYR	**-5.81**	**-13.41**
SYR	**-6.44**	**-15.02**
SHYR	**-5.87**	**-14.07**
HYR	**-10.19**	**-15.57**
TYRxRTFP	**-4.86**	**-8.62**
SYRxRTFP	**-4.91**	**-8.66**
SHYRxRTFP	**-5.01**	**-8.78**
HYRxRTFP	**-5.34**	**-8.87**
R&D	-0.1	**-3.95**
R&DxTYR	-0.60	**-4.26**
R&DxSYR	**-1.52**	**-4.68**
R&DxSHYR	**-1.44**	**-4.59**
R&DxHYR	-0.15	**-3.54**
IMPS	**-2.28**	**-4.02**
IMPSxTYR	**-2.37**	**-4.24**
IMPSxSYR	**-2.69**	**-4.53**
IMPSxSHYR	**-2.48**	**-4.41**
IMPSxHYR	**-4.10**	**6.87**

Notes: The model under consideration is defined as: $\Delta y_{i,t} = \alpha_{0,i} + \alpha_1 t + \delta_i y_{i,t-1} + \sum_{L=1}^{P_i} \theta_{iL} \Delta y_{i,t-L} + \varepsilon_{i,t}$. Coefficients in bold are significant at least at the 10% significance level. The tests were performed with WINRATS 6.0 using the procedure PANCOINT.SRC written by Peter Pedroni. The statistics are distributed standard normal under the null hypothesis of non-stationarity. The test results are based on the data for the 15 industries of the 11 OECD countries ranging from 1981 to 2000.

Table 4.14. Panel Unit Root tests results for the OECD data at the industry-level

These results lend support to the results from the main text since all the variables are stationary so we avoid the problem of spurious relations and can apply the standard econometric procedures for stationary panels.

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Chapter 5
Levels of education, technology and growth: An industry-level analysis of the Portuguese manufacturing sector

5.1. Introduction

This chapter analyses the importance of education for productivity growth in the Portuguese economy at the sectoral level focusing on fourteen manufacturing industries[86] during the period 1986–1997. The contribution of education for technological change and economic growth at the aggregate country level for Portugal has been addressed in a small set of papers but there is no work, to our knowledge, that studies the issue from this more disaggregate industry level perspective. This is in our opinion an important shortcoming since the manufacturing sector has been responsible for most of aggregate growth in developed countries (see e.g. (Scarpetta, Bassanini, Pilat, & Schreyer, 2000)), Portugal included (see e.g. (Aguiar & Martins, 2005)).

We want specifically to investigate if disparities in productivity growth rates across Portuguese manufacturing industries are related to workers' education levels, the main focus of this thesis, and international trade, an unquestionable source of growth of the Portuguese economy (see e.g., (Silva Lopes, 1996), (Neves, 1994), (Afonso & Aguiar, 2005)), particularly in what concerns industries with different technological characteristics since traditional industries represent the biggest share of the Portuguese manufacturing sector. In order to do this, we continue to use endogenous growth theory predictions on the relationship between human capital, technological change, and growth and a modified and augmented version of the (Benhabib & Spiegel, 1994) empirical growth specification. Particularly, we want to estimate the effects of the two separate influences of education on Portuguese manufacturing industry's productivity performance – domestic innovation and technological diffusion (relative to the United States, the frontier country) – emphasizing the interactions with the other technological change determinant, international trade, and identify potential distinct roles for each educational sub-category.

The low educational levels of the Portuguese workforce can constitute impediments to higher rates of productivity growth if a skilled workforce contributes to higher productivity growth through its influence on the domestic

[86] Due to lack of data we do not include Coke, refined petroleum products and nuclear fuel industries in the analysis, as we did in the previous chapter.

rate of innovation and to the exhaustion of catch up gains from imitation. Since, as we show below, the levels of TFP in Portugal lie well below the US levels in all manufacturing industries throughout the sample period, none of the Portuguese manufacturing industries has exhausted the catch up gains from imitation and one of the main reasons for this situation can be the low education levels of its workforce. For instance, (Lança, 2000) based on a survey that included 1157 firms of the Portuguese manufacturing industry during 1996 and 1997, concludes that the educational attainment of the workforce constitutes the major comparative disadvantage of the manufacturing sector with 65% of the firms employing workers with at most primary education and about half with no employee with tertiary education.

The analysis of the Portuguese situation has also some important advantages as far as the empirical analysis is concerned. By focusing on a single country it is possible to overcome the issue of cross-country comparability of the education data used. On the other hand, Portugal has experienced rapid growth in the educational attainment of its population. This high variability over time of the Portuguese education data makes the econometric analysis more efficient. Dealing with only one country also makes the task of constructing an industry-specific education measure more manageable and less subject to the strong restrictions implied by limited data availability across countries.

Empirical evidence for the Portuguese manufacturing industries favours the hypothesis that education at the secondary level is crucial to exploit the productivity growth benefits from embodied technology diffusion in all industries. Disaggregating the sample in low technology and high technology industries reveals that this is the only influence that is common to both industry groups. Common to both industry groups is also the fact that the empirical evidence does not support a direct influence for education nor relative TFP indicating that technological catch up is not an automatically guaranteed process. Additionally, the results concerning the influence of TFP growth of the leader for the whole sample are driven by low technology industries.

The remainder of this chapter is structured as follows. The following section briefly describes the patterns of growth of the Portuguese manufacturing sector during the second half of the twentieth century. A brief overview of the existing evidence on the importance of education for Portugal's economic growth during the post-war period may be found in Section 3. Section 4 describes the empirical specification and provides an overview of the data used. The results from the empirical analysis are presented in Section 5. Finally, conclusions may be found in Section 6.

5.2. Patterns of growth in the Portuguese manufacturing sector

According to (Scarpetta, Bassanini, Pilat, & Schreyer, 2000), in 1950 aggregate GDP per man-hour in Portugal was only 20 per cent of that of the United States, the second lowest value in the European Union (EU) only surpassed by Greece with a GDP per man-hour at 19 percent of the US value, the country at the top of the OECD income distribution. By 1973, Portugal had considerably improved its situation with GDP per man-hour at 42 per cent of the US value and this improvement continued until 1998 (with GDP per man-hour at 50 per cent of the US value) although at a much slower rate in the 1980s and the 1990s. Over the last two decades of the twentieth century, GDP per man-hour grew around 2.2% annually in both decades, higher than the average OECD value. Multi-factor productivity also grew at an average annual rate of 1.9% and 2.2%, respectively.

At the manufacturing sector level however the performance of the Portuguese economy was not so impressive. In 1950, GDP per person employed represented only 10.2% of the US level, by 1970 it had more than doubled its value reaching 21.1%, in 1980 it represented 26.3% of the US level, but it fell to 24.8% in 1990 and to 23.2% in 1995. Although most European countries showed the same tendency to stop converging to the US standards at the manufacturing sector level in the 1990's, Portugal's situation raises more concerns since it is still far behind and at the bottom rank of OECD productivity levels. In fact, in 1995 productivity in Portugal relative to the USA was lower than that of Mexico (25.6%) and Korea (43.3%) with this last country maintaining its tendency to converge to the US levels. The same conclusion is reached by (Lança, 2001) according to whom the performance of the Portuguese manufacturing sector productivity relative to the USA is especially poor from 1973 until 1992, especially when compared to that of Spain.

(Aguiar & Martins, 2005) analyse the growth cycles of the Portuguese industry[87] productivity, measured as value added per worker, during the twentieth century identifying industry productivity as the main factor behind the increase in Portuguese income per capita during this period[88]. According to the authors, the recent growth experience of the Portuguese industry can be divided into three broad episodes that cover the periods 1951-1973, 1974-1984, and 1985-2000. These fluctuations were a major determinant of the catch up (or lack of) of Portuguese income levels towards the developed countries levels and is thus of major importance to study its causes, especially since, as (Aguiar & Martins, 2005) point out, the performance of the Portuguese industry was rather disappointing when compared to the performance of the other EU member states.

During the first period, 1951-1973, that coincides with the "golden years" of the World economy, the Portuguese industry maintained reasonable growth rates, it grew on average 5.4%, a performance similar to that of European countries like the UK, Sweden or Ireland, but worst than that of Germany, Greece, or Spain. This positive performance was rooted not only on the favourable international context but also on new industrial policies that favoured investment and mostly on the opening up of the Portuguese economy by joining the EFTA (as a founding member), the OECD, the IMF, the World Bank and the GATT.

[87] Defined as including Manufacturing, Mining and Quarrying, Electricity, Gas and Water, and Construction.

[88] According to the authors, industrial productivity growth was the major contributor (50.16%, 1910-1995) to aggregate productivity growth during the twentieth century.

The manufacturing sector was responsible for more than 80% of industry productivity growth during this period, which the authors attribute to the fact that it incorporates the production of tradable goods and this was the period when Portugal opened up its economy having access to larger markets and becoming exposed to increased international competition. Within this sector the industries traditionally more important in the Portuguese economy, Textiles, Wood, and Food industries, lost ground to more modern industries, especially Fabricated Metal Products, and Machinery and Equipment industries, responsible for 30% of the manufacturing sector productivity growth.

The second period that lasts from 1974 until 1984 and starts shortly after the international oil crisis and coincides with the political turmoil in the Portuguese society when democracy was restored, is characterized by negative industry productivity growth (-1% on average). In fact, Portugal was the only EU member state that registered a negative average industry productivity growth rate. The performance of the manufacturing sector however continued to be positive although now the major contributors were the more traditional sub-sectors of Food, Beverages and Tobacco and Textiles, due to the depreciation of the Portuguese Escudo (PTE), while Fabricated Metal Products, and Machinery and Equipment industries registered negative growth due to the high share of intermediate goods used in the production and its high capital-output ratio.

A third episode of growth begins approximately in 1985 and lasts until the end of the twentieth century, when Portuguese industrial productivity growth recovered and was higher than in most other European countries (with the exception of Austria, Sweden, Norway, and Ireland). The recovery in the last fifteen years of the twentieth century was due to the achieved political, social and economic stability, joining the EEC in 1986 and the Common Market in 1992, and occurred despite the 1993 international recession and the desinflationary policy based on the appreciation of the PTE followed during the period.

As far as the manufacturing sector is concerned it registered a positive average growth rate of 4.1% but, contrary to what happened in the previous period, Textiles and Wood industries registered a very poor performance (negative productivity growth from 1993 onwards) not being able to face the international competition from developing countries. Food and Paper industries were able to restructure and adapt to new markets, especially the first one, and thus maintained its productivity growth. But the recovery was due mainly to the performance of Chemicals and Petroleum, Non-Metallic Mineral Products, Basic Metals, and Fabricated Metal Products, and Machinery and Equipment industries, which leads the authors to conclude with a positive note on the ability of the Portuguese manufacturing sector to adapt to the increased international competition by reallocating resources to more modern industries. Since this period was also characterized by the loss of the importance of the Industry sector relative to the Services sector, further technological restructuring is needed in the Portuguese economy, especially in what concerns the adaptation to Information and Communication Technologies in order to fully exploit the potential productivity growth gains in the Services sector.

Nevertheless, according to (Lança, 2000) and (Lança, 2001) from 1970 until 1994, the Portuguese manufacturing sector was centred on the Textiles industries and, to a less extent, on Wood and Non-metallic Mineral Products industries that use Portugal's natural resources, which reflects major competitive disadvantages, especially the low educational levels of the workforce employed in these industries where more than 90% of the employees have 6 years of education or less.

5.3. Selective review of the empirical literature

To our knowledge, research on the importance of education for Portuguese economic growth is limited to a small set of papers that focus on the aggregate country-level analysis. In this section we briefly review this aggregate evidence for comparison purposes with our industry-level analysis.

(Nunes, 1993) studies this issue from an economic historian point of view. She uses long time series (1833-1990) to study the correlation between Portuguese GDP per capita and literacy rates in order to test three so called "classical hypotheses": a) the existence of a literacy threshold as a necessary condition for sustained economic growth; b) the appropriate time lag for GDP per capita in order to exist a significant statistical correlation with education; and c) the appropriate time lag for education in order to exist a significant statistical correlation with GDP per capita[89]. Using time-series analysis, the author concludes that education has the strongest positive impact on economic growth after a time lag of 25-35 years while GDP per capita has the strongest positive association with literacy rates after 70 years, which seems to indicate that education has a stronger impact on GDP per capita rather than the opposite. Using these conclusions she then performs a cross-section regional analysis using data on twenty Portuguese regions to check if the results corroborate the ones from the time series analysis, which is indeed the case.

(Neves, 1994), chapter 2, and (Neves, 1996) also takes a long time series perspective (1890-1991) to determine, through a descriptive analysis, the importance of education for Portuguese economic growth. Based on data on adult illiteracy rates and the percentage of total population in primary and higher education he concludes for the existence of a strong long-term correlation between economic growth and human capital widening. The author warns however for the still very low educational achievement of the Portuguese population despite its rapid improvement.

(Domingos, 1997) carries out an analysis similar to that of (Nunes, 1993) but focusing on the post-war period (1940-1993) with a remarkable effort to collect data on the number of people that concluded six different education levels: basic, first cycle; basic, second cycle; lower secondary; upper secondary; higher education, short courses; and higher education, first and second cycle. She then

[89] "We tried to find out after what time-lag changes in literacy levels had a (more) significant impact over per capita GDP and, reciprocally, after what time-lag have changes in income levels had a larger effect on basic education in Portugal."p.184, (Nunes, 1993).

regresses GDP per capita on the percentage of the population that concluded each of these levels (and additionally on the literacy rate) and vice versa, considering different time lags for the influences, ranging from five to thirty years.

Based on the relationship between the correlation coefficients and the time lag considered the author concludes that: literacy rates have the strongest positive impact on GDP per capita with a time lag of twenty years, which can be explained by the full participation of the respective population in the labour market; basic, first cycle education has an almost immediate impact on GDP per capita that is probably due to the immediate participation of people with this degree in the labour market in the Portuguese economy; basic, second cycle, lower secondary, and upper secondary education show a different pattern since GDP per capita presents a greater impact on these variables than the opposite, which can be explained by the fact that still very few people attended these education levels during the period covered by the analysis; the impact of higher education, short courses over GDP per capita is greater than the opposite influence and is almost immediate; finally, GDP per capita has a stronger influence on higher education than vice versa since the attendance of this schooling level during the period was not free. Although the empirical analysis carried out in this study is quite simple it is still very interesting since it tries to disentangle the contribution of different schooling levels for Portuguese economic growth, an objective similar to our own.

Other studies use more sophisticated time series econometric techniques to quantify the causal impact of education on Portuguese economic growth. (Teixeira, 1999) and (Teixeira & Fortuna, 2004) use Johansen's cointegration methodology to determine whether there is a long run relationship between the level of TFP, human capital and the stock of knowledge for the Portuguese economy, based on the predictions of endogenous growth models. We focus on the results from (Teixeira & Fortuna, 2004), an update of the previous study for the period 1960-2001, where human capital is proxied by average years of schooling constructed by (Teixeira, 1998) and the internal stock of knowledge is proxied by the accumulated R&D expenditures constructed by (Teixeira, 1999). The authors confirm the positive influence of both human capital and the knowledge stock on the level of TFP, and additionally that human capital has not only a direct positive influence but also an indirect one through the enhancement of the innovations resulting from the internal knowledge stock, concluding that human capital has had a greater impact on TFP than the internal stock of knowledge. The result concerning the importance of human capital for the absorption of domestic R&D efforts is especially interesting.

Pina and St. Aubyn's (2002) objective is to quantify the contribution of public and human capital to Portuguese growth over the period 1977-2001 in order to derive some implications as to the long run effects of the funds transferred from the EU, responsible for the financing of an important share of public and human capital formation in Portugal. Using Engle and Granger's cointegration methodology they regress output on private capital, public capital, human capital, and labour for the whole economy and for the tradable goods sector[90] alone. They find that the series are indeed cointegrated and that output has a human capital elasticity higher than private and public capital elasticities, with no significant differences in the tradable goods sector or when training is considered besides formal education as a proxy for human capital.

(Pina & St Aubyn, 2005) is an extension of their previous study aiming at computing the rate of return to investments in public and human capital using a cointegrated VAR model to estimate the elasticities of output to these two inputs. They compute an implied rate of return to human capital which is close to the rate of return to private capital and lower than the return to public capital. The authors also compute what they call the dynamic feedbacks rates of return by considering the impulse response functions of shocks to public and human capital. In this case, the return to human capital falls because it crowds out private physical capital investment. (Pina & St Aubyn, 2005) warn however that these weak results may be due to the fact that the quality of education is more important for growth than the quantity of education[91] or due to the fact that different schooling levels have different impacts on GDP.

(João Pereira, 2003) and (João Pereira, 2005) constructs his own proxies of human capital for the Portuguese economy and uses them to determine whether there is a long run relationship between output and human capital based on the Engle and Granger cointegration methodology. These proxies are average years of schooling of the population aged between 15 and 64 years of age and an income based measure. Only in the first case does the evidence support the existence of a long run relationship.

(João Pereira & St Aubyn, 2009) use this same data on average years of schooling and the basic information contained in Pereira (2003) on the number of people that concluded different schooling levels to determine whether different schooling levels have different long run impacts on the level of GDP per worker. Using the cointegrated VAR methodology and impulse response functions of GDP per worker and physical capital investment to shocks in the different human capital variables they conclude that one additional year of schooling increases Portuguese GDP per worker by 36.3% in the long run. Primary and secondary education have a positive and significant impact on growth but the same does not apply to tertiary education, which can be explained by the very recent increases in this education level in the Portuguese economy. Additionally, there is no evidence of a differentiated growth impact between primary and secondary education. This is an interesting study from our point of view since it analyses the growth impact of different schooling levels.

The evidence from the papers reviewed in this section confirms the importance of education for economic growth in Portugal at the aggregate country level. Two of the papers ((Domingos, 1997) and (João Pereira & St Aubyn, 2009)) also try to differentiate the impact of different schooling levels but they are not very conclusive. We aim at contributing to this literature in two

[90] Defined as manufacturing plus air and water transports.

[91] Portugal performs pretty badly in the student international assessment tests.

ways: by focusing on a more disaggregate level of analysis, the industry level, and investigating in further detail the contribution of different schooling levels.

5.4. Empirical specification and data overview

We start by presenting the empirical specification used in this chapter to assess the importance of education for productivity growth in the Portuguese manufacturing sector, that differs from the ones used in the previous chapters in the control variables included due to data availability. Afterwards we highlight some features of the data used to test the empirical specification.

5.4.1. Empirical specification

The productivity growth regression that we estimate is similar to the one presented in chapter 2 but due to limited data availability it was not possible to consider neither the influence of domestic R&D efforts nor FDI. The only additional technological change determinant that we take into account is thus international trade.

Portugal carries out very little own R&D. According to the OECD Main Science and Technology Indicators, in 1997 Portugal's R&D expenditures represented only 0.62% of its GDP, less than a third of the OECD average at 2.15% and less than half of the European Union average (1.8%). In the EU only Greece spent a lower proportion of its GDP in R&D, 0.51%. Additionally, this low amount is quite differently distributed across performance sectors and is especially low at the business sector industry level. Business sector R&D expenditures represented less than a fourth of total R&D expenditures (22.5%) when the OECD average is 68.9% (see also (Lança, 2001)). Since we have no industry level data on R&D expenditures for the Portuguese manufacturing industries we have to ignore the role of domestic R&D expenditures as a determinant of productivity growth. This does not however seem like a gross simplification since the amounts spent are very small.

International trade on the other hand has been identified as a major source of growth of the Portuguese economy at the aggregate level (see e.g. (Afonso & Aguiar, 2005)), so an industry level analysis should include its influence as a vehicle of technology transfers considering also that a more highly educated workforce is more likely to use technology incorporated in imports more effectively. We thus evaluate the contribution of this channel of technology diffusion and its interaction with education for TFP growth.

The econometric specification for the growth rate of productivity that we estimate in the empirical analysis is thus given by:

$$\Delta \log A_{it} = \beta_i + \beta_t + \lambda \Delta \log A_{it}^{USA} + \theta \log\left(\frac{A_{it-1}^{USA}}{A_{it-1}}\right) + gH_{it-1} + mH_{it-1} \log\left(\frac{A_{it-1}^{USA}}{A_{it-1}}\right) + \quad (5.1)$$
$$+ \delta_1 IMPS_{it-1} + \delta_2 (IMPSxH)_{it-1} + \mu_{it}$$

According to equation (5.1), the growth rate of productivity ($\Delta\log A_{it}$)) in each Portuguese manufacturing industry i at time t is determined by: **i)** an industry-specific effect that captures idiosyncratic shocks to productivity growth, β_i; **ii)** a time-specific effect that captures year-specific shocks common to all industries, β_t; **iii)** the contemporaneous rate of TFP growth in its US counterpart, $\Delta\log A^{USA}_{it}$, a specification consistent with an ADL(1,1) and a long-run cointegration relationship between the level of productivity in frontier (US) and non-frontier industries (Portuguese); **iv)** catch up with the level of productivity in its US counterpart proxied by $\log(A^{USA}_{it-1}/A_{it-1})$; **v)** domestic innovation influenced by the level of education of the workforce, H_{it-1}; **vi)** the influence of education over the capacity to absorb ideas developed abroad, $H_{it-1}\log(A^{USA}_{it-1}/A_{it-1})$; **vii)** exploring ideas induced by international trade ($IMPS_{it-1}$), **viii)** whose impact may also be determined by human capital availability, $H_{it-1}IMPS_{it-1}$; and **ix)** a serially uncorrelated error term, μ_{it}.

5.4.2. Overview of data

The focus of this work is on the manufacturing sector of the Portuguese economy. Data availability across the different data sets used resulted in a sample of fourteen manufacturing industries[92] for the period 1986-1997, classified according to the OECD classification scheme based on R&D intensities into low technology and high technology industries. In this section we highlight some features of the data. In the appendix we provide details about data sources and computation.

5.4.2.1. TFP growth and levels

As in the previous chapters, the level of TFP is measured as a superlative index number derived from a constant returns to scale translog production function[93] so that the level of TFP in Portugal's industry i relative to the level of TFP in USA's industry i at any point in time t (RTFP) is given by:

$$RTFP_{it} = \log\left(\frac{Y_{USAit}}{Y_{PRTit}}\right) - (1 - \frac{\alpha_{USAit} + \alpha_{PRTit}}{2})\log\left(\frac{K_{USAit}}{K_{PRTit}}\right) - \frac{\alpha_{USAit} + \alpha_{PRTit}}{2}\log\left(\frac{L_{USAit}}{L_{PRTit}}\right) \quad (5.2)$$

[92] The fourteen manufacturing industries are: FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork; PAP - Pulp, paper, paper products, printing and publishing; RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment; OMAN - Manufacturing n.e.c.; CHE - Chemicals and chemical products; MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment; MED - Medical, precision and optical instruments. The first nine industries form the low technology cluster and the remaining five the high technology cluster. This classification is based on the R&D intensities of thirteen OECD manufacturing industries for the period 1991-1997. See (OECD, 2001b), Annex I.

[93] See chapter 2 for further details. Using a Cobb-Douglas specification does not significantly alter the results.

where Y is real value added, K is the real physical capital stock, L is a measure of the labour input, and α is the labour income share, all relative to industry i at time t. The first term on the right-hand side of equation (5.2) is the log difference in the industry value-added levels of the two countries. The other two terms adjust the relative value-added levels for differences in relative input levels. For instance, relative efficiency is equal to one (i.e. $TFP_{USA}/TFP_{PRT}=1$) if industry i in the USA produces twice as much output from twice as many inputs as industry i in Portugal, and is equal to two if industry i in the USA produces twice as much output with only the same level of inputs.

The growth rate of TFP, ΔlogTFP, equals the rate of growth of industry value-added, ΔlogY, minus the rate of growth of the industry inputs, assuming that industry value-added is produced using physical capital, K, and labour, L, weighted by the respective income shares (where α is the labour input income share).

Industry level data for the Portuguese manufacturing industry has been originally put together by (Alessandro Nicita & Olarreaga, 2001) [94] using the Industrial Statistics of the United Nations Industrial Development Organization (UNIDO)[95]. Data to compute TFP growth and levels for the USA, the frontier country, comes also from (Alessandro Nicita & Olarreaga, 2001), for comparison purposes.

Variables Y and K are real variables and have to be expressed in a common currency unit. In this work they are expressed in constant 1995 USD[96]. Labour input is measured as total annual hours worked from (M. O'Mahony & B. van Ark, 2003). Finally, since the share of labour in value added is quite volatile, which is suggestive of measurement error, we use estimated values (obtained from regressing the labour share on the capital-labour ratio and industry fixed-effects) in order to obtain smoother, less volatile values[97].

Table 5.1 reports time-averaged TFP growth during 1986–1997 in Portugal and the USA. All industries registered a positive TFP growth rate in Portugal during this period. In the USA, FOOD, WOOD, and PAP industries registered negative rates of TFP growth. The remaining industries registered positive rates of TFP growth in both countries. OMAN, followed by ONMP and RUB were the industries with higher productivity growth rates in Portugal. In the USA, it was BMI, CHE and MEL that grew the most. In any case, business cycles seem to be synchronized in most industries (eleven out of fourteen) of the two countries. On average, in the USA high-tech industries registered higher growth rates. The same applies to Portugal if we exclude OMAN. All industries registered higher

[94] See also (Nicita & Olarreaga, 2007) for the most recent update to this database.

[95] Contrary to what we did in the previous chapter we do not use data from the OECD, STAN, 2004 edition database for Portugal since it has more limited data availability.

[96] See the appendix for further details on the construction of these variables. Conceptually, the appropriate rate of exchange to convert the variables into a common currency unit is an industry-specific purchasing power parity (PPP) (see (Sorensen, 2001) for biases concerning cross-country comparability of TFP levels). Data restrictions did not allow us to use this ideal methodology.

[97] See (Harrigan, 1997) and (Harrigan, 1999).

growth rates in Portugal than in the USA, a behaviour consistent with technological catch up.

	Portugal	USA
Low technology		
FOOD	2.63	-0.19
TEX	5.67	3.16
WOOD	4.33	-0.21
PAP	2.33	-0.55
RUB	7.46	3.95
ONMP	7.97	3.33
BMI	6.46	4.72
FMP	7.11	1.39
OMAN	18.57	1.81
Mean	*6.95 (5.50[a])*	*1.93*
St. Deviation	*4.81 (2.18[a])*	*1.96*
High technology		
CHE	4.44	2.87
MAI	7.33	4.46
MEL	7.09	3.98
MTR	6.91	0.47
MED	5.66	2.61
Mean	*6.29*	*2.88*
St. Deviation	*1.22*	*1.55*

Notes: FOOD - Food products, beverages and tobacco;
TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork;
PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products; .
PETRO - Coke, refined petroleum products and nuclear fuel; RUB - Rubber and plastic products;
ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment;
MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery;
MEL - Electrical machinery and apparatus and Radio, television and communication equipment;
MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c.
[a] Excluding OMAN.

Table 5.1. Average TFP growth 1986-1997 (%), Portuguese manufacturing industries

Table 5.2 reports the level of TFP in Portugal relative to the USA (TFP_{PRT} /TFP_{USA}) at the beginning and end year of the sample period. As is clear from Table 5.2, all Portuguese industries were considerably less productive than the corresponding US industries at the beginning and end of the period. OMAN was by far the less productive, followed by MED and MEL. The most productive industry relative to the USA in 1985 was PAP followed by BMI and RUB. In 1997 it was FMP followed by PAP and WOOD. The period as a whole was characterized by convergence of Portugal's TFP towards US levels since in all manufacturing industries relative levels of TFP were higher in 1997 than in 1985.

	1985	1997
Low technology		
FOOD	15.46	26.24
TEX	14.25	24.02
WOOD	16.02	40.04
PAP	21.96	42.60
RUB	19.19	32.77
ONMP	18.01	39.88
BMI	20.92	30.86
FMP	17.30	50.61
OMAN	1.80	13.52
Mean	*16.10*	*33.39*
St. Deviation	*5.92*	*11.23*
High technology		
CHE	17.55	27.59
MAI	15.87	32.72
MEL	13.25	22.19
MTR	11.52	29.02
MED	9.50	20.61
Mean	*13.54*	*26.43*
St. Deviation	*3.24*	*4.99*

Notes: The relative level of TFP is measured by taking exponents of the *RTFP* computed as described in the text and then computing its inverse. A value equal to 100% corresponds to the same level of efficiency in the respective industry of Portugal and the USA. Values lower than 100% mean that the Portuguese industry is less efficient than the corresponding US industry. FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products; PETRO - Coke, refined petroleum products and nuclear fuel; RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment; MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery; MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c.

Table 5.2. Relative levels of TFP (TFP_{PRT}/TFP_{USA}), %

5.4.2.2. Education

Since we have industry-specific education data available for the Portuguese manufacturing industry we use this data to construct a human capital industry-specific proxy to test the productivity growth specification. In the appendix we provide details on the economy-wide variables and the results for the sensitivity analysis using an economy-wide proxy.

The industry-specific human capital proxy refers to average years of education, total and by schooling level, of the workforce employed in each industry i at time t. We compute these series using data on the number of workers with a given schooling level employed in each industry-year from the Quadros de Pessoal database from the Portuguese government department Ministério da Segurança Social e do Trabalho for the period 1985-1997. This database is the result of an annual compulsory survey conducted by the Ministério da Segurança Social e do Trabalho where firms are required to provide information about their workers on items such as monthly compensation, highest schooling level attained, age, tenure and monthly hours worked.

We use the data on the number of workers of industry i for which schooling level s is the highest level attained to compute average years of schooling, total, primary, secondary, and tertiary, of the workforce employed in each industry i at time t. For the years 1985 to 1993 the schooling levels are classified according to fourteen education categories (see Table 5.3). For the years 1994 to 1997 the schooling levels are classified according to nine education categories (see Table 5.4).

Level (s)	Definition	Assumed cumulated duration in years (Dur_s)
0	Illiterate (não sabe ler nem escrever)	0
1	Can read and right (sabe ler e escrever)	1
2	Basic 1st cycle (ensino básico primário)	4
3	Basic 2nd cycle (ensino básico preparatório)	6
4	Lower secondary (Curso geral dos liceus)	9
5	Upper secondary (Curso complementar dos liceus)	12
6	Commercial vocational training (Ensino Técnico Comercial)	12
7	Industrial vocational training (Ensino Técnico Industrial)	12
8	Agriculture vocational training (Ensino Técnico Agrícola)	12
9	Other secondary schooling (Outros ensinos secundários)	12
10	Higher education, short courses (Ensino médio)	14
11	Higher education, 1st cycle (Bacharelato)	17
12	Higher education, 2nd cycle (Licenciatura)	17
13	Others (Outras)	---------
14	Ignored (Ignorado)	---------

Table 5.3. Schooling levels classification of Quadros de Pessoal database for the 1985-1993 period

Level (s)	Definition	Assumed cumulated duration in years (Dur_s)
1	Less than basic (< ensino básico)	1
2	Basic 1st cycle (1º ciclo)	4
3	Basic 2nd cycle (2º ciclo)	6
4	Lower secondary (3º ciclo)	9
5	Upper secondary (ensino secundário)	12
6	Vocational training (cursos das escolas profissionais)	12
7	Higher education, 1st cycle (Bacharelato)	17
8	Higher education, 2nd cycle (Licenciatura)	17
9	Ignored (Ignorado)	---------

Table 5.4. Schooling levels classification of Quadros de Pessoal database for the 1994-1997 period

Based on the assumed durations for the different schooling levels in (Domingos, 1997), (Teixeira, 2005) and (Pereira, 2003) we assigned a cumulated duration in years, Dur_s, to each schooling level s in order to compute average years of schooling according to the formulas below[98], assuming that all workers completed the respective highest schooling level attained:

$$TYRind_{it} = \sum_{s=1}^{12} Dur\_s x \frac{L_{sit}}{L_{it}} \tag{5.3}$$

$$PYRind_{it} = Dur\_1x \frac{L_{1it}}{L_{it}} + \sum_{s=2}^{12} Dur\_2x \frac{L_{sit}}{L_{it}} \tag{5.4}$$

$$\begin{aligned} SYRind_{it} = {} & (Dur\_3 - Dur\_2)x \frac{L_{3it}}{L_{it}} + (Dur\_4 - Dur\_2)x \frac{L_{4it}}{L_{it}} + \\ & + (Dur\_5 - Dur\_2)x \sum_{s=5}^{12} \frac{L_{sit}}{L_{it}} \end{aligned} \tag{5.5}$$

$$HYRind_{it} = (Dur\_10 - Dur\_5)x \frac{L_{10it}}{L_{it}} + (Dur\_11 - Dur\_5)x \left(\frac{L_{11it} + L_{12it}}{L_{it}} \right) \tag{5.6}$$

where $TYRind_{it}$ is average years of total schooling, $PYRind_{it}$ is average years of primary schooling, $SYRind_{it}$ is average years of secondary schooling, $HYRind_{it}$ is average years of tertiary schooling all relative to the workforce employed in industry i at time t, L_{sit} is the number of workers with schooling level s in industry i at time t, and L_{it} is the total number of workers in industry i at time t.

Table 5.5 reports some summary data for the different education series in the fourteen manufacturing industries in the period 1985-1997. In every industry except BMI the average educational attainment of the workforce increased during the period. This increase was due mostly to the increase in average years of secondary and tertiary education, with average years of primary education also growing but at a much lower rate. The average educational attainment of the workforce is higher in the high-tech industries but PAP, a low-tech industry, also presents values similar or higher than those of some high-tech industries. Average years of primary education are similar in all industries, while average years of secondary and tertiary education are higher in high-tech industries.

[98] These formulas refer to the 1985-1993 period when workers are classified according to twelve education levels. Similar formulas apply to the 1994-1997 period when only eight schooling levels are considered.

Industries	TYRind Average value	TYRind Total growth (%)	TYRind Av. annual growth (%)	PYRind Average value	PYRind Total growth (%)	PYRind Av. annual growth (%)	SYRind Average value	SYRind Total growth (%)	SYRind Av. annual growth (%)	HYRind Average value	HYRind Total growth (%)	HYRind Av. annual growth (%)
Low technology												
FOOD	5.195	28.47	2.09	3.613	11.35	0.90	1.456	77.17	4.77	0.126	90.77	5.38
TEX	5.023	35.25	2.52	3.709	5.46	0.44	1.275	181.35	8.62	0.039	36.46	2.59
WOOD	4.649	29.48	2.15	3.621	12.32	0.97	0.992	119.43	6.55	0.036	-1.08	-0.09
PAP	6.564	35.92	2.56	3.777	6.69	0.54	2.574	84.63	5.11	0.213	162.65	8.05
RUB	5.676	27.70	2.04	3.682	7.35	0.59	1.850	73.10	4.57	0.144	108.57	6.13
ONMP	5.066	29.73	2.17	3.561	13.32	1.04	1.399	79.47	4.87	0.106	71.28	4.48
BMI	5.888	-0.56	-0.05	3.749	5.43	0.44	1.950	-4.08	-0.35	0.189	-41.43	-4.46
FMP	5.434	20.82	1.58	3.737	5.92	0.48	1.601	61.27	3.98	0.096	43.89	3.03
OMAN	5.298	12.20	0.96	3.721	7.22	0.58	1.518	24.93	1.85	0.059	47.77	3.25
Mean	*5.421*			*3.686*			*1.624*			*0.112*		
St. Dev.	*0.56*			*0.07*			*0.46*			*0.06*		
High technology												
CHE	7.211	25.03	1.86	3.780	4.23	0.35	3.019	48.55	3.30	0.411	87.35	5.23
MAI	6.110	24.48	1.82	3.790	4.36	0.36	2.157	64.50	4.15	0.164	82.97	5.03
MEL	6.949	32.27	2.33	3.809	2.99	0.25	2.838	82.06	4.99	0.302	68.44	4.34
MTR	6.270	41.48	2.89	3.825	6.93	0.56	2.222	117.72	6.48	0.222	100.60	5.80
MED	6.325	29.42	2.15	3.775	1.01	0.08	2.408	81.08	4.95	0.141	133.88	7.08
Mean	*6.226*			*3.769*			*2.255*			*0.202*		
St. Dev.	*0.48*			*0.02*			*0.38*			*0.11*		
TOTAL MAN	5.391	24.64	1.84	3.705	7.66	0.61	1.572	72.79	4.56	0.115	53.58	3.58

Notes: TYRind is average years of total schooling of the workforce employed in industry *i*;
PYRind is average years of primary schooling of the workforce employed in industry *i*;
SYRind is average years of secondary schooling of the workforce employed in industry *i*;
HYRind is average years of tertiary schooling of the workforce employed in industry *i*.
FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear;
WOOD - Wood and products of wood and cork
PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products;
RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products; BMI - Basic Metals Industries;
FMP - Fabricated metal products, except machinery and equipment;
MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery;
MEL - Electrical machinery and apparatus and Radio, television and communication equipment; MTR - Transport equipment;
MED - Medical, precision and optical instruments;OMAN - Manufacturing n.e.c.

Table 5.5. Average years of schooling of the manufacturing industry workforce, Portugal 1985-1997

5.4.2.3. International trade

To study the influence of international trade we use data from the OECD, Bilateral Trade, 2000 edition database ((OECD, 2000)). Our measure of international trade is the ratio of a Portuguese industry's imports from the OECD to gross output. Table 5.6 reports this data for the fourteen manufacturing industries over the period 1980-1997. The import ratios are on average higher for the high-tech industries since these are more capital intensive or use more intermediate goods in their production than the traditional industries.

Low technology	
FOOD	18.05
TEX	23.1
WOOD	6.8
PAP	16.65
OMAN	168.78
RUB	40.58
ONMP	11.29
BMI	100.14
FMP	452.24
Mean	*93.07*
St. Deviation	*144.93*
High technology	
CHE	75.23
MAI	237.96
MEL	82.76
MTR	146.06
MED	400.64
Mean	*188.53*
St. Deviation	*135.33*

Notes: FOOD - Food products, beverages and tobacco;
TEX - Textiles, textile products, leather and footwear; WOOD - Wood and products of wood and cork
PAP - Pulp, paper, paper products, printing and publishing; CHE - Chemicals and chemical products;
RUB - Rubber and plastic products; ONMP - Other non-metallic mineral products;
BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment;
MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery
MEL - Electrical machinery and apparatus and Radio, television and communication equipment;
MTR - Transport equipment; MED - Medical, precision and optical instruments;
OMAN - Manufacturing n.e.c.

Table 5.6. Average ratio of Portuguese industries imports from the OECD to gross output (%), 1985-1997

5.5. Empirical findings

The empirical analysis is conducted in three separate stages. In the first, we estimate equation (5.1) including only education variables as regressors (besides TFP growth of the leader and relative TFP) in order to select the appropriate schooling level that explains productivity growth, through both innovation and imitation activities.

In the second stage and in light of the conclusions concerning the influence of the educational sub-categories, we add international trade to the productivity growth regression so that we can select a final specification with all the relevant technological change determinants.

In the third stage, we repeat the analysis for the two technology groups considered, low technology and high technology industries, in order to identify potential differences concerning the influence of the different technological change determinants according to technological characteristics.

We estimated a fixed effects regression model, so as to capture the industry-specific effects. We added time-dummies to capture time-specific effects and used the Huber-White sandwich estimator of variance to correct for heteroscedasticity. Finally, we use the Diff-GMM estimator to obtain results robust to the possible endogeneity of the regressors.

5.5.1. Results for the fourteen Portuguese manufacturing industries

Table 5.7 presents the estimation results for the whole sample of fourteen manufacturing industries. Columns (1) to (8) give the results regarding the effect of education and its sub-categories on TFP growth where TFP growth depends only on TFP growth of the leader, the USA, $\Delta \log TFP_{USA}$, the technological gap proxied by relative TFP, RTFP, and the education variables under analysis. Our aim is to select the relevant schooling level or educational sub-category, if any, for innovation and imitation activities in the Portuguese manufacturing sector.

Empirical evidence favours the existence of a long run relationship between TFP growth of the Portuguese manufacturing industries and the respective US counterparts since in all specifications the estimated coefficient is positive and statistically significant.

As for the existence of technological catch up, Portuguese manufacturing industries only grow faster the further they are from the leader industry if the interaction term with the education variable is not considered. This seems to indicate that technological catch up is not automatic but requires a sufficient educational level. However, this is not the case since all the education variables interacted with the technological gap revealed not to be statistically significant. These results indicate that education does not facilitate the assimilation of disembodied technology (columns (2), (4), (6) and (8)).

Since the direct influence of any of the education variables is also not statistically significant (columns (1), (3), (5) and (7)) there seems to be no evidence supporting a role for the educational attainment of the workforce in the Portuguese manufacturing sector productivity growth, either through innovation activities or disembodied technology diffusion. It can be the case nevertheless that education matters through embodied technology diffusion so we proceed to the analysis of the influence of international trade (IMPS) on technological change and growth of the Portuguese manufacturing sector, retaining only as statistically significant influences TFP growth of the leader and RTFP.

	1	2	3	4	5	6	7	8
$\Delta logTFP_{USAit}$	**0.2516**	**0.2831**	**0.25**	**0.2841**	**0.2468**	**0.2806**	**0.2333**	**0.2651**
	(1.56)	**(1.80)**	**(1.55)**	**(1.82)**	**(1.53)**	**(1.80)**	**(1.45)**	**(1.68)**
$RTFP_{it-1}$	**0.1719**	-0.127	**0.1718**	0.053	**0.1717**	0.061	**0.1706**	0.1392
	(1.45)	(-0.36)	**(1.44)**	(0.28)	**(1.44)**	(0.33)	**(1.43)**	(0.95)
TYR_{it-1}	0.0004	-0.054						
	(0.01)	(-0.77)						
$(TYRxRTFP)_{it-1}$		0.058						
		(1.07)						
SYR_{it-1}			0.004	-0.074				
			(0.08)	(-0.85)				
$(SYRxRTFP)_{it-1}$				0.084				
				(1.21)				
$SHYR_{it-1}$					0.0093	-0.058		
					(0.20)	(-0.76)		
$(SHYRxRTFP)_{it-1}$						0.075		
						(1.20)		
HYR_{it-1}							0.2408	-0.255
							(0.75)	(-0.41)
$(HYRxRTFP)_{it-1}$								0.5239
								(0.94)
$\bar{R}$ -squared	.5112	.5120	.5112	.5128	.5113	.513	.5123	.5130
Root MSE	.16394	.1638	.16393	.16367	.16392	.16364	.16374	.16363

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling, all industry-specific. The sample includes 168 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 5.7. Roles of the different schooling levels in TFP growth, 14 Portuguese manufacturing industries

Table 5.8 presents the results of the estimations to investigate the role of international trade as an additional technological change determinant, highlighting the possible complementarity with education. When the proxy for technology spillovers through international trade is introduced on its own (column (1)) the estimated coefficient is positive and significant as expected and the remaining influences also remain statistically significant except for relative TFP, which might indicate that embodied technology diffusion is more important for productivity growth in the Portuguese manufacturing sector than disembodied technology diffusion proxied by the technology gap.

In column (2) we drop RTFP from the regression and proceed to examine the hypothesis of complementarity between education and international trade (columns (3)-(8)). When the different interaction terms are introduced the direct influence of international trade becomes statistically insignificant. Regarding the estimated coefficients of the interaction terms, only the interaction terms with secondary education and secondary and higher education together are statistically significant and positive as expected.

We retain specification (4) as our preferred specification since it presents a higher R-squared, and in column (7) we present the results of regressing TFP growth on the identified statistically significant influences, TFP growth of the leader and the complementarity between international trade and secondary education.

In column (8) we estimate our selected specification using the Diff-GMM estimator. We consider all the regressors but TFP growth of the leader as potentially endogenous and use the adequate lagged values as instruments (see the notes on each table for details). Since explanatory variables are measured at the beginning of each period we consider them as predetermined. The results with the Diff-GMM estimator confirm the previous results. The employed specification tests support the GMM estimation of our model: the Sargan test and second-order serial correlation tests p-values are within the acceptable values and cannot reject the null hypothesis of correct specification of the different models.

	1	2	3	4	5	6	7	8 Diff-GMM
$\Delta logTFP_{USAit}$	**.2478**	**.2478**	**.27**	**.2858**	**.2801**	**.2472**	**.2826**	**0.4001**
	(1.50)	**(1.47)**	**(1.67)**	**(1.76)**	**(1.72)**	**(1.47)**	**(1.69)**	**(2.23)**
$RTFP_{it-1}$	.0668							
	(0.59)							
$IMPS_{it-1}$	**.0581**	**.0764**	-.119	-.008	.0020	.0838		
	(2.02)	**(1.95)**	(-0.76)	(-0.13)	(0.03)	(1.25)		
$(IMPSxTYR)_{it-1}$			**.038**					
			(1.38)					
$(IMPSxSYR)_{it-1}$				**.0594**			**.0546**	**0.0711**
				(2.01)			**(2.23)**	**(3.86)**
$(IMPSxSHYR)_{it-1}$					**.0499**			
					(1.75)			
$(IMPSxHYR)_{it-1}$						-.0976		
						(-0.22)		
$\bar{R}$-squared	.5282	.5281	.5300	.5337	.5320	.5252	.5369	
Root MSE	.16106	.16107	.16074	.16012	.1604	.16158	.15957	0.1662
Sargan test								24.54
[*p-value*]								[0.220]
AR(2)								0.5311
[*p-value*]								[0.595]

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling, all industry-specific. IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 168 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (8) estimates the specification in column (7) using as instruments all values of $\Delta logTFP_{USA}$ and values of IMPSxSYR lagged two periods. Since the cross-sectional dimension of our data set is small to avoid over-fitting problems we work with a reduced number of instrumental variables so we only use the first acceptable lag as instrument for the endogenous variables (predetermined). Results for the one-step GMM estimator with standard errors robust to heteroscedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards.

Table 5.8. Roles of the different schooling levels and international trade in TFP growth, 14 Portuguese manufacturing industries

The above-described results indicate that the dominant effect of education on productivity growth of the Portuguese manufacturing sector is felt through the assimilation of ideas and technologies developed abroad, with no evidence of a robust direct role of education in the production of new ideas and technologies. Since the Portuguese manufacturing industries are, as we saw in the previous section, still far behind the respective US counterparts, with relative TFP levels not higher than fifty per cent in 1997, this is not a surprising result – the Portuguese economy is mainly a follower economy not a technological leader. This feature renders education a fundamental role in the process of technological catch up – it is crucial to exploit the productivity growth benefits of embodied technology spillovers. Furthermore, the assimilation of foreign technologies requires more than basic skill levels: embodied technology diffusion requires skills acquired in secondary education.

In the next sections we proceed with the empirical analysis by disaggregating the sample of fourteen manufacturing industries according to the OECD technology classification based on R&D intensities into a group of nine low technology industries and a group of five high technology industries. Our aim is to test the robustness of the results from this section to the consideration of different technological characteristics.

5.5.2. Results for the nine Portuguese low technology industries

We start by presenting the results of the estimations to select the relevant education variables for productivity growth in low technology industries in Table 5.9. For this group, TFP growth of the leader has a positive and statistically significant influence on productivity growth in all regressions, and stronger than for the aggregate sample of fourteen manufacturing industries. Regarding the influence of relative TFP, its estimated coefficient is both positive and negative but not statistically significant (except in column (2)).

Regarding the direct influence alone of the different education variables (columns 1, 3, 5, and 7) none of the estimated coefficients is statistically significant. When both the direct and indirect influences are considered however the estimated coefficients on the direct influence become statistically significant (except for the direct role of higher education, column (8)), but since they are negative this is a result difficult to interpret in economic terms.

We retain the specification in column (4) that considers the influence of secondary education since it presents the highest R-squared and estimate it in column (9) dropping the none statistically significant influence, RTFP. In this case only the influence of TFP growth of the leader is statistically significant and positive as expected so in column (10) we regress TFP growth on this influence alone.

As in the fourteen manufacturing industries sample, in low-tech industries the evidence also does not support the hypothesis that education influences TFP growth through innovation nor through disembodied technology diffusion. In the next table we check the robustness of these results to the introduction of the additional technological change determinant (IMPS) and whether there is still a possible role for education through its complementarity with embodied technology diffusion.

	1	2	3	4	5	6	7	8	9	10
$\Delta logTFP_{USAit}$	**0.6375**	**0.7091**	**0.6367**	**0.7092**	**0.6344**	**0.6984**	**0.5888**	**0.6056**	**.68**	**.7385**
	(1.77)	**(2.10)**	**(1.77)**	**(2.10)**	**(1.76)**	**(2.06)**	**(1.62)**	**(1.68)**	**(1.88)**	**(2.22)**
$RTFP_{it-1}$	0.1387	**-0.494**	0.1389	-0.073	0.1385	-0.048	0.1368	0.1186		
	(0.94)	**(-1.30)**	(0.94)	(-0.44)	(0.94)	(-0.28)	(0.93)	(0.68)		
TYR_{it-1}	-0.017	**-0.16**								
	(-0.29)	**(-1.5)**								
$(TYRxRTFP)_{it-1}$		**0.1285**								
		(1.67)								
SYR_{it-1}			-0.023	**-0.21**					-.1544	
			(-0.37)	**(-1.6)**					(-1.2)	
$(SYRxRTFP)_{it-1}$				**0.1686**					.1177	
				(1.69)					(1.12)	
$SHYR_{it-1}$					-0.012	**-0.171**				
					(-0.20)	**(-1.45**				
$(SHYRxRTFP)_{it-1}$						**0.1436**				
						(1.72)				
HYR_{it-1}							0.3235	-0.268		
							(0.77)	(-0.25)		
$(HYRxRTFP)_{it-1}$								0.467		
								(0.56)		
$\bar{R}$ -squared	.5249	.5298	.5249	.5299	.5248	.5287	.5259	.5216	.5344	.5077
Root MSE	.17432	.17341	.1743	.17339	.17433	.17362	.17412	.17491	.17257	.17137

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all industry-specific. The sample includes 108 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 5.9. Roles of the different schooling levels in TFP growth,
9 Portuguese low technology industries

Table 5.10 reports the results for the regressions that consider the influence of international trade on productivity growth of low-tech industries. The influence of TFP growth of the leader remains positive and statistically significant in all specifications. When only the direct influence of international trade is considered, the respective estimated coefficient is positive and significant as expected (column (1)). When we test the complementarity between international trade and the different education variables (columns (2)-(5)) all estimated coefficients are positive and statistically significant as expected (except in column (5)) but render the direct influence negative and statistically significant in columns (2) and (4). Specification (3) that considers the interaction term between international trade and secondary education presents the highest R-squared so we retain only this influence on our preferred specification for low technology industries, column (6), dropping the direct influence of IMPS since it is not statistically significant.

Productivity growth in low technology industries is thus determined by productivity growth of the leader and the influence of secondary education on the absorption of technologies incorporated in imports from OECD countries.

In column (7) we estimate our selected specification using the Diff-GMM estimator. We consider all the regressors but TFP growth of the leader as potentially endogenous and use the adequate lagged values as instruments (see the notes on each table for details). Since explanatory variables are measured at the beginning of each period we consider them as predetermined. The results with the Diff-GMM estimator confirm the previous results on the influence of the

TFP growth of the leader and IMPSxSYR. The second-order serial correlation test and the Sargan test support the GMM estimation of our model: the p-value is within the acceptable values and cannot reject the null hypothesis of correct specification of the different models.

The results are thus similar to the ones for the fourteen manufacturing industries together.

	1	2	3	4	5	6	7 Diff-GMM
$\Delta logTFP_{USAit}$	**.6838**	**.6274**	**.6049**	**.6078**	**.7231**	**.6386**	**0.5613**
	(1.86)	**(1.73)**	**(1.67)**	**(1.68)**	**(1.82)**	**(1.76)**	**(1.44)**
$IMPS_{it-1}$	**.07581**	**-.3405**	-.0786	-.0738	.1637		
	(1.35)	**(-1.69)**	(-1.17)	(-1.2)	(0.94)		
$(IMPSxTYR)_{it-1}$		**.0839**					
		(1.72)					
$(IMPSxSYR)_{it-1}$			**.1244**			**.0649**	**0.0766**
			(1.45)			**(1.41)**	**(2.16)**
$(IMPSxSHYR)_{it-1}$				**.1149**			
				(1.54)			
$(IMPSxHYR)_{it-1}$					-1.44		
					(-0.7)		
$\bar{R}$-squared	.5528	.5585	.5622	.56	.5613	.5638	
Root MSE	.16912	.16804	.16733	.16775	.16751	.16703	0.1788
Sargan test [*p-value*]							25.87
							[0.170]
AR(2) [*p-value*]							0.9965
							[0.319]

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all industry-specific. IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 108 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (7) estimates the specification in column (6) using as instruments all values of $\Delta logTFP_{USA}$ and values of IMPSxSYR lagged two periods. Since the cross-sectional dimension of our data set is small to avoid over-fitting problems we work with a reduced number of instrumental variables so we only use the first acceptable lag as instruments for the endogenous variables (predetermined). Results for the one-step GMM estimator with standard errors robust to heteroskedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards.

Table 5.10. Roles of the different schooling levels and international trade in TFP growth, 9 low technology industries

5.5.3. Results for the five Portuguese high technology industries

The results regarding the selection of the relevant education variables to explain productivity growth in the group of high technology industries are reported in Table 5.11. The estimated coefficient on TFP growth of the leader is positive but never statistically significant contrary to the results for the previous two samples. The estimated coefficient on RTFP is positive and significant when only the direct influence of the education variables is considered (columns (1), (3), (5) and (7)).

Regarding the direct influence of education (columns (1), (3), (5), and (7)) all the estimated coefficients are positive but not statistically significant. When the interaction term with relative TFP is also included (columns (2), (4), (6), and (8)) its estimated coefficient is always positive but statistically significant only with SHYR and HYR.

We retain the influence of the interaction term between higher education and relative TFP (column (8)) since it has the highest R-squared. In this case the estimated coefficients on TFP growth of the leader, relative TFP and the direct influence of HYR are not statistically significant so we drop them from our preferred specification in column (9). TFP growth of high technology industries is thus only explained by the interaction term between HYR and relative TFP so that there is technological catch up with its US counterparts but only if the Portuguese high tech industries employ a workforce with qualifications at the tertiary level.

We next check the robustness of this result to the introduction of international trade as a determinant of TFP growth.

	1	2	3	4	5	6	7	8	9
$\Delta logTFP_{USAit}$	0.103	0.1451	0.0851	0.1423	0.0881	0.1516	0.1039	0.201	
	(0.66)	(0.82)	(0.55)	(0.81)	(0.57)	(0.87)	(0.71)	(1.13)	
$RTFP_{it-1}$	**0.23**	-0.307	**0.234**	-0.074	**0.233**	-0.089	**0.23**	0.0529	
	(2.33)	(-0.5)	**(2.28)**	(-0.26)	**(2.28)**	(-0.34)	**(2.31)**	(0.32)	
TYR_{it-1}	0.006	-0.072							
	(0.05)	(-0.5)							
$(TYRxRTFP)_{it-1}$		0.089							
		(0.85)							
SYR_{it-1}			0.083	-0.064					
			(0.57)	(-0.33)					
$(SYRxRTFP)_{it-1}$				0.149					
				(1.19)					
$SHYR_{it-1}$					0.069	-0.056			
					(0.52)	(-0.35)			
$(SHYRxRTFP)_{it-1}$						**0.1462**			
						(1.35)			
HYR_{it-1}							0.099	-0.630	
							(0.16)	(-0.8)	
$(HYRxRTFP)_{it-1}$								**1.199**	**1.156**
								(1.50)	**(2.51)**
$\bar{R}$ -squared	.4199	.4122	.4235	.4221	.423	.4251	.4201	.4296	.4502
Root MSE	.15152	.15252	.15105	.15122	.15111	.15083	.15149	.15025	.14751

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; RTFP is relative TFP; TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all industry-specific. IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 60 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 5.11. Roles of the different schooling levels in TFP growth, 5 Portuguese high technology industries

Table 5.12 reports the results for the group of five high technology industries considering the additional influence of international trade. Regarding the results from the introduction of international trade alone (column (1)), the estimated coefficient on the direct impact of international trade is positive and statistically significant as expected but renders the estimated coefficient on RTFPxHYR not statistically significant. We thus drop its influence in the following regressions. When the interaction terms between IMPS and the different education variables are introduced (columns (2)-(5)) the direct impact of international trade becomes statistically insignificant.

We selected specification (3) as our preferred specification since it presents a higher R-squared so that as in the previous sample embodied technology diffusion is the main determinant of TFP growth and, in the case of high tech industries, the only one. In column (6) we regress TFP growth of high-tech industries on the interaction term between secondary education and international trade alone, getting a positive and statistically significant coefficient as expected.

In column (7) we estimate our selected specification using the Diff-GMM estimator. We consider all the regressors but TFP growth of the leader as potentially endogenous and use the adequate lagged values as instruments (see the notes on each table for details). Since explanatory variables are measured at the beginning of each period we consider them as predetermined. The results with the Diff-GMM estimator confirm the previous results. The employed specification tests support the GMM estimation of our model: the Sargan test and second-order serial correlation tests p-values are within the acceptable values and cannot reject the null hypothesis of correct specification of the different models.

	1	2	3	4	5	6	7 Diff-GMM
$(HYRxRTFP)_{cit-1}$	.6160 (1.29)						
$IMPS_{cit-1}$	**.0545** **(1.32)**	-.1905 (-0.59)	-.1058 (-0.98)	-.0934 (-0.85)	.0758 (1.23)		
$(IMPSxTYR)_{cit-1}$		.0476 (0.81)					
$(IMPSxSYR)_{cit-1}$			**.1034** **(1.66)**			**.0474** **(2.44)**	**0.0599** **(3.73)**
$(IMPSxSHYR)_{cit-1}$				**.0909** **(1.55)**			
$(IMPSxHYR)_{cit-1}$					.0367 (0.08)		
$\bar{R}$ -squared	.4625	.4558	.4748	.4719	.4491	.4792	
Root MSE	.14585	.14676	.14417	.14457	.14765	.14356	0.14
Sargan test [*p-value*]							8.119 [0.617]
AR(2) [*p-value*]							-0.3464 [0.729]

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. TYR is average years of total schooling; HYR is average years of tertiary schooling; SYR is average years of secondary schooling; SHYR is average years of secondary and tertiary schooling all industry-specific. IMPS is the ratio of an industry's imports from the OECD to gross output. The sample includes 60 observations between 1986 and 1997. All columns include a full set of time dummies and industry fixed effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level. Column (7) estimates the specification in column (6) using IMPSxSYR lagged two periods as instruments. Since the cross-sectional dimension of our data set is small to avoid over-fitting problems we work with a reduced number of instrumental variables so we only use the first acceptable lag as instruments for the endogenous variables (predetermined). Results for the one-step GMM estimator with standard errors robust to heteroskedasticity since the standard errors of the two-step GMM estimator can be seriously biased downwards.

Table 5.12. Roles of the different schooling levels and international trade in TFP growth, 5 Portuguese high technology industries

5.5.4. Quantifying the contribution of education for TFP growth

In the case of the Portuguese manufacturing industries, the evidence only supports the importance of education for productivity growth through technology spillovers and specifically embodied technology diffusion, both in low technology and high technology industries. Additionally, it is education at the secondary level that allows these industries to imitate technology embodied in international trade.

In Table 5.13 we quantify the contribution of education for TFP growth in each low-tech and high-tech industry in the period 1985-1997 based on the estimated coefficients from the previous sections. For each industry the total impact of education on productivity growth will differ according to its import ratio so that industries that use a higher proportion of imported goods in its production will have higher growth returns to increased educational attainment at the secondary level. The estimated impact of education through embodied technology diffusion is given by $\hat{\delta}_2 IMPS$, where $\hat{\delta}_2$ is equal to 0.0766 in low-tech industries and 0.0599 in high-tech industries.

Industry	avIMPS	Embodied Technology Diffusion
Low-tech		
FOOD	0.181	0.0138
TEX	0.231	0.0177
WOOD	0.068	0.0052
PAP	0.166	0.0128
RUB	1.230	0.0942
ONMP	0.113	0.0087
BMI	1.001	0.0767
FMP	4.522	0.3464
OMAN	1.688	0.1293
	Mean	*0.0783*
High-tech		
CHE	0.752	0.0451
MAI	2.380	0.1425
MEL	0.828	0.0496
MTR	1.461	0.0875
MED	4.006	0.2400
	Mean	*0.1129*

Notes: The parameters used in the computations are those in column (8), Table 5.10 for low-tech industries and column (7), Table 5.12 for high-tech industries. Av.IMPS is the average of the imports ratio for the period.
FOOD - Food products, beverages and tobacco; TEX - Textiles, textile products, leather and footwear;
WOOD - Wood and products of wood and cork PAP - Pulp, paper, paper products, printing and publishing;
CHE - Chemicals and chemical products; RUB - Rubber and plastic products ONMP - Other non-metallic mineral products;
BMI - Basic Metals Industries; FMP - Fabricated metal products, except machinery and equipment;
MAI - Machinery and equipment n.e.c. and Office, accounting and computing machinery
MEL - Electrical machinery and apparatus and Radio, television and communication equipment;
MTR - Transport equipment; MED - Medical, precision and optical instruments; OMAN - Manufacturing n.e.c.

Table 5.13. Contribution of education to TFP growth in the Portuguese manufacturing industries (1986-1997)

The impact of secondary education on productivity growth is on average higher in high technology industries. However, the highest impact is on FMP, a low-tech industry, since this industry presents by far the highest import ratio. The other three low-tech industries with an impact of education on the respective productivity growth higher than in some high-tech industry are OMAN, RUB and BMI. In the group of high-tech industries, CHE presents the lowest impact of education but the figure is any case much higher (more than two times) than the ones for the low-tech industries that occupy the bottom five positions.

5.6. Summary and Conclusions

The purpose of this chapter was to analyse the importance of education for technological change and growth in the Portuguese economy at a sectoral level. We looked at the role of education, and education sub-categories, in the production of new knowledge and in the process of assimilation and diffusion of technologies as in the (Benhabib & Spiegel, 1994) model. We also investigated whether a large stock of educated workers is beneficial in order to internalise spillovers from international trade, as in (Cameron, Proudman, & Redding, 2005). Total factor productivity is thus explained not only by human capital acquired in the formal education sector but also international trade. We used panel data for fourteen manufacturing industries for Portugal over the period 1986-1997. The method is similar to the one employed in the previous chapter.

Concerning the attempt to unravel the several potential roles of education in productivity growth, directly through innovation activities and indirectly through disembodied and embodied technology diffusion, the results only support the indirect role through the enhancement of the assimilation of technology from abroad embodied in international trade. Distinguishing between low-tech and high-tech industries does not change this result.

Our most robust finding thus concerns the relevance of technology spillovers embodied in imports from OECD countries for productivity growth, as long as manufacturing industries employ workers with skills provided by secondary education. (Afonso & Aguiar, 2005) also stress the importance of increased international trade and its interaction with the industrialization process to the process catch up of the Portuguese economy at the aggregate country level in the second half of the twentieth century. The Portuguese manufacturing industry cannot rely on automatic technological catch up for productivity growth so active trade and education policies are crucial to recover from the present bottom position in the rank of OECD productivity levels.

Portugal has known several attempts to redesign its education policy in the last two decades. Our results seem to favour a redefinition of education policy based not only on quantitative goals but, more importantly, on the definition of a structure for the education system that allows the economy to fully exploit the benefits from its technological backwardness, i.e., to produce a growth enhancing human capital. Besides registering a general lack of human capital when compared with other EU countries and the US (see chapter 2), Portugal needs to concentrate its efforts at the secondary education level. Bearing also in mind that Portuguese students tend to perform badly in international assessment tests this redefinition involves not only a quantity but also a quality dimension since higher quantity does not necessarily provide the necessary skills for growth, as pointed out by (Pina & St Aubyn, 2005). On the other hand, as Portugal approaches the technological frontier more attention needs to be devoted to education at the tertiary level since productivity growth will be based essentially in innovation activities that require a highly educated labour force, whereas before imitation activities could be carried out by workers with tertiary but also secondary (and eventually primary) education. Failing to promote higher education at this stage can put Portuguese growth at risk.

The lack of results concerning the direct influence of education on TFP growth might indicate that it is not sufficient only to concentrate on general educational levels, but that the distribution of skill groups as well as their educational level, for example science and engineering vs. humanities degrees or general vs. vocational education, might be a more important determinant of technological innovations and economic growth.

5.7. Appendix

5.7.1. Data sources

Output: value added in 1995 USD. Data on value added expressed in current USD was taken from (Alessandro Nicita & Olarreaga, 2001) that provide industry production and trade data for 67 developed and developing countries collected from the CD-ROM versions of the United Nations Industrial Development Organization (UNIDO) Industrial Statistics Database, available at www.worldbank.org/research/trade. We do not use data from the OECD, STAN database, 2004 edition due to its more limited data availability for Portugal. To compute real value added in 1995 USD we computed industry-specific US value added deflators using data on nominal and real value added from the OECD, STAN database, 2004 edition.

Physical capital: real capital stock expressed in 1995 USD. For the years 1976 through 1995 data on gross fixed capital formation (GFCF) expressed in current USD was taken from (Alessandro Nicita & Olarreaga, 2001) and for the years 1996 and 1997 from the OECD, STAN database, 2004 (expressed in local currency and converted to USD using the yearly nominal exchange rate). To compute real GFCF in 1995 USD we used the US deflator for GFCF computed using the available data for each US industry on nominal and real GFCF from the OECD, STAN database, 2004. Finally, the perpetual inventory method was used to construct a proxy for the real physical capital stock, K, as a distributed lag of past investment flows, I, as:

$$K_{it} = (1-d)K_{it-1} + I_{it-1} \tag{5.7}$$

$$K_{i0} = \frac{I_{i0}}{(g_{GFCFi} + d)} \tag{5.8}$$

where the capital stock in year t does not include investment in year t, but only investment up to t-1, and d is the common depreciation rate. (Nadiri & Prucha, 1996) estimate that d=0.059 for the US total manufacturing sector and this is the value we use for the depreciation rate, common across all industries. K_0 is the initial real physical capital stock, and g_{GFCF} is the average annual growth rate of I over the period where data is available.

Labour input: we use data on hours worked from the Groningen Growth and Development Centre, Industry and Labour Productivity Database, (M. O'Mahony & B. van Ark, 2003), downloadable from http://www.ggdc.net/index-dseries.html#top available for the 1979-1997 period.

Education: the industry-specific education variables refer to average years of education, total and by schooling level, of the workforce employed in each industry i at time t. See the main text for details on the construction of this variable.

International trade: ratio of imports from the OECD to gross output:

$$IMPS_{it} = \frac{TIMPS_{it}}{PROD_{it}} x100 \tag{5.9}$$

where TIMPS is total imports from the OECD of industry i at time t and PROD is gross output in industry i at time t. Gross output data is from (Alessandro Nicita & Olarreaga, 2001). Imports data is from the OECD, Bilateral Trade Database, 2000 edition available for the years 1980-1997.

5.7.2. Panel unit root tests for the Portuguese manufacturing industries data[99]

Table 5.14 presents the results of the panel unit root tests for the industry-level series of the Portuguese manufacturing sector. Both the LL and the IPS tests allow for the rejection of the null hypothesis of non-stationarity for the series $\Delta logTFP_{PRT}$, $\Delta logTFP_{USA}$, HYR, IMPS, IMPSxTYR, IMPSxSYR, IMPSxSHYR and IMPSxHYR. For the series RTFP, TYR, SYR, SHYR, RTFPxTYR, RTFPxSYR, and RTFPxSHYR however the null hypothesis cannot be rejected with either test. In the case of the RTFP and RTFPxTYR series if we consider a homogenous trend instead of individual-specific trends in the underlying model both tests allow us to reject the null hypothesis of non-stationarity. In the case of the education series RTFPxHYR we reject the null hypothesis of non-stationarity with the LL

[99] Please refer to the appendix to chapter 4 for a description of the panel unit root tests used in this section.

test but accept it with the IPS test. In any case the only education variable that the results support as important for productivity growth in the Portuguese manufacturing industry is IMPSxSYR, stationary according to both tests.

Variables	LL	IPS
$\Delta logTFP_{PRT}$	**-7.1**	**-9.47**
$\Delta logTFP_{USA}$	**-6.19**	**-10.06**
RTFP[a]	-1.00	-0.29
RTFP[b]	**-2.55**	**-3.38**
TYR	-0.75	-1.11
SYR	-1.07	-0.61
SHYR	-0.21	-0.77
HYR	**-1.95**	**-1.86**
RTFPxTYR[b]	**-2.2**	**-3.14**
RTFPxSYR	-0.15	1.22
RTFPxSHYR	-0.35	0.75
RTFPxHYR	-0.83	**-1.63**
IMPS	**-2.70**	**-4.92**
IMPSxTYR	**-3.1**	**-4.4**
IMPSxSYR	**-3.09**	**-3.53**
IMPSxSHYR	**-3.35**	**-3.68**
IMPSxHYR	**-3.67**	**-5.00**

Notes: The model under consideration is defined as: $\Delta y_{i,t} = \alpha_{0,i} + \alpha_{1,i}t + \delta_i y_{i,t-1} + \sum_{L=1}^{P_i} \theta_{iL} \Delta y_{i,t-L} + \varepsilon_{i,t}$.
Coefficients in bold are significant at least at the 10% significance level. The tests were performed with WINRATS 6.0 using the procedure PANCOINT.SRC written by Peter Pedroni. The statistics are distributed standard normal under the null hypothesis of non-stationarity. The test results are based on the data for the 14 industries of the Portuguese manufacturing sector ranging from 1986 to 1997.
[a] The underlying model considers heterogeneous trends. [b] The underlying model considers homogeneous trends.

Table 5.14. Panel Unit Root tests results for the industry-level data for the Portuguese manufacturing sector

In view of these results we checked the robustness of the results of our preferred specifications for the three samples in the main text to the inclusion of individual-specific time trends instead of considering a common time trend. Table 5.15 presents the results of these estimations. As we can see the variables remain significant at least at the 10% significance level except for the sample of high tech industries. In this case the coefficient is positive as expected but only significant at the 25% significance level.

	14 industries	9 low tech industries	5 high tech industries
$\Delta logTFP_{USAit}$	**.708**	**1.02**	
	(3.00)	**(3.16)**	
$(IMPSxSYR)_{cit-1}$	**.0685**	**.0928**	.0331
	(1.71)	**(1.31)**	(1.00)
R-squared	0.2488	0.2883	0.1798
Root MSE	.2236	.2353	.1977

Notes: Dependent variable is the rate of TFP (translog) growth adjusted for total hours worked. $\Delta logTFP_{USA}$ is TFP growth of the leader, the USA; SYR is average years of secondary schooling of the workforce employed in each industry *i*. IMPS is the ratio of an industry's imports from the OECD to gross output. All columns include a full set of industry fixed effects and industry-specific time effects. Heteroscedasticity-consistent t-statistics in parenthesis. Coefficients in bold are significant at least at the 10% significance level.

Table 5.15. Robustness of the results to the introduction of individual-specific time trends, Portugal

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Chapter 6
Conclusions

6.1. Summary of the main results

The belief that more education leads to higher economic growth has strong roots across the world and rests to a large extent on the idea that countries need educated people, since these are crucial for technological progress. The main aim of this thesis was to empirically examine this proposition under the theoretical predictions of new growth theory that attributes to human capital a fundamental role in the generation of technological progress. Human capital acts as an engine of growth due to externalities associated with innovation activities and as a determinant of the absorptive capacity of technologies developed elsewhere in the World. These externalities clearly affect the level of income and short run growth and, if sufficiently strong, may also affect the long run growth rate.

The empirical analyses developed offer a number of original approaches with respect to the existing literature. Three characteristics, which appear in chapters 3, 4 and 5, deserve to be mentioned. The first one is that the analysis of the importance of education for technological change is investigated within a homogenous empirical framework. The role of education in productivity growth is not only analyzed on its own but in a wider context of its complementarity with other technological change determinants where each chapter focuses on a particular aggregation level of analysis, cross-country, cross-country-industry, and single-country-industry. The second characteristic is the particular attention devoted to the empirical identification of a role for specific education levels as opposed to the usual overall educational attainment measure used in the empirical literature. The third characteristic is that all chapters rely on time series cross section data sets, whereas many existing studies on the topic rely on cross section data.

Chapter 2 constitutes an introductory chapter for the subsequent three chapters by presenting a selective overview of the theoretical and empirical analyses of education, technological change and growth that provide the general analytical framework we use in our research of the topic. The theoretical literature reviewed concentrates on the models that contain interesting predictions on the issues that we want to examine in the subsequent chapters. These are the models that view technological change as a supply-driven phenomenon that uses primarily human capital and the existing knowledge stock in the production of new knowledge. Education determines growth through its influence on the technological progress growth rate both as a fundamental input in the ideas production function and as a facilitator of technology diffusion.

To test the empirical predictions of the endogenous growth models the researcher has to face some common problems and can choose between different econometric approaches. We highlighted model uncertainty, endogeneity, measurement error, and parameter heterogeneity among the most common problems facing empirical growth studies due to their relevance for the analysis of the importance of education for growth. To deal with these problems panel data econometrics seems to be the most promising econometric approach although it raises some issues of its own.

Chapters 3, 4 and 5 use an extended and augmented version of the Benhabib and Spiegel (1994) empirical specification of the role of human capital, in the form of education, on growth to bring out the full length of the mechanisms by which education and its sub-categories affect productivity growth, namely its interplay with other determinants of innovation and imitation activities proposed by the literature, R&D, international trade and FDI.

Overall the evidence collected from the different chapters, no matter the level of aggregation used, points to a fundamental role of education as a facilitator of the absorption of technology developed abroad, either disembodied or embodied. Furthermore, education and its sub-categories affect productivity growth to a great extent through its interaction with other technological change determinants, namely R&D and international trade.

Chapter 3 conducts the empirical evaluation of the importance of education for technological change at the cross-country level in a sample of twenty-three OECD countries highlighting its complementarity with three other determinants of technological change, R&D, international trade and FDI, while the usual practise in empirical growth studies is to investigate each influence separately.

The main conclusion emanating from Chapter 3 is that although OECD countries represent a rather homogeneous group of countries the fact is that research efforts worldwide are carried out by a small number of countries so, contrary to the results of (Benhabib & Spiegel, 1994), we find that education plays a crucial role as a determinant of the absorptive capacity of technology spillovers in the average OECD country.

Some other interesting findings emerge as well. To fully exploit the benefits from R&D expenses the average OECD country needs a sufficient level of secondary and tertiary education, thus confirming the argument of endogenous growth theory that innovation requires advanced skills that can only be provided by education at higher levels. The empirical findings also endorsed the hypothesis that the productivity growth benefits from imports of machinery are enhanced when interacted with overall educational attainment. The results regarding the introduction of FDI inflows do not support its influence on productivity growth, neither directly nor through its complementarity with education. Finally, the estimated coefficient associated with the domestic innovation term is not statistically significant.

The quantification of the relative importance of education for technological change through these different channels in each country revealed that the influence through technology diffusion is quantitatively more important. However, since the benefits from technology diffusion are bound to be exhausted as countries close the technology gap a change of policy focus will become inevitable.

Following the country-level analysis of Chapter 3, Chapter 4 contributes to the literature on the empirical evaluation of the importance of education for technological change and growth by examining this relationship from a more disaggregate perspective in a panel of fifteen manufacturing industries in eleven OECD countries. We wanted to know whether the trends observed at the aggregate level, such as the complementarity between education and R&D efforts are representative of movements at the industry level. Additionally, the fifteen manufacturing industries were divided into two groups, low technology and high technology industries according to the respective R&D intensities, to test whether the role of education in productivity growth depends on technological characteristics.

The investigation of the importance of education for productivity growth at the industry level can shed additional light on the factors that drive growth especially if there are persistent differences in the determinants of growth across industries. This is quite an important issue since, for instance (Scarpetta, Bassanini, Pilat, & Schreyer, 2000) show that around half of the productivity growth over 1990-1997 in the non-farm business sector of countries like Australia, Canada, Finland, France, Italy, Japan, the United States and Western Germany was due to the manufacturing sector.

Industry-specific peculiarities appear regarding the role of education. In low-tech industries tertiary education boosts productivity growth through technology diffusion, disembodied and embodied, and overall educational attainment interacts with R&D efforts. In high-tech industries, both secondary and tertiary education determine the rate of innovation and overall educational attainment influences the absorptive capacity of technologies from abroad. Additionally, in high-tech industries technological catch-up will only take place if the countries where these industries operate possess a sufficient education level.

These results are robust to the introduction of the additional technological change determinants but the role assumed by the different education variables at the country level is not always confirmed at the industry level. At this level only in low-tech industries does R&D interact with education in determining in productivity growth, and in this case the relevant education variable is overall educational attainment. International trade, on the other hand, influences productivity growth in quite distinct ways according to industries' technological characteristics: in low-tech industries international trade only affects productivity growth if the population of the countries where these industries operate have a sufficient level of tertiary education, while in high-tech industries only the direct impact of increased international trade matters (but does not survive the use of Diff-GMM).

Finally, we used the estimated coefficients from the econometric analysis to quantify the importance of education for productivity growth in low-tech and high-tech industries. The impact of education is higher in low-tech than in high-tech industries, both through innovation and imitation activities. In the average low-tech industry most countries have higher TFP growth returns to education from imitation than from innovation activities. Only in the USA is the contribution of education through technology diffusion less than the contribution of education through innovation activities. In the average high-tech industry in all countries TFP growth returns to education from innovation activities are higher than from imitation activities.

In chapter 5 we turn to the analysis of the role of education in productivity growth of a particular country, Portugal, in a sample of fourteen manufacturing industries. Despite the recovery in relative productivity levels in the second half of the twentieth century, Portugal still lagged quite behind the USA by the end of the century suggesting that there is still scope for catching up. Industrial productivity growth, and among this manufacturing productivity growth, was the major contributor to aggregate productivity growth during this period (see (Aguiar & Martins, 2005)). During the last fifteen years of the twentieth Portuguese industrial productivity average growth rate was higher than in most other European countries which makes this an adequate period to investigate why nevertheless the performance of the Portuguese manufacturing industry productivity was not very impressive when compared to that of the USA, highlighting the role of education. The low educational levels of the Portuguese workforce can constitute impediments to higher rates of productivity growth if a skilled workforce contributes to higher productivity growth through its influence on the domestic rate of innovation and to the exhaustion of catch up gains from imitation.

Our most robust finding concerns the relevance of technology spillovers embodied in imports from OECD countries for productivity growth both when considering the entire fourteen manufacturing industries sample and when distinguishing between low technology and high technology industries, as long as manufacturing industries employ workers with skills provided by secondary education. (Afonso & Aguiar, 2005) also stress the importance of increased international trade and its interaction with the industrialization process to the catch up process of the Portuguese economy at the aggregate country level in the second half of the twentieth century.

Common to both low and high technology Portuguese industries is the fact that the empirical evidence does not support a direct influence for relative TFP indicating that technological catch up is not an automatically guaranteed process. Additionally, the results concerning the positive influence of TFP growth of the leader for the whole sample are driven by low technology industries. There is also no evidence of a direct positive influence of education through the rate of innovation.

The impact of secondary education on productivity growth is on average higher in high technology industries. However, the highest impact is felt on a low-tech industry that presents by far the highest import ratio.

6.2. Policy implications and recommendations

Several policy issues emerge from the empirical evidence collected from chapters 3, 4 and 5 of this thesis. First and foremost is the understanding that governments should induce the capacity to produce new knowledge and adopt innovations developed abroad, which underlines the role of the educational system, but education alone does not necessarily lead to an improved economic performance. Education policies are certainly not the only force affecting technological change. A nation's policies concerning science and technology, openness to trade and foreign direct investments have substantial effects on its rate of productivity growth so that the wrong mix of economic policies can lead to a failure of any specific policy targeting productivity growth.

It should also be kept in mind that the effectiveness of education policies might be improved by paying particular attention to specific educational categories instead of subsidizing overall educational attainment. The composition of human capital is important to fully exploit the productivity growth benefits of the different technological change determinants. As OECD countries and industries close the technology gap only education at the higher levels will allow them to sustain productivity improvements since these are the relevant schooling levels to benefit from innovation activities. Despite the benefits from education through technology diffusion they are bound to be exhausted as countries close the technology gap and governments should focus on policies that promote growth through innovation and not imitation.

Specifically at the industry level, the specialisation of countries in industries with different technological characteristics, low-tech or high-tech, requires the education of a country's population on the appropriate schooling levels for industries to boost productivity growth through innovation and taking advantage of new technologies available in the technological leaders. The productivity growth returns to investing in education also differ across industries and countries depending on whether they are technological leaders or not. For instance, follower countries specialised in low-tech industries will have greater returns to tertiary education while those specialised in high-tech industries will have greater returns to all schooling levels through disembodied technology diffusion.

Finally, the Portuguese manufacturing sector cannot rely on automatic technological catch up for productivity growth so active trade and education policies are crucial to recover from the present bottom position in the rank of OECD productivity levels. Our results seem to favour a redefinition of education policy based not only on quantitative goals but, more importantly, on the definition of a structure for the education system that allows the economy to fully exploit the benefits from its technological backwardness. Besides registering a general lack of human capital when compared with other EU countries and the US, Portugal needs to concentrate its efforts at the secondary education level. Bearing also in mind that Portuguese students tend to perform badly in international assessment tests this redefinition involves not only a quantity but also a quality dimension.

6.3. Research agenda

The evidence that we have presented is reassuring in the sense that it endorses investing in education, and in specific schooling levels, as a means of improving the growth performance of OECD countries but a number of empirical extensions would be worthwhile.

More attention needs to be devoted to the characteristics and mechanisms of innovation and technology diffusion in wider samples that include both developed and developing countries. The importance of the different schooling levels and the several potential channels through which they exert their growth influence should be better explored in this context as has already been done using different specifications by, among others, (Gemmell, 1996), (Mingat & Tan, 1996), (Petrakis & Stamatakis, 2002), and (Papageorgiou, 2003).

Further research should also focus on the incorporation in the study of the impact of high quality tertiary education (e.g. scientists and engineers) that can provide an answer to the puzzling results regarding the role of education through the domestic rate of innovation.

As far as the empirical methodology is concerned an interesting extension would be to test for threshold effects of the different levels of education, i.e. allowing the contribution of education to vary across countries/industries and even time, especially important if we are dealing with samples of both developed and developing countries. Appropriate techniques for this evaluation include the regression-tree methodology used by (S. Durlauf & Johnson, 1995) that imposes data splits exogenously, the sample splitting econometric technique proposed by (Hansen, 2000) that allows one to estimate and make valid statistical inferences on the threshold, or the smooth coefficient semiparametric methodology applied by (Mamuneas, Savvides, & Stengos, 2006). This empirical extension also implies dealing with a wider set of growth models such as the (Azariadis & Drazen, 1990) growth model with threshold externalities to human capital accumulation that allows for multiple equilibrium (consistent with a nonlinear treatment of education) due to the existence of increasing returns to human capital beyond a certain critical value. As a consequence economies with the same structural characteristics can exhibit different growth rates if they lie on different sides of the threshold.

Recently Philippe Aghion and several co-authors ((Philippe Aghion, Boustan, Hoxby, & Vandenbussche, 2005), (Philippe Aghion & Peter Howitt, 2005), and (Vandenbussche, Aghion, & Meghir, 2006)) have worked on the theoretical modeling and empirical testing of the importance of the different levels of education for technological change and growth based on Schumpeterian growth models. The basic idea is that less qualified workers (with education at the primary/secondary level) are more prone to imitate, whereas workers with tertiary education are more likely to become innovators, so that as a country moves closer to the technological frontier tertiary education becomes increasingly more important for growth relative to primary/secondary education. Using data for twenty-two OECD countries and the US states they confirm these predictions concluding that this type of models is the best suited to explain why

Europe lags behind the US in terms of growth – Europe spends only 1.4% of its GDP in higher education as opposed to 3% spent by the US, and only 23.8% of its population aged 25-64 has completed higher education (37.3% in the US). Interesting extensions of our work would be to use their theoretical and empirical framework to evaluate if the complementarity of the levels of education with the other technological change determinants is still supported by the data and to determine the threshold level of the distance to the frontier for which tertiary education becomes more growth enhancing than primary/secondary education (using the techniques described in the previous paragraphs).

Feasible extensions of Chapter 4 would be the use of industry-specific PPPs instead of aggregate PPPs to convert the data needed to compute TFP growth and levels into comparable units, the use of a labour input measure that takes into account differences in the quality of raw labour and the use of industry-specific education variables.

Both Chapters 4 and 5 do not consider the services industry although it accounts for about 70% of aggregate production and employment in OECD economies (see (Wölfl, 2005)) so an interesting extension would be to include the services industry in the analysis to check for the robustness of the education results[100]. The data for this industry however has the reputation of being less reliable since it faces additional measurement problems related to the independence of the quantity and price indexes used to compute the respective productivity measures (see e.g. (OECD, 2001a), (Wölfl, 2004)).

Nevertheless, it is our understanding that the inclusion of the services industry, or at least of specific services industries like transport and communications services and financial intermediation[101] in the analysis can only reinforce the role of education in productivity growth since due to its characteristics such as a greater dependence on information and communication technologies it relies more heavily on human capital for productivity growth.

A number of criticisms could also be raised against the empirical analyses that apply to most of the empirical studies on this subject and were not the focus of the work developed here.

To assess the importance of education for technological change we use empirical specifications derived from the insights of endogenous growth models that view technological change as a supply driven phenomenon, i.e. determined by the production function of new ideas whose inputs are the existing knowledge stock and human capital. Although it should be kept in mind that this assumption is not specific to our analysis but rather it is applicable to most of the existing literature in this sphere of research, an alternative analysis of technological change-driven growth that goes as far back as (Schmookler, 1966) defends that technological change is a demand driven phenomenon in the sense that only the technological problems that are deemed useful will be pursued.

[100] Despite its growing weight however, productivity growth in services has been slow in many OECD countries.

[101] That account for 20%-30% of value-added in the total economy.

The main consequence of this assumption to the endogenous growth models analysed previously is that expanding the knowledge stock and human resources devoted to R&D need not induce technological change and, consequently, output growth.

(Keely, 2002a) calls our attention to the fact that endogenous growth literature has done little effort to incorporate this idea of demand driven technological change into theoretical growth models despite the existence of some empirical support[102] to this hypothesis. To overcome this lack of interest for Schmookler's argument by theoretical growth she develops a model where the choice of technological problems to be pursued is determined by demand so that an idea is turned into an innovation with a probability less than one. It is not the existing stock of technology that determines which problems will be solved but rather their usefulness for market production and this in turn determines whether there is continuous growth. Notice however that the author does not ignore the supply-side influences on technology growth but rather highlights the complementarity between supply and demand side influences on technological change[103].

Using simulation techniques (Keely, 2002a) is able to reproduce the three stylised facts concerning the USA and Europe that were at the basis of the development of some of the most important supply-driven growth models of the 1990's, namely: the growth rate of labour allocated to the research sector has been higher than overall population growth; the growth rate of technology has been lower than the growth rate of labour allocated to the research sector; and, the growth rate of per capita income has roughly been constant. In a working paper, (Keely, 2002b) uses cross-country industry-level panel data to assess the empirical validity of Schmookler's hypothesis by estimating a two-way relationship in which capital investment influences R&D but R&D also determines capital investment, as well as considering the influence of exogenous technological opportunities. The evidence supports the existence of the three different types of effects so that critiques that Schmookler's view is incomplete are validated.

Specifically on the empirical side of the analysis a number of criticisms could also be raised that apply to all chapters. A common concern to most empirical research on education and growth is the reliability of the education data used, an issue dealt with in Chapter 2. The fact that we analyse a sample of OECD countries reduces to some extent the lack of trust in the collection of the original data but concerns about cross-country comparability and the methodologies used to construct the educational attainment series remain. Our purpose was not

102 As examples of empirical studies of Schmookler's argument, (Keely, 2002a) cites (Scherer, 1982), (Jaffe, 1988), (Kleinknecht & Verspagen, 1990), and (Geroski & Walters, 1995), as well as historical examples from the twentieth century US chemical industry, the eighteenth century British textile industry, and the fifteenth century European printing industry.

103 "An ongoing increase of research labour does not ensure an ongoing increase in technology growth. This is because there must be an ongoing increase in technological problems relative to the technology stock in order for technology growth to increase, and as resources are allocated to research labour and not to manufacturing overall investment is diminished." (Keely, 2002a), p.300.

however to propose a new methodology to construct internationally comparable education data but to use the existing ones in order to get comparable results with existing research on the education-growth link.

This thesis also does not address the issue of the quality of education, i.e. it does not take into consideration that an additional year of schooling does not provide the same amount of knowledge in all countries due to differences in, for instance, the organisation of the school system or the duration of the school year. (Hanushek & Kimko, 2000) try to correct the education stock series for the fact that they do not reflect variations in educational quality across countries using data on the scores on international assessment tests of the educational achievement of students. However, the limited number of countries that has participated in these international assessment tests and the limited number of times that they have been carried out makes the sample sizes much smaller than for average years of schooling and thus limits its applicability in international comparisons. Furthermore, they measure the quality of education received by students not by the labour force.

In this respect the International Adult Literacy Survey (IALS) that tests the skills of individuals aged between 15 and 65 over three domains of literacy (prose, quantitative and document) is a promising path. The IALS involved twenty-two countries and was carried out in 1994 and 1998. (Coulombe, Tremblay, & Marchand, 2004) use the results from the 1994 IALS to construct a human capital indicator based on literacy scores of labour market entrants for fourteen OECD countries between 1960 and 1995. The strong data requirements and limited data availability of these alternative human capital indexes are the reasons why we focus on average years of schooling measures.

The empirical analysis uses TFP growth as the measure of technological change. A lack of robustness of this research might stem from the methodology used to compute the TFP growth measure. The method used assumes perfect competition and constant returns to scale so that factors are paid the respective marginal products and, as a consequence wage income shares can be used to compute TFP growth and levels (see e.g., (R. Hall, 1990), (Barro, 1998)). The use of this methodology reflects prior empirical analysis and the objective to reassess its empirical findings on education and growth. A possible extension of this work would be to estimate TFP growth and levels as the residuals of an equation that regresses output growth on input growth instead of a growth accounting framework. In any case, for instance (Braun, 2000) computes TFP measures for the manufacturing sector and industries of G-7 countries adjusted for market power and increasing returns to scale and finds high correlation coefficients between the adjusted measures and the more conventional unadjusted ones in most industries in most countries. (Griffith, Redding, & Van Reenen, 2004) also check the robustness of their results to the use of a TFP growth measure that controls for the degree of imperfect competition by using data on the markup of price over marginal cost in individual country-industries concluding for the robustness of the results.

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