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Essays on the economics of human capital

Stefania Zotou

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Consulting Committee:

1. Nikos Benos, Assistant Professor, Department of Economics, University of Ioannina (supervisor).
2. Nikolaos Mylonidis, Associate Professor, Department of Economics, University of Ioannina.
3. Sotiris Karkalakos, Associate Professor, Department of Economics, University of Piraeus.

Defense Committee:

1. Nikos Benos, Assistant Professor, Department of Economics, University of Ioannina.
2. Nikolaos Mylonidis, Associate Professor, Department of Economics, University of Ioannina.
3. Sotiris Karkalakos, Associate Professor, Department of Economics, University of Piraeus.
4. Antonis Adam, Assistant Professor, Department of Economics, University of Ioannina.
5. Michael Chletsos, Professor, Department of Economics, University of Ioannina.
6. Spyridon Symeonides, Associate Professor, Department of Economics, University of Ioannina.
7. Claire Economidou, Associate Professor, Department of Economics, University of Piraeus.

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Contents

Introduction

Theoretical literature review

This dissertation combines the strands of literature that examine the relation between human capital in the form of education and health in a growth framework where fiscal policy plays an active role. Following Schultz (1961) and Becker (1964), we can define human capital as the set of knowledge, skills, competencies and abilities embodied in individuals and acquired through education, health, training and other investments that enhance individual productivity. Economists refer to expenditures on education, medical care and training as investments in human capital. Education and health, in fact, are considered to be the most significant investments in human capital.

Human capital has been demonstrated theoretically and empirically to contribute to higher levels of economic activity. Thus, human capital plays a key role in many growth models. This reflects the view of many researchers about its contribution in the process of economic growth. From a theoretical point of view, a classification of theoretical works arises from the different roles human capital can play in the process of economic growth. In particular, growth models can be divided into two basic categories: exogenous and endogenous growth models. Exogenous growth models include the Solow-Swan model and its extensions (augmented neoclassical models). Classical and neoclassical studies of economic growth focus on the role of physical capital. Growth, in this case, is modelled as a function of physical capital and labor inputs. Human capital plays no role in most of these models. However, input accumulation is subject to decreasing returns to scale, which result in increasing marginal costs and eventually lead to a steady-state equilibrium, where all aggregate macroeconomic variables grow at a constant rate.

The standard neoclassical growth model is developed by Solow (1956) and Swan (1956). Specifically, they consider that technological advancement increases productivity, and as a result it fosters growth. Their basic model can be expressed by using output as a function of physical capital, labor and technological change. Moreover, it is assumed that technological change is exogenous. Thus, the model attributes long-run growth to technological progress. This approach suggests that poorer economies can "catch up" with wealthy ones through higher growth rates. Countries/regions (economies) with similar labor, physical capital and technological progress should converge in terms of income and productivity. As a result, neoclassical models, do not fully explain historical rates of growth. Thus, there must be some other forces that explain changes in growth rates and the lack of economic convergence among countries.

Starting from the original Solow model, the simplest way to introduce human capital is the one suggested by Mankiw, Romer and Weil (1992). These authors augment the Solow model in order to account for human capital accumulation, by assuming that the rates of saving, population growth and technological process are exogenous. In this case, output is produced by physical capital, human capital and labor and is used for investment in physical and human capital, as well as consumption. A higher saving rate on physical and human capital leads to higher income at the steady-state, which in turn leads to a higher steady-state level of human capital, even if the share of income devoted to human capital accumulation is unchanged. Hence, the accumulation of physical capital has a larger impact on income per capita than the Solow model implies. As a result, differences in saving rates devoted to physical and human capital, as well as population growth should explain cross-country differences in income per capita.

In this direction, Solow (1999) focuses on the versatility of his one-sector growth model, in the sense that it can easily be adapted to allow for the analysis of important issues that are excluded from it, such as: increasing returns to scale, human capital and renewable natural resources. In particular, his model can accommodate increasing returns to scale, as long as there are diminishing returns to capital and augmented labor separately. Regarding human capital, the neoclassical model can accommodate its role, by using a scalar index of the stock of human capital as an additional input in the aggregate production function. So, fractions of output are invested in physical and human capital and thus, starting from any initial conditions, both types of capital as well as output eventually grow at the same rate. In this way, this model is exactly analogous to the original one. As far as renewable resources are concerned, they can be thought of as providing a technology for converting capital and labor into usable energy.

On the contrary, endogenous growth models broaden the concept of capital to include human capital. In fact, such contributions have attributed increasing importance to the accumulation of human capital and productive knowledge as driving forces of economic growth. Such approaches assume that human capital accumulation depends on the intrinsic characteristics of an economic system. Theoretical models of human capital and growth assume that knowledge and skills embodied in humans directly raise productivity and increase an economy's ability to develop and adopt new technologies.

Since human capital is related to knowledge and skills and economic growth depends upon the technological progress, economic growth is a function of human capital.

Education

Theoretical approaches examine different mechanisms through which education affects economic growth. From this point of view, endogenous growth models can be further distinguished into three subcategories: growth models with human capital accumulation, growth models featuring human capital and technological change, and growth models with human capital and threshold effects. The first two categories imply a linear relationship between human capital and economic growth (similarly to exogenous growth models), whereas the last one indicates a nonlinear treatment of human capital.

In the first category of endogenous growth models, economic growth is sustained by the accumulation of human capital. That is, human capital is considered as a direct factor of production, and its accumulation influences the growth process of the economy. In these growth models, human capital enters the production function similarly with technology in the Solow-Swan model, that is, in labor-augmenting form. Thus, such models regard human accumulation as the engine of growth.

In this context, Uzawa (1965) argues that output can be uniquely determined in terms of the existing capital stock and the quantity of labor employed in production. He assumes that all changes in technological knowledge are embodied in labor and the improvement in labor efficiency does not depend upon the amount of capital employed. He also considers that various education activities, which result in higher labor efficiency, are put together in the educational sector. The time path of the economy is determined by the specification of the allocation of labor between two sectors (the educational and the productive sector) and the division of output between consumption and investment. If the initial capital-labor ratio in efficiency units is equal to its level in the steady-state, optimal growth is achieved by allocating labor and output such that the rate of increase in labor efficiency equals the rate of increase in the capital-labor ratio.

Following Uzawa's approach, Lucas (1988) analyzes a closed economy with a given rate of population growth, where physical capital is accumulated and utilized in the context of a neoclassical production technology, while human capital enhances the productivity of both labor and physical capital. If labor mobility is introduced, everything hinges on whether the effect of human capital is internal (effect of an individual's human capital on his/her own productivity) or external (the average level of human capital contributes to the productivity of all factors of production). Only in the latter case the wage rate at any skill level increases with the wealth of the country in which it is employed. If labor is mobile, it will move from poor to wealthy countries. Moreover, Lucas (1988) refers to a two-good system, in which human capital accumulation is taken to be specific to the production of particular goods and is acquired through on-the-job training or learning-by-doing, while population growth is constant. If different goods are taken to have different potentials for human capital growth, the comparative advantage will determine which goods will be produced and dictate each country's rate of human capital growth. Therefore, sustained differences in growth rates across countries can be linked to each country's initial human capital level.

Focusing on human capital investment through formal schooling, Glomm and Ravikumar (1992) develop an Overlapping Generations (OLG) model with heterogeneous agents living for two periods. Each agent's human capital depends on the parent's stock of human capital, time spent in school and school quality. Under the public education regime, a government levies taxes and uses tax revenues to provide public education. In the private education regime, individuals allocate their income between the quality of education, determined by education expenditure passed on to the offspring, and consumption. Thus, income depends on the stock of human capital of parents and the quality of education received by the children. However, time devoted to human capital accumulation in a private education economy is higher than that in the public education economy and hence per capita incomes are higher unless initial income inequality is sufficiently high.

In the second category of endogenous growth models, economic growth depends on the existing stock of human capital, which can be useful for generating new knowledge or imitating and adopting foreign technologies. Such models place investment in Research and Development (R&D) activities at centre stage in accounting for technical progress. As a result, human capital enters into these models as a catalyst of technological progress rather than as an independent source of growth. By assuming that a higher rate of innovation is associated with a higher stock of human capital, this approach suggests that an increase in the stock of human capital has positive effects on the growth rate of productivity and therefore on income growth.

Despite the productivity-enhancing role of human capital, an alternative perspective is provided by Nelson and Phelps (1966). According to them, the major role of human capital is to enable workers to adapt to change and introduce new technologies. Specifically, they consider two models of the process of technological diffusion and the role of education, which assume that technical progress is labor augmenting. In addition, they introduce the notion of the theoretical level of technology (a measure of the stock of knowledge or techniques available to the innovators), which advances exogenously. The first model states that the time lag between the creation and adoption of a new technique is a decreasing function of educational attainment. As a result, ceteris paribus, the returns to education are greater, the faster the theoretical level of technology advances. The second model assumes that the rate at which theoretical technology improves depends upon educational attainment and the gap between the levels of the theoretical technology and technology used. So, the rate of return to education is greater, the more technologically advanced is the economy. Thus, growth depends on the existing stock of human capital, which can be useful for imitating and adopting foreign technologies.

This concept was extended by Romer (1989) to the advancement of new technologies. He refers to a closed economy where each agent has an endowment of physical skills, educational skills and scientific talent. The aggregate output is expressed as a function of labor, educational inputs, years of experience, capital used in the production of goods and a list of designs or goods in existence. The production technology for creating new designs depends on the scientific and educated labor used in this process, the stock of basic science and the stock of existing designs. Moreover, the production of the basic science depends on the amount of scientific talent devoted to this activity and the intermediate inputs available. However, what matters for output growth is growth in the production technology for creating new designs. If this is constant, the economy will reach a stationary state in per capita income, because of diminishing returns to capital accumulation. Therefore, human capital affects significantly the subsequent rate of investment, and indirectly, the rate of growth.

A different growth model has been specified by Benhabib and Spiegel (1994), which assumes that the growth rate of Total Factor Productivity (TFP) depends on a nation's human capital stock. In particular, they allow for technological "catch-up", not to an exogenously growing theoretical level of knowledge, but to the technology of the leading country. As a result, human capital has a negative effect on growth, since TFP growth depends on two factors: the level of human capital, reflecting the effect of domestic endogenous innovation, and an interaction factor that involves the level of human capital and the technological lag of a country behind the leader, to capture the "catch-up" effect. The obtained results favour catch-up over endogenous country-specific technological progress as the channel through which human capital accumulation affects productivity growth. Therefore, human capital stock in levels plays a role in the determination of per capita income growth. Moreover, they examine a different channel through which human capital contributes to growth. Human capital may encourage accumulation of other factors necessary for growth, particularly physical capital.

Therefore, the growth literature emphasizes the role of human capital in driving technical progress. Theoretical support for this assertion is strong in the literature. Adjusting human capital for quality has received less emphasis, however. Such approaches study the effect of the quality of human capital on productivity growth and indirectly on income growth. The role of education in promoting economic growth, with a particular focus on the role of educational quality, is examined by Hanushek, Jamison and Woessmann (2008). Considering the quality of education, measured by cognitive skills, dramatically alters the assessment of the role of education in economic development. The analysis suggests that the quality of education, measured by the knowledge students gain as depicted in tests of cognitive skills, is substantially more important for economic growth than the mere quantity of schooling. Economic institutions appear to interact with the effect of educational quality on economic growth. The institutional framework of a country affects the relative profitability of piracy and productive activity. Both quality of the institutional environment and quality of education are important for economic development. Furthermore, the effect of educational quality on growth is significantly larger in countries with a productive institutional framework, so that good institutional and educational quality can reinforce each other. But cognitive skills have a significant positive growth effect even in countries with a poor institutional environment. Thus, the quality of education, measured on an outcome basis of cognitive skills, has powerful economic growth effects.

In the third category of endogenous growth models, human capital exerts a nonlinear influence on economic growth. In particular, there could be a threshold level of human capital below which poorer countries do not catch up with the richer ones. For this reason, various models that emphasize threshold effects and multiple equilibria, are consistent with a nonlinear treatment of human capital. In these models, even if the notion of threshold refers to the stock of human capital, the accumulation process of human capital is fundamental to achieve this threshold level.

A seminal work in this field is conducted by Azariadis and Drazen (1990), by introducing neutral technological externalities in their growth model, where social returns to scale are increasing. Technological externalities mean that private rates of return on human capital investment depend on the average quality of existing human resources. They show that in the absence of a mechanism leading to a threshold effect (radical difference in dynamic behaviour arising from local variations in social returns to scale), the resulting increasing returns need not yield multiple locally stable steady states. Alternating increasing and decreasing returns may do so. Moreover, they refer to threshold externalities that may arise in human capital accumulation. That is, the existence of increasing social returns to scale becomes pronounced, when economic state variables attain critical mass values. In fact, they use another model and focus on labor-augmenting externalities that relate private rates of return on human investment to current and past values of aggregate human capital. Such externalities can induce multiple balanced growth paths as stationary equilibria. They conclude that multiplicity is due to increasing social returns to scale in the accumulation of human capital.

In another approach, Growiec (2010) argues that human capital is embodied in people of different generations whose lifetimes are finite. He also examines human capital externalities by assuming that the increments to individual human capital are proportional to a constant returns to scale Cobb–Douglas bundle of individual and average human capital in the society. Average human capital may increase due to schooling and on-the-job training, and decrease due to births and deaths, so its overall evolution can go in either direction. The prediction of long-run growth is rescued by introducing externalities from aggregate individual human capital accumulation. There are two alternative interpretations for these externalities: pure knowledge spillovers and public education spending. In the second case, if the human capital accumulation technology requires physical capital inputs, public education spending creates externalities because physical capital will be provided in proportion to the total (or average) human capital in the population. Such externalities must be sufficiently strong, however, to generate the required result. Growiec calculates a precise threshold value for the minimum magnitude of such externalities such that human capital accumulation becomes capable of driving aggregate growth.

Health

Growth theorists have also studied the impact of a form of human capital investment in addition to education, namely health, on economic growth. Such models are examined separately and can be divided into three groups: growth models with health and human capital accumulation, growth models with health and human capital stocks, as well as growth models with health and threshold effects. According to all these approaches, human capital accumulated through education and health, is a fundamental determinant of economic growth.

Poor health may lead to a reduced rate of human capital accumulation, and thus, may hamper economic growth. From this point of view, several studies have focused on the direct effect of health on economic growth. Initially, Weil (2007) examines the role that health differences play in explaining income differences between rich and poor countries. He focuses on what he calls the proximate or direct effect of health. In particular, he examines the effect of better health in enabling workers to work harder and more intelligently, holding constant the level of physical capital, education and the quality of institutions. He uses an aggregate production function that associates output with physical capital, a country-specific productivity term, and a labor composite input. The last term is determined by human capital per worker in the form of education and health, as well as the number of workers. The wage earned by a worker is a function of his own health and education, as well as the national wage of the labor composite. Moreover, he constructs estimates of the return to health and shows that health is an important determinant of income differences among countries. Health, however, is less important than education and physical capital (especially the latter) as a determinant of income differences among countries.

From another point of view, Osang and Sarkar (2008) examine an economy with human capital-led endogenous growth, where lifetime uncertainty reduces private incentives to invest in physical and human capital. They use a three-period OLG model in which survival of an individual in the third period is uncertain. The probability of survival depends on public health spending. To the extent that good (poor) health and consequent higher (lower) longevity generates (dis) incentives for private human capital accumulation, public health expenditure plays an important role in the generation of human capital, thereby affecting long-run growth. However, the more the government spends on health, the less it can spend on public education, adversely affecting future human capital. Differences between public spending on health and education on one side, and public and private spending on education on the other, constitute the two fundamental trade-offs that generate important economic growth consequences.

In addition, many theoretical studies suggest that an improvement of health status can cause higher incomes by promoting technical progress and dissemination of new health technologies. In this framework, some representative works are presented. With regard to the impact of the stock of health on economic growth, Gyimah-Brempong and Wilson (2004) use an endogenous growth model. Per capita income is a function of the stocks of physical capital, health human capital, technology and education. Health human capital stock is the sum of the stock of health human capital in the previous and current periods. Additions to the stock of health human capital depend on the amount of resources devoted to health care and the efficiency with which such expenditure is converted into health stock. The quantity of resources devoted to health is a product of the proportion of income devoted to health care and the income level. Assuming no depreciation, the stock of health human capital is associated with its stock in the previous period and the productivity of health expenditure. The ability to transform health expenditure into health stock depends on health human capital stock. The income growth equation relates per capita income growth with the stock of health human capital in the previous period, the stock of physical capital, technology and education.

While a range of micro studies demonstrate the importance of health for individual productivity, they do not resolve the question of whether health differences are at the root of the large income differences observed, because they do not incorporate general equilibrium effects. The most important general equilibrium effect arises because of diminishing returns to effective units of labor, for example, because land and/or physical capital are supplied inelastically. In the presence of such returns, micro approaches may exaggerate the aggregate productivity benefits from improved health, particularly when health improvements are accompanied by population increases.

In this direction, Acemoglu and Johnson (2007), investigate the effect of life expectancy at birth on economic growth. Labor and land are supplied inelastically. Economy faces a constant returns to scale aggregate production function, where output is related to capital, the supply of land and effective units of labor given by human capital per person multiplied by total population. They also assume that life expectancy may increase output per capita through a variety of channels, including more rapid human capital accumulation or direct positive effects on TFP. In addition, they argue that higher life expectancy naturally leads to larger population. Thus, an increase in life expectancy will raise income per capita if the positive effects of health on TFP and human capital exceed the potential negative effects arising from the increase in population because of fixed land and capital supply. They find that an increase in life expectancy leads to an increase in population and a smaller increase in GDP.

There could also exist a strong nonlinearity in the relation between income and health, implying threshold effects of health in the process of economic growth. In this context, de la Croix and Licandro (1999) develop an OLG model with uncertain lifetime. At each point in time, there is a continuum of generations indexed by the date at which they are born and life expectancy is independent of age. Individuals have to choose the length of time devoted to schooling before starting to work. There is, also, a unique material good for consumption. Moreover, they assume perfect insurance markets and wages depending on individual human capital, which is a function of the time spent at school and the average human capital at birth. Total output is given by the aggregate human capital stock, which is computed from the capital stock of all generations currently at work. Thus, the total effect of an increase in life expectancy results from combining three factors: agents die later on average and the depreciation rate of aggregate human capital decreases, agents tend to study more because the expected flow of future wages has risen and the human capital per capita increases, and the economy consists of more old agents who did their schooling a long time ago. The first two effects have a positive influence on growth, but the third effect has a negative influence. Their results show that, when life expectancy is below a certain threshold, or when the discount rate is above a certain threshold, the former two effects dominate. Therefore, the effect of life expectancy on growth is positive for economies with a relatively low life expectancy, but is possibly negative in more advanced economies.

In a different analysis, Deaton (2003) explores the theoretical basis for a connection between inequality and health, among poor as well as rich countries. He refers to the absolute income hypothesis, in order to emphasize that among the poorest countries, it is income that matters for health, not income relative to other peoples' incomes or income inequality. This hypothesis explains how average income and income inequality affects population health at different levels of development. The effects of per capita income mirror those of individual income, and become less important the richer is the country. As a result, as a country becomes richer and average income rises, the effect of income inequality on population health becomes more important relative to the effect of average income on population health. Furthermore, he argues that health depends on income relative to average incomes of one or more reference groups (relative income hypothesis). The argument is that if health is lower for those whose income is relatively low, then higher inequality makes the poor even poorer in relative terms, and so worsens population health. This theory also, has three important implications. Within groups, health is a concave increasing function of income, inequality does not matter for individual health conditional on an individual's income within the group and groups' average health depends positively on group income and negatively on group income inequality. Thus, while income has a nonlinear effect on health and there is no direct effect of income inequality on health, redistribution of income towards the poor improves their average health by more than the loss of health among the rich. People who are income-poor are also health poor, so that looking at well-being as dependent on both income and health reveals wide disparities between rich and poor.

According to such theoretical approaches, the channels through which human capital may affect output growth include direct productivity effects and indirect effects due to externalities, technological adoption or enhanced productivity of R&D activities. In addition, higher human capital is associated with a higher investment rate. Thus, part of the positive effect of human capital on growth is transmitted via increased investment in physical capital, rather than through enhanced productivity of labor. As far as health is concerned, it constitutes an important form of human capital, the improvement of which, ceteris paribus, enhances workers' productivity, hence wages and earnings, as healthier people are better workers, work harder and longer. In this way, good health leads directly to higher income. Health, also, contributes to economic growth through its indirect effects on labor supply and market participation, investments in human capital, savings available for investment in physical and human capital, individual fertility choices and population growth. Thus, growth theories as a whole incorporate human capital not only in terms of education, but also health as important determinants of economic growth.

Empirical literature review

Growth empirics attempt to empirically test for the validity of the aforementioned theoretical models. In most instances, these studies use cross-sectional data for a large number of countries. Fewer studies use time series or panel data for a smaller group of countries (e.g. OECD). These studies can be further classified to two main categories: growth accounting exercises which split the growth of an economy into the contribution of various inputs, such as labor and human capital, and growth regressions, which exploit cross-country variation to estimate the relationship between education and growth. Overall, the results provide controversial evidence on the growth effects of human capital. In this dissertation, however, we focus on growth regressions, leaving the analysis of growth accounting exercises for future research.

Cross-sectional studies try to explain the differences in growth rates across countries or regions. One of the earliest studies in this strand of empirical literature is provided by Romer (1989), who finds via OLS (Ordinary Least Squares) and IV (Instrumental Variables) a significant and positive effect of adult literacy rates on growth across 112 developed and developing countries from 1960 to 1985.

Then, Barro's (1991) OLS estimates for 98 developed and developing countries show that a country's growth rate is significantly and positively related to school enrolment rates and adult literacy rates. Instead, the student-teacher ratio for primary schools appears to have a negative effect on economic growth. From a different point of view, Murphy, Shleifer and Vishny (1991) show using OLS for 91 developed and less developed countries, that the allocation of talent, as proxied by enrolment in engineering and law over total college enrolment, is positively and negatively associated with growth respectively.

Panel approaches on the link between human capital and economic growth examine both the cross-section differences in growth as well as the dynamic behavior of the performance over time. In this context, Bassanini and Scarpetta (2001) using the PMG (Pooled Mean Group) estimator across 21 OECD countries, indicate that an increase in years of schooling is associated with a rise in per-capita GDP. Moreover, Dessus (2001) relies mainly on GMM (Generalized Method of Moments) over 83 developing areas and demonstrates that years of schooling and pupil-teacher ratios have a significant impact on growth.

In a different approach, Sterlacchini (2008) provides results from correlation matrices arising from the entire set of European regions, which show that R&D, and especially higher education, exert a significant impact on GDP growth. While the educational variable is significant for the whole regional set over 1995-2002, the impact of R&D is significant only for the regions that are above a given threshold of per capita GDP. Moreover, remarkable disparities arise among the regions of different countries. In particular, only within North European countries there is a significant relationship between regional growth and the intensity of R&D and higher education.

Furthermore, a regional production function model is developed by Benos and Karagiannis (2010). Their GLS (Generalized Least Squares) and GMM estimations for 51 regions of Greece during 1981-2003 show that enrolment rates have a positive effect on growth, while a higher student-teacher ratio exerts a negative influence on growth. Also, the number of medical doctors fosters growth, whereas hospital beds bear an insignificant impact on growth. Moreover, they provide strong evidence of differential effects of education and health among regions. Specifically, they find a positive impact of education on growth in high-income regions, while the evidence is weaker for low-income regions. On the contrary, health appears to be more important for growth in poor regions relative to rich ones.

Time series approaches examining the nature of the relationship between human capital and economic growth refer to a particular country and therefore, try to explain the country-specific differences in growth rates throughout time. In a time series framework, Lee (2000) applies OLS and finds that schooling years and enrolment rates have a positive effect on economic growth in Korea, while student-teacher ratios affect negatively growth. Later, Odularu and Olowookere (2010) find a positive impact of expenditure on education on real GDP in West Africa.

Similarly, Dauda (2010), using data for Nigeria, shows a positive effect of total expenditure on education on real GDP. Turning the focus on the impact of both education and health on economic growth, Owolabi and Okwu (2010) show that government’s expenditure on health and education, as well as primary and secondary enrolment rates exerts a positive effect on economic growth in Nigeria, while tertiary enrolment rates have a negative contribution in economic growth.

The aforementioned studies are often subject to a number of methodological and conceptual problems, such as data quality, the measurement of human capital, systematic differences in parameters across countries or regions, correlation with omitted variables, parameter heterogeneity (systematic differences in the coefficient of education or health across countries and regions within countries), reverse causality (running from growth to education or health) and non-linearity (non-linear relationship between education or health and growth).

Overall, these studies provide contrasting evidence regarding the impact of education on growth. Effects are found to be positive, statistically insignificant and sometimes even negative. Many empirical works, though, indicate that education affects positively and significantly the accumulation of human capital, and thus, can foster economic growth.

In addition, as plenty of empirical works focus on health as a human capital component, these studies are examined as a separate category. Such works include cross-sectional, time-series as well as panel approaches. All approaches again are divided into growth accounting and growth regression exercises. Health proxied by alternative indicators has appeared in a number of cross-country empirics, which examine its effect on the rate of growth. In particular, several papers include health variables in growth exercises in an effort to incorporate direct or indirect effects on economic growth.

In a cross-country framework, Chakraborty (2004) examines the impact of education and health on growth for 95 developed and developing countries. In particular, he regresses GDP per worker growth on enrolment rates and initial income over 1970-1990. The initial stock of educational capital significantly increases per capita growth. Adding another explanatory variable, namely the life expectancy, the results are striking. Schooling ceases to be significant, while GDP per worker and life expectancy have the correct signs (negative and positive respectively) and continue to be statistically significant.

In a different approach, Aghion, Howitt and Murtin (2010) investigate the relationship between health and growth for 96 developed and developing countries. In particular, they employ both OLS and IV estimators over 1960-2000. The obtained results imply a negative influence of health measured by the average child and adult mortality rates on per capita GDP growth. On the contrary, choosing life expectancy rather than mortality indicators for health, they show that life expectancy is significantly and positively correlated with per capita GDP growth. Moreover, the IV approach validates the OLS results, namely that of a significant and positive impact of initial life expectancy on growth.

Moreover, panel approaches treat health as a human capital component and use either growth accounting or growth regressions. In a linear specification, Cole and Neumayer (2006) use an aggregate production function, which relates real GDP with TFP, physical capital, human capital and labor force across 52 developed and developing countries. TFP is expressed as a function of health (proxied by malaria, malnutrition and access to safe water), trade openness, inflation rate and the share of agriculture in GDP. At first, he reports fixed effects and random effects results. Because of the potential endogeneity of health, though, he also employs IV as well as 2SLS (Two-Stage Least Squares) estimates. The findings show that poor health has a strong negative impact on TFP. The share of agriculture in GDP is also a negative determinant of TFP, whereas trade openness and inflation do not affect significantly TFP. Therefore, a key mechanism through which health affects growth is via TFP, as poor health can reduce aggregate productivity and thus, growth.

A growth regression framework is employed by Bose et al (2007) in a panel set-up of 30 developing countries over the 1970s and 1980s. They estimate their model by the seemingly unrelated regression method and show that initial human capital proxied by enrolment rates is found to have a negative effect on the growth rate of real GDP per capita, with this sometimes being significant. Also, life expectancy has a negative, but insignificant impact on growth.

Some other studies use time-series data and explore the linkage between health and economic growth. The long-term relationship between health and economic growth in Pakistan is analyzed by Akram et al (2008). Per capita income growth is a function of the stocks of physical capital, health human capital, education human capital and a vector of other variables that include technology and environmental variables. In order to determine the linkage between the variables of interest, different health indicators have been used in this approach. In particular, life expectancy and infant mortality are employed as health input indicators, whereas the major output variable adopted is health expenditure. The dependent variable of this model is per capita GDP and is used as a proxy for economic growth. Johansen cointegration test results indicate that in the long-run, public health expenditures have a positive, but insignificant impact on per capita GDP. Nevertheless, other health status indicators like life expectancy, mortality rate and population per bed exert a significant impact on growth. However, in the short run these effects are negligible. Thus, health is only a long-run phenomenon and in the short-run there is no significant relationship between health variables and economic growth.

Furthermore, Nketiah-Amponsah (2009) examines aggregated and disaggregated expenditure on economic growth in Ghana from 1970 to 2004. In particular, he regresses the rate of change of real GDP on the rate of population growth, the rate of growth of real exports, the ratio of investment to GDP (both private and public), the rate of change of real government expenditure, as well as on a political instability dummy, a governance index and the shares of total expenditure on infrastructure, education and health. The study's findings show that expenditures on health promote growth, while those on education have no significant impact in the short-run. Moreover, education, as well as health fosters economic growth in the long-run.

Overall, these empirical results incorporating direct and indirect effects on economic growth, suggest a positive impact of health on human capital accumulation and thus, on growth rates. In this way, by taking empirical studies as a whole, the majority of them indicate that education as well as health affect positively the accumulation of human capital, and therefore, can promote economic growth.

Turning the focus on the structure of the particular thesis, given these contradictory theoretical and empirical approaches, I begin with a theoretical and empirical research on the interaction between education, health, and economic growth. Regarding theory, there is a large literature on human capital formation through education and on-the-job training dating back to the 1960s with the work of Becker (1964) and others (Nelson-Phelps, 1966, Lucas, 1988, Benhabib-Spiegel, 1994). More recently, there has been a focus on health as a form of human capital (Van Zon & Muysken, 2001; Bloom et al., 2004, Weil, 2007). At first, I wrote a survey of these literatures, in which I provided a classification of the various works, so that the reader can understand in a clear and concise way the similarities and differences between as well as within the branches.

In addition, I combine these three strands of literature in my work. My framework incorporates the following assumptions: a) education enhances human capital accumulation, therefore output growth; b) health status affects the probability of future survival, therefore the returns to human capital accumulation and output growth; c) health is affected by public health spending, private health spending and education; d) output production is influenced by human capital and physical capital; e) government collects tax revenues and conducts expenditures on education, health and R&D. The aim of my research is to compare the decentralized equilibrium with the equilibrium, where the social planner maximizes the welfare of the representative household. In this context, I study the optimal level of public spending assuming balanced budget, as well as the optimal composition of expenditures on education, health and R&D. The analysis gives new insights into the relation between education and health in a growth framework, where fiscal policy plays an active role.

Regarding empirics, in Chapter 1, I employ meta-analysis of the effect of education on economic growth including all relevant empirical studies at the macroeconomic level. I apply recently developed meta-analytic methods to examine if there is a genuine empirical effect of education on growth accounting for publication selection bias. Also, I investigate if there is systematic heterogeneity of this effect according to various factors, e.g. the education variable and the type of data (cross-section, time-series or panel) used in the analyses. Meta-analysis is the most appropriate way to summarize the empirical literature on the subject and explain the wide variation in research findings. Conventional reviews can not identify and account for publication bias, since authors make idiosyncratic choices about the studies they include, give emphasis or omit (Groot et al., 2000, Stanley et al, 2008, Doucouliagos & Stanley, 2009). This methodology has not been employed before in this branch of empirical literature. I investigate the impact of several factors on the variation of estimates of the growth impact of education. My MRA analysis produces interesting results, which are robust to different estimators, the inclusion of various controls for the quality of research outlets and the presence of outliers in the data set. In particular, I show that there is substantial publication selection bias towards a positive impact of education on growth. Once I account for this, I do find evidence of a genuine growth effect of education. The variation in reported estimates is attributed to differences in education measurement and study characteristics, mainly model specification as well as type of data used, and the quality of research outlets where studies are published, e.g. academic journals vs. working papers.

Afterwards, in Chapter 2, I employ panel unit root and panel cointegration techniques (Levin, Lin & Chu, 2002, Breitung, 2000, Im, Pesaran & Shin, 2003, Maddala & Wu, 1999, Pedroni, 1995, 1997, 1999) to study the relation between output growth, TFP growth, labour productivity growth on the one hand and physical capital, education, health as well as R&D on the other, using state-level data for the US (Bronzini & Piselli, 2009, Pereira & Aubyn, 2009). I apply multiple tests in order to check the robustness of the results. This way, I examine the possible existence and strength of short-run and long-run relationships between the variables mentioned above. If there are long-run relationships between the variables, I also estimate the speeds of adjustment to long-run equilibrium following a disturbance through estimation of error correction models applying alternative estimation methods (Pesaran & Smith, 1995, Pesaran, Shin & Smith, 1999). The obtained findings suggest that labor, private capital and educational human capital exert a positive and significant effect on state income. In contrast, the income effect of public capital stock is negative.

Finally, in Chapter 3, I use spatial econometric methods to study the probability of US states falling into a specific income class depending on their characteristics, e.g. human capital, physical capital, proximity to other regions with regard to geographic, social and economic characteristics etc. (Fingleton, 2004, Reggiani & Nijkamp, 2006, Vaya et al., 2004, Fujita et al, 1999; Fingleton & Lopez-Bazo, 2006). The thresholds separating the income classes are determined so that these classes include approximately the same number of states. The emphasis is on the role that different types of spillovers (geographic, social and economic) have on the economic status of the US states. Specifically, the relative strength of such spillovers is examined in the process of clustering of US states in various income classes. This has serious implications for US policy towards regional convergence, since it uncovers the factors determining the relative income position of states, therefore the most effective way to boost development of the poorest states and contribute to regional convergence, which is a major goal of the US set out by its founding treaties. The results suggest that education and health expenditure are the main determinants for improving longevity, whereas smoking seems to bear a strong negative influence. For robustness purposes, I also use health spending as well as education criteria, apart from the geographical ones. In the first case, states with similar health expenditure are "neighbors" and affect in turn positively the life expectancy process, whereas in the second one, the spatial correlation is insignificant, thus education neighbors do not affect life expectancy.

Chapter 1: Education and Economic Growth: A Meta-Regression Analysis

1.1. Introduction

The importance of human capital for economic growth has been an extremely debated topic. Following Schultz (1961) and Becker (1964), we define human capital as the set of knowledge, skills, competencies and abilities embodied in individuals and acquired through education, training, medical care and experience. Education is considered as one of the most significant human capital investments. It plays a vital role in the process of economic growth and a significant amount of research has been devoted to the education-growth nexus.

From a theoretical point of view, there is an important distinction between neo-classical and endogenous growth theories regarding the linkage between human capital and economic growth. The former argue that a one-off permanent increase in the stock of human capital results in a one-off increase in the economy's growth rate. On the contrary, new growth theories argue that the same one-off rise in human capital causes a permanent increase in growth. The social benefits of education are much greater in the latter case (Sianesi and Van Reenen, 2003).

Theoretical contributions emphasize different mechanisms through which education affects economic growth. First, education increases the human capital of the labor force, which increases labor productivity and transitional growth towards a higher equilibrium output level. Second, in endogenous growth theories, education increases the innovative capacity of the economy, knowledge of new technologies, products and processes and thus promotes growth (Hanushek and Woessmann, 2008).

From an empirical point of view, the macroeconomic literature on the relationship between education and economic growth attempts to test empirically various model specifications. Usually, these empirical approaches employ cross-section data. Other studies adopt time-series analysis for small groups of countries (e.g. OECD), where data quality is better. Finally, some research combines cross-section data with time-series information using panel datasets. However, the impact of human capital on economic growth remains controversial, due to a number of conceptual and methodological problems, such as the measurement of human capital and growth, as well as differences in parameters across countries or regions.

In my opinion, the most important issue is education measurement. Ideally the best measures would be based on education output, but they are very difficult to obtain, so input measures are employed. These use information on formal education attainment, ignoring on-the-job training, experience and learning-by-doing, usually they do not account for education quality and focus on academic education, overlooking vocational education. Moreover, data quality varies widely across countries, implying measurement error, especially for changes in education, which may severely bias estimates. This chapter surveys the empirical literature on the education-economic growth relationship. I account for differences in empirical findings due to the use of all available education (quantity and quality) variables and I am fully aware that, being imperfect proxies, they all suffer from weaknesses. However, this is the only way to conduct a quantitative review of the education-growth literature.

In particular, I provide a quantitative review of the empirical literature on the relationship between education, not human capital, and economic growth. In this framework, I make clear the distinction between human capital and education and my focus on the latter. Since, resolution of theoretical debates requires empirical analysis and single empirical study can not resolve a theoretical debate, I employ the method of meta-analysis. Meta-analysis refers to the statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings.

Given the diversity of findings on the link between education and growth, I conduct meta-regression analysis (MRA). MRA is a subset of meta-analysis. Meta-analysis combines and integrates the results of several studies that share a common aspect so as to be combinable in a statistical manner (Harmon et al, 2003). MRA is a quantitative literature review of the estimates obtained from previous regression analyses and attempts to explain the variation in their results (Stanley and Jarrell, 1989). It aims at explaining the excess study-to-study variation typically found in empirical results and investigates the presence of publication selection bias (Stanley, 2005).

Publication bias arises when editors, reviewers and researchers prefer to report findings, which are statistically significant and/or satisfy certain theoretical expectations (Doucouliagos et al, 2005, Stanley, 2008). As a result, it biases the literature's average reported effect away from zero. An additional advantage of MRA is that it allows the researcher to include aggregate data, e.g. data on aggregate labor supply that can not be included in individual studies (Groot and Maassen van den Brink, 2000). MRA allows me to examine factors that are likely to explain the heterogeneity of findings in the education-economic growth literature and the potential impact of study characteristics on the estimated relationship between education and growth.

Different empirical results may either reflect sampling errors or bias, mistakes in the analysis, or reveal true differences in the population that are reflected by the analyzed sample. Meta-regression analysis (MRA) enables to identify those issues, thus providing a quantitative overview across previous findings that allow identifying "true" growth effects as well as the tendency to preferably report statistically significant results. Moreover, MRA provides a setting to identify important study characteristics such as analyzed country, time span or population, as well as employed data sets and econometric estimators that drive heterogeneity in reported results.

As a consequence, I provide evidence that different measures of education give rise to different coefficients of the size effect of education on growth. Moreover, the variation in empirical estimates can be partially explained by the type of data, model specification, estimation methodology, and whether a particular study has been published or not in an academic journal, a journal listed in the "best" journals listed in Mamuneas et al (2010) and ESA (Economic Society of Australia, 2008).

1.2. Review of the literature

The empirical literature starts with cross-section studies. Two of the earliest works have been those by Romer (1989), and Azariadis and Drazen (1990), who find that literacy is positively associated with growth. The former uses data on 112 economies for 1960-1985 and the latter on 71 low- and middle- income countries during 1960-1980.

Barro (1991) shows that growth is positively related to primary and secondary enrollments and negatively associated with student-teacher ratios in 98 countries for 1960-1985. Murphy et al. (1991) report a positive relation between growth and primary education as well as engineering enrollments and a negative one between growth and law school enrollments in 91 countries for 1970-1985. Levine and Renelt (1992) also suggest a positive, though non-robust, link between primary, secondary enrollment as well as literacy rates and growth in 1960-1989 and 103 countries, while Mankiw et al. (1992) find a positive relationship between growth and working-age population in secondary school for 1960-1985 in 121 countries. However, Benhabib and Spiegel (1994) reveal that growth in schooling years and literacy rates are not growth-related, but schooling years in levels display a positive association with growth in 78 economies for 1965-1985. According to Durlauf and Johnson (1995), there is positive nexus between growth and working-age population in secondary school only for intermediate initial income/low initial literacy countries and high initial income countries in 1960-1985 for 119 countries. Moreover, Lee and Lee (1995) report a positive growth influence of secondary school test scores during 1970-1985 in 17 countries. Gemmell (1996) concludes that growth is positively associated with labor force education attainment in 98 countries for 1960-1985. Collins and Bosworth (1996) find the same relationship using schooling years for 1960-1994 in 88 countries. On the contrary, Bloom et al (1998) reports an insignificant association of secondary schooling years and growth in 77 countries for 1965-1990. Temple (1999) reveals a positive schooling-growth relationship in 1965-1985 and 78 countries.

Furthermore, Hanushek and Kimko (2000) show that labor force quality measured by mathematics and science test scores is growth-enhancing, while schooling years are not growth determinants for 1960-1990 in 80 countries. Bils and Klenow (2000) conclude that the cross-country schooling-growth association reported in the literature does not primarily reflect the growth effect of schooling, but may partially due to the impact of growth on schooling using enrollments for 93 countries in 1960-1990. Ranis et al. (2000) find a positive literacy-growth relationship for 1970-1992 in 79 LDCs, while Krueger and Lindahl (2001) show that schooling years have no growth impact, when estimated with high frequency changes (i.e. five years), but a strong positive effect over periods of 10 or 20 years in 110 countries for 1960-1990. Kalaitzidakis et al. (2001) find a nonlinear schooling years-growth association in 93 economies during 1960- 1990, while Pritchett (2001), an insignificant growth influence of schooling years in 91 countries for 1960-1987. Moreover, Knowles et al (2002) show a positive relationship between female schooling years and growth in 1960-1990 and 73 countries. Furthermore, Bosworth and Collins (2003) find a stronger positive correlation between growth and schooling years than between growth and change in schooling, as well as a positive correlation with education quality measured by scores in mathematics and science tests in 84 countries during 1960-2000. Papageorgiou (2003) provides evidence for a positive role of schooling years in growth in 80 countries during 1960-1987. Chakraborty (2004) shows that secondary enrollments exhibit a positive relation with growth, but not jointly with initial life expectancy, in 94 countries for 1970-1989. Finally, Lee (2010) reports a positive growth-schooling years relation, in 75 countries during 1960-2000.

Panel data analysis becomes common later than cross-section analysis due to the availability of more complete data sets. Barro (1996, 2001) shows that male secondary and higher schooling years are positively related to growth for 91 countries in 1965-1990 and 84 countries in 1965-1995 respectively. However, these relations weaken considerably, once growth-promoting test scores are incorporated in the regressions. Barro and Sala-i-Martin (2004) confirm the positive schooling-growth nexus, but in the presence of scores, which exert a highly significant positive growth impact, male upper-level schooling becomes insignificant in 1965-2000 for 87 economies. Bassanini and Scarpetta (2001) find that growth is positively associated with schooling years in 21 OECD countries for 1971-1998. Appiah and McMahon (2002) show that the primary/secondary enrollments-growth association is not significant in 52 African countries during 1965-1990. Furthermore, Gyimah-Brempong et al. (2006) find a stronger association between growth and tertiary schooling than primary and secondary schooling years in 34 African countries during 1960-2000. Keller (2006) shows a positive relation between secondary education enrollments as well as primary education expenditure and growth in 40 Asian countries during 1971-2000. The opposite holds for secondary as well as tertiary education spending. Siddiqui (2006) finds that schooling years display a positive relation with growth, whereas schooling growth is not related to output growth in five South Asian economies in 1960-2000. Female and male education are associated with growth positively and negatively respectively, while current education spending is positively related to growth.

Bose et al. (2007) find a positive growth impact of government total education expenditure and education investment in 30 LDCs during 1970-1990, while school enrollments inhibit growth. Hanushek et al. (2007), Hanushek and Woessmann (2008, 2011) show that schooling quantity (schooling years) has a strong positive association with growth, which becomes insignificant once education quality (mathematics, science and reading test scores) is considered in 62, 50 countries respectively during 1960-2000. The latter has a robust positive relation with growth. Cohen and Soto (2007) show that growth estimates of schooling are positive for 1960-2000 in 95 national economies. Sterlacchini (2008) reports a positive relationship between growth and population with tertiary education in 197 NUTS II EU regions during 1995-2002. Baldacci et al (2008) find that primary and secondary enrollments are positively related to growth in 118 LDCs for 1971-2000.

Costantini and Monni (2008) find a negative secondary enrollments-growth relationship for 1970-2003 in 95 countries. Bhattacharyya (2009) and Seetanah (2009) report also a positive growth effect of schooling years and secondary enrollments respectively. Their datasets concern 95 countries for 1980-2004 and 40 African countries for 1980-2000 respectively. Sandar-Kyaw and Macdonald (2009) find that tertiary education has a positive growth impact in low-income, lower-middle income and upper-middle income countries in 1985-2002 for 126 LDCs. Chen and Gupta (2009) provide controversial results regarding the growth influence of secondary enrollments in 13 African countries in 1990-2003. Lee and Kim (2009) suggest that secondary and tertiary education enrollments are important for growth in 1965-2002 and 63 countries. Földvári and Van Leeuwen (2009) find an inverse U-shaped education years-growth relation, while schooling growth is negatively associated with 21 OECD countries' growth during 1960-1995. Benos and Karagiannis (2010) show that secondary enrollments and student-teacher ratios have positive and negative growth effects respectively in 51 Greek regions during 1981-2003. Tsai et al (2010) suggest that secondary enrollment is more important for growth in developing than developed countries, while tertiary education is significant for both, in 1996-2006 for 60 countries. Suri et al. (2011) find a positive growth secondary enrollment relationship in 79 nations during 1960-2001, while Phillips and Chen (2011) report a negative secondary education teacher-growth correlation in 30 Chinese regions for 1978-1997.

The least common type of analyses uses time series data. Musila and Belassi (2004) and Dauda (2010) report a positive public education expenditure-growth nexus in Uganda in 1965-1999 and Nigeria for 1977-2007, while Ndiyo (2007) and Nurudeen and Usman (2010) conclude exactly the opposite for Nigeria in 1970-2000 and 1970-2008 respectively. Ndiyo (2007) finds also a negative effect of university graduates. Furthermore, Lawal and Iyiola (2011) conclude that primary and tertiary education enrollments exhibit a negative and positive relation with growth respectively in Nigeria for 1980-2008. Nketiah and Amponsah (2009) show no public education expenditures-growth relation in Ghana during 1970-2004. Finally, Odit et al (2010) report a positive schooling years-growth nexus in Mauritious during 1990-2006.

1.3. Alternative measures of education and economic growth

As it is evident from the previous section, measures of education and economic growth used in the empirical literature vary. Education is a broad term and as a result, empirical studies face difficulties with its measurement. The literature uses several proxies. Most proxies concern measures of formal education and include literacy rates, enrollment rates and years of schooling. Literacy rates are typically defined as the proportion of the population aged 15 and older who are able to read and write a simple statement on his/her everyday life (UNESCO, 1993). However, literacy rates are not objectively and consistently defined across countries and omit important components of human capital (Le et al., 2005).

Enrollment rates measure the number of students enrolled at a given level of education relative to the population that, according to legislation, should be attending school at that level. Enrollment rates measure the current investment in human capital that will be reflected in the future stock of human capital. Nevertheless, they are poor proxies for the present stock of human capital for many reasons. For instance, enrollment rates can be at best satisfactory proxies for human capital only in some countries. Judson (2002) argues that secondary enrollment rates will only be good indicators for human capital accumulation in countries where secondary education is expanding rapidly.

The deficiencies of literacy and enrollment rates as measures of human capital have motivated researchers to look for a more powerful human capital proxy, namely years of schooling of the workforce. Schooling years quantify the accumulated educational investment in the current workforce and assume that human capital embodied in workers is proportional to the years of schooling they have attained. With respect to literacy and enrollment rates, schooling years take into account the total amount of formal education acquired by the workforce, that is, schooling years proxy more accurately the existing stock of human capital in a country (Bassetti, 2007). In this context, some studies use the percentage of the working age population with primary, secondary and tertiary education. All these measures reflect the quantity of human capital. So, the above proxies do not give an indication of the skill level of the workforce.

Here comes the issue of education quality. The lack of education quality data in most studies considering the relationship between education and growth may be the biggest challenge in this area of research. The quantity of education is an inadequate measure of human capital differences, since school systems vary across countries in terms of resources, organization and duration. One solution in order to account for qualitative differences across education systems, is to focus on human-capital quality measures, such as educational expenditure, student-teacher ratios and test scores. These indicators can be measured at different levels of education. However, using such quality measures as proxies of human capital, it is very difficult to get a measure that can be reliably extrapolated for the entire workforce. As a result, any possible measure of education has advantages and disadvantages, and they must be taken into account when the effect of education on economic growth is estimated.

Moreover, the output measure used as dependent variable varies across studies. Plenty of studies use Gross Domestic Product (GDP), GDP per-capita and GDP per worker in real terms[1]. The respective output growth measures are real GDP growth, real GDP per capita growth and real GDP per worker growth. Therefore, it is likely that the coefficients estimating the relationship between education and economic growth will differ between studies partly due to differences in the type of the education and output data used.

[1] I do not consider studies that examine other measures of growth, e.g. TFP growth.

1.4. Meta-data set and strategy

Systematic reviews aim to find and assess with statistical and analytical methods for inclusion all high quality studies addressing a question and integrate the study results into a common result. In order to conduct a meta-analysis I have to define the question with excluding and including criteria for the research studies and then perform a systematic search for literature in order to capture all available studies addressing the question. Afterwards, I proceed with mathematical and statistical calculations for each study and combine the obtained results. The final step is the interpretation of the results of meta-analysis and an answer and conclusion to the question. Thus, MRA is based on a comprehensive search for relevant studies. For this reason, researchers have to collect and code comparable estimates. Afterwards, they should identify and code moderator variables in order to employ a model specification (research process, genuine and artificial heterogeneity).

Following Stanley (2001), I proceed in two steps for conducting meta-regression analysis. First, I construct the meta-data set. In particular, I collect empirical studies examining the link between education and economic growth. Second, I define a meta-regression model. In this context, I examine particular independent meta-variables in order to distinguish between numerous criteria that appear important. Meta-regression analysis allows me to synthesize all empirical results in a common framework. The adopted expression for the meta-regression analysis is similar to the relation described by Stanley and Jarrell (1989).

At this point, I should note that the empirical studies on the relationship between education and income growth can be attributed to two theoretical approaches: the first is the micro literature based on the Mincer approach implying a positive relation between individual education and earnings (private returns), and the second is the macro literature which studies the relation between education and the capacity of a society to grow (social returns). I proceed by including only macro studies in my meta-sample which include the coefficient of the size effect of education on economic growth. Therefore, only studies providing regression results where economic growth is considered as the dependent variable and education as one explanatory variable are included in the meta-data set. I exclude from the analysis papers that focus on education as a private human capital investment estimating the rate of return to this investment (Harmon et al, 2003)[2]. This process does not imply bias for my results, since this chapter examines the macroeconomic effects of education on economic growth.

Furthermore, the empirical literature that investigates the impact of education on growth includes estimates that have been reported in published academic journals as well as working papers, such as NBER or MPRA series. Many such works have been found in my search and, as a result, I included them in the meta-regression analysis. In particular, I have searched on the internet, the Econlit database, as well as the Google Scholar search engine, in order to find published articles in academic journals and working papers, concerning the education-economic growth nexus. The keywords used in this

[2] In several studies the authors do not report t-statistics. These studies were either excluded from the analysis or, if they provide standard errors or p-values, the missing t-statistics were retrieved.

process were: human capital, education and economic growth and my last search was conducted on September 29, 2011.

In particular, I perform a meta-regression analysis using data from 57 empirical studies. As I include all reported estimates in each study, any potential dependence among estimates is best captured by using study identifiers. Given that most studies include plenty of estimations, I use all of them as independent regressions and as a result, I report a total of 989 observations. For comparison, Nelson and Kennedy (2009) in a survey of 140 meta-analyses conducted in economics since 1989, report that an average meta-analysis employs 92 estimates (Irsova and Havranek, 2013). Therefore, my dataset is large relative to that of conventional economics meta-analyses.

Table 1 presents all studies employed in my meta-regression analysis and descriptive statistics of the estimated coefficient of education on economic growth. This table shows that there is great variation in findings across as well as within studies. Each study has a different mean value of the education coefficients and a different number of coefficients, which may be positive or negative.

Table 1: Summary statistics of the studies included in meta-regression analysis

Authors, publication year	Number of coefficients	Minimum	Maximum	Median	Standard deviation	Mean
Romer, 1989	3	0.0062	0.0386	0.0155	0.0166826	0.0201
Azariadis-Drazen, 1990	3	0.0025	0.0122	0.0103	0.0051404	0.0083333
Barro, 1991	48	-0.0171	0.0385	0.02365	0.01288	.0197125
Murphy-Shleifer-Vishny, 1991	10	-0.078	0.125	0.001	0.0611763	0.0059
Levine-Renelt, 1992	10	0.63	3.71	1.5	1.128.315	1.915
Mankiw-Romer-Weil, 1992	3	0.223	0.271	0.233	0.0253246	0.2423333
Benhabib-Spiegel, 1994	23	-0.092	0.167	-0.028	0.0755928	-0.0051522
Durlauf-Johnson, 1995	7	-0.114	0.469	0.209	0.2028804	0.1748571
Lee-Lee, 1995	11	-0.0042	0.0128	0.0016	0.0040339	0.0019455
Barro, 1996	9	-0.0032	0.11	0.0116	0.0337612	0.0209889
Gemmell, 1996	30	-2.21	6.07	1.11	2.016.531	1.619
Collins and Bosworth, 1996	7	0.04	0.25	0.15	0.0759072	0.1457143
Bloom et al, 1998	2	0.087	0.37	0.2285	0.2001112	0.2285
Temple, 1999	4	0.063	0.165	0.109	0.0417732	0.1115
Bils-Klenow, 2000	2	0.213	0.3	.2565	0.0615183	0.2565
Hanushek-Kimko, 2000	24	0.034	0.548	0.105	0.1244175	0.1368333
Ranis-Stewart-Ramirez, 2001	2	0.03	0.03	0.03	0.01	0.03
Bassanini- Scarpetta, 2001	16	0.41	1.76	0.9	0.3266235	0.898125
Kalaitzidakis et al, 2001	64	-2.19	0.288	0.007	0.2965526	-0.0371875
Prichett, 2001	7	-0.12	0.058	-0.049	0.0629085	-0.0448571
Krueger-Lindahl, 2001	58	-0.072	0.614	0.006	0.0921753	0.0317914
Barro, 2001	22	-0.025	0.129	0.0032	0.0435263	0.0305091
Appiah-McMahon, 2002	2	0.0003	0.0016	0.00095	0.0009192	0.00095
Knowles et al, 2002	4	0.076	0.23	0.149	0.084998	0.151
Papageorgiou, 2003	48	-0.4087	0.3415	0.0405	0.1243565	0.0588646
Bosworth-Collins, 2003	10	0.07	1.55	0.33	0.4817618	0.465
Chakraborty, 2004	5	0.27	4.45	1.43	1.64963	2.124
Barro-Sala-i-Martin, 2004	14	-0.057	0.121	0.00235	0.0366192	0.0071143
Musila-Belassi, 2004	1	0.036	0.036	0.036	.	0.036
Gyimah-Brempong et al, 2006	10	-0.0299	0.1281	0.05915	0.051956	0.05392
Keller, 2006	63	-5.545	4.675	-0.009	1.630.914	-0.2065714
Siddiqui, 2006	18	-0.78	0.4475	0.063	0.2993191	-0.0020222
Bose et al, 2007	11	-0.016	1.582	-0.012	.5026619	0.1931818
Cohen-Soto, 2007	25	-0.049	0.123	0.017	.0471837	0.029068
Ndiyo, 2007	1	-0.327	-0.327	-0.0327	.	-0.327
Hanushek et al, 2007	10	.00078	0.459	0.0855	.1599448	0.15661
Sterlacchini, 2008	7	0.052	0.394	0.321	.1297701	0.2664286
Costantini-Monni, 2008	6	-2.537	-1.568	-1.9605	.3449232	-2.021
Baldacci et al, 2008	10	-0.011	0.135	0.0875	.0531931	0.0718
Hanushek-Woessmann, 2008	20	-0.031	2.286	0.2605	.8501372	0.76135
Bhattacharyya, 2009	30	-0.0007	0.01	0.006	.0020144	0.0054767
Nketiah-Amponsah, 2009	1	-0.3	-0.3	-0.3	.	-0.3
Seetanah, 2009	2	0.01	0.08	0.045	.0494975	0.045
Sandar-Macdonald, 2009	23	-0.001	0.019	0.0007	.0041933	0.0019522
Chen-Gupta, 2009	12	-0.007	0.1429	0.01575	.0457068	0.0318833
Lee-Kim, 2009	20	0.001	0.033	0.013	.0086876	0.013
Földvári-van Leeuwen, 2009	10	-0.305	0.0612	0.00395	.1330808	-0.05692
Lee, 2010	6	0.0006	0.0032	0.00115	.0011321	0.0015833
Dauda, 2010	1	1.4155	1.4155	1.4155	.	1.4155
Benos-Karagiannis, 2010	132	-0.086	0.783	0.001	.113151	0.0431742
Odit-Dookhan-Fauzel, 2010	3	0.0985	16547	1.3378	8.726.787	1.000.783
Tsai et al, 2010	24	-0.0029	0.0969	0.0024	.0322937	0.0225917
Nurudeen-Usman, 2010	1	-0.0667	-0.0667	-0.0667	.	-0.0667
Suri et al, 2011	2	0.0183	0.0282	0.02325	.0070004	0.02325
Phillips-Chen, 2011	16	-4.4663	3.5154	0.3519	1890251	-0.1446999
Lawal-Iyola, 2011	6	-2.643	1.984	0.4365	1.799.473	-0.1031666
Hanushek-Woessmann, 2011	70	0.012	2.35	0.161	.8422545	0.8147143
Total	989	-0.663	3.5154	0.0181	2586951	0.2138548

I employ meta-regression analysis, in order to explain the excess study-to-study variation found. Such an empirical research environment suggests using the following meta-regression model to integrate and explain the above mentioned diverse findings:

$$\beta_j = \beta_0 + \sum_{k=1}^{K} \alpha_k Z_{jk} + \beta_1 se_j + u_j \quad (j=1,2,...,57) \qquad (1)$$

where β_j is the reported estimate of the education coefficient of the j^{th} study, β_0 is the true value of the education coefficient, Z_{jk} are the moderator variables that influence the magnitude of the published results and explain variation in coefficients β_j, α_k are the meta-regression coefficients which reflect the effect of particular study characteristics, se_j is the standard error of the coefficient of the j^{th} study and u_j is the meta-regression disturbance term. I introduce se_j because if there is publication selection, authors of small-sample studies search for larger estimates since such studies tend to have large standard errors. Large-sample studies typically find statistically significant estimates and can be published with smaller estimated effects. Therefore, the reported effect will be proportional to its standard error, *ceteris paribus* (Stanley et al., 2008).

In economics, though, empirical studies use different sample sizes and different econometric specifications and estimation procedures. Hence, the random estimation errors of the previous MRA model (u_j), are likely to be heteroscedastic.[3] Thus, the above equation is rarely estimated. Rather, its Weighted Least Squares (WLS) version, which

[3] I employed a Cook-Weisberg test in order to test the residuals for heteroscedasticity. In this case, I obtain a significant test statistic implying heteroscedasticity in the residual series in regression (1) in the text in my case.

divides this equation by se_j, becomes the obvious method of obtaining efficient estimates:

$$t_j = \beta_1 + \sum \gamma_i K_{ij} + \beta_0 (1 / se_j) + \sum \alpha_k Z_{jk} / se_j + v_j \quad (2)$$

where t_j is the t-statistic which corresponds to the estimate β_j. Because publication selection is a complex phenomenon, we have replaced β_1 in (1) by $\beta_1 + \Sigma\gamma_i K_{ij}$ in (2), where K_{ij} are additional factors correlated with the publication process itself, e.g. socio-economic variables thought to affect publication selection (Doucouliagos and Stanley, 2009). That is, I control for heterogeneity in the Z variables, but not the *K* variables. Equation (2) can be used as a valid test for both the presence of publication selection bias (variables not divided by se_j) and genuine education effects on economic growth corrected for publication selection (variables divided by se_j) (Stanley 2005, 2008). I follow Effendic et al (2011) and use the Funnel Assymetry Test (FAT) to formally test for the presence of publication bias.[4]

I estimate my meta-regression model, in order to examine the extent to which the variables, with values defined for each study in the analysis, explain heterogeneity in the education effect on growth. My meta-regression analysis focuses on the results of general-to-specific modelling, applied to the complete set of 989 estimates. That is, all Z and K variables were included in a general meta-regression model estimated, and then the statistically insignificant ones were removed, one at a time, to derive the specific

[4] Monte Carlo simulations have shown FAT to perform reasonably well even when publication selection is severe (see Stanley, 2008, p.106).

model. In this framework, both genuine effect and publication bias are more complicated. Genuine effects (and/or large-sample biases) are now captured by the combination of all the Z-variables (divided by se), while the K-variables (not divided by se), along with the intercept, together represent publication selection (Doucouliagos and Stanley, 2009).

I introduce variables expected to have a systematic impact on the reported effect of education on economic growth. At the same time, it is necessary to limit the number of covariates relative to the number of studies in order to avoid false positive results (Thomson and Higgins, 2002). Specifically, I examine whether differences across studies can be attributed to differences in the measurement of education and economic growth. Among the most popular proxies for the quantity of education are literacy rates, school enrollment rates and educational attainment, measured in years of schooling of the working-age population. Also, three measures are used in order to account for qualitative differences across education systems, being student-teacher ratios, educational expenditures and international test scores. As a result, in order to examine the impact of alternative education proxies I use six dummy variables. The first three dummy variables (literacy, enrollment and schooling years) equal one, if the study uses the literacy rate, the school enrollment rate and years of schooling as proxies of the quantity of human capital respectively. The other three variables (student-teacher ratios, educational expenditure and scores), equal one, if the study uses student-teacher ratios, expenditure on education and international test scores as alternative measures of the quality of human capital. I omit the percentage of working-age population with primary, secondary or tertiary education as a proxy for the quantity of human capital, in order to avoid multicollinearity.

Furthermore, the output measure employed as dependent variable varies across studies. In order to study the effect of alternative economic growth measures on the reported findings, I include one dummy variable in my meta-regression model which equals one, if the study uses the real GDP growth rate as a proxy for economic growth. I omit real GDP per-capita growth as a proxy for economic growth due to multicollinearity.

I adopt additional moderator variables in order to examine whether particular characteristics of empirical approaches explain the variation in the reported findings. These variables were chosen on the basis of theoretical literature concerning the importance of each variable (Doucouliagos and Stanley, 2009, Adam, Kammas and Lagou, 2013). In particular, I use the earliest and the latest year of the sample in each study to explore if the sample period influences the estimated education coefficient due to structural change. I also include dummy variables examining whether each study has been published in an academic journal or in the "best" 65 journals listed in Mamuneas et al (2010) and ESA (2008). In order to achieve comparable results, I include the same number of the "best" journals in the latter two cases. Moreover, I employ dummies reporting whether estimates are related to cross-sectional or panel data, with time series as the base, and whether the OLS method of estimation is employed, in order to control for differences in the type of data and methods of estimation respectively.

Here I should note that, I include a dummy equal to one if coefficient estimates are obtained by OLS and zero otherwise, to account for differences due to estimation methodology, since the majority of my meta-sample estimates are obtained by OLS. Almost all remaining coefficients are estimated via IV methods (2SLS, 3SLS and dynamic GMM estimators) (Arellano and Bond, 1991, AB from now on, Arellano and Bover, 1995, Blundell and Bond, 1998, AB-BB from now onwards) to control for endogeneity and reverse causality in the education-growth nexus. The AB estimator requires first differencing, lags of the dependent as well as explanatory variables and current values of the exogenous variables as instruments, since they are correlated with the endogenous regressors, but not the error terms. First differencing removes country-specific effects, a potential source of omitted variable bias, and deals with series' non-stationarity. The AB-BB system GMM estimator was developed because Blundell and Bond (1998) showed that the lagged level instruments of the Arellano and Bond (1991) estimator become weak as the autoregressive process becomes too persistent or the ratio of the variance of the panel-level effects to the variance of the idiosyncratic error becomes too large. So, Blundell and Bond (1998) building on Arellano and Bover (1995), proposed this estimator, which uses moment conditions in which lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the differenced equation.

Therefore, my OLS dummy essentially captures any potential difference in the estimated education impact on growth due to the use of IV vs. non-IV techniques. However, I should also note that the vast majority of studies using OLS acknowledges the potential endogeneity and reverse causality problems and employs initial values of the education variables to mitigate them.

In addition, I use dummy variables reflecting whether estimations include openness, a political measure, government spending and population growth as explanatory variables. I also use a dummy reflecting whether estimates rely on log specification, which is commonly used in empirical studies. Finally, I introduce the publication year of each study to investigate the existence of a time pattern in research output. All these are used as Z moderator variables that explain variation in the education coefficients. As a K variable correlated with the publication process itself, I use the sample size employed in each empirical work. This is because I expect that reviewers and editors tend to be suspicious and less favorable towards small-sample studies, reducing the chances for them to be published. All potential Z and K moderator variables employed in the meta-regression analysis are presented in Table 2.

Table 2: K and Z variables for Meta-Regression Analysis (MRA)

Variable[a]	Description of the variable
t-statistic	the t-statistic of the coefficient of interest of the study
K-variables[b]	
sample size	the sample size used in the study
Z-variables[c]	
antse=1/standerror	1 / the standard error of the coefficient of interest of the study
Education variables	
literacy	=1, if the study uses the literacy rate as a proxy for human capital (quantity)
enrollment	=1, if the study uses the school-enrollment rate as a proxy for human capital (quantity)
schooling years	=1, if the study uses years of schooling as a proxy for human capital (quantity)
student-teacher ratios	=1, if the study uses the student-teacher ratio as a proxy for human capital (quality)
educational expenditure	=1, if the study uses educational expenditure as a proxy for human capital (quality)
scores	=1, if the study uses international test scores as a proxy for human capital (quality)
Output variables	
real GDP growth	=1, if the study uses real GDP growth as a proxy for economic growth
Publication characteristics	
journal	=1, if the study has been published in an academic journal
Mamuneas et al	=1, if the study has been published in a journal listed in Mamuneas et al (2010)
ESA	=1, if the study has been published in a journal listed in ESA (2008)
publication year	the year the study was published
Estimation and data	
ols	=1, if the study employs the OLS method of estimation
cross	=1, if estimate relates to cross-sectional data, with time series as the base
panel	=1, if estimate relates to panel data, with time series as the base
Empirical specification	
log specification	=1, if the study employs a log specification
openness	=1, if the study uses openness of the economies as an explanatory variable
political	=1, if the study uses a political measure as an explanatory variable
government spending	=1, if the study uses government spending as an explanatory variable
population growth	=1, if the study uses population growth as an explanatory variable
Sample	
earliest year	the earliest year of the sample in the study
latest year	the latest year of the sample in the study

[a] All variables are included as Z and K variables in a general-to-specific modelling approach. [b] K variables may affect the likelihood of being selected for publication.
[c] Z variables may affect the magnitude of the education coefficient.

1.5. Estimation methodology

Meta-regression analysis, or meta-regression, is an extension to standard meta-analysis that investigates the extent to which statistical heterogeneity between results of multiple studies can be related to one or more characteristics of the studies (Thompson and Higgins, 2002). It is very unlikely that all heterogeneity will be explained, so there will be "residual heterogeneity", therefore random effects rather than fixed effects meta-regression is appropriate. All algorithms for random-effects meta-regression first estimate the between-study variance and then estimate the coefficients by weighted least squares, using as weights the inverse sum of the standard error of the estimated effect in each study and the between-study variance. So, more accurate studies have more weight in the analysis. In my case, the between-study variance represents the excess variation in observed growth effects of education that is expected from the imprecision of results within each study.

Several methods have been proposed for the estimation of the between-study variance in meta-regressions. As suggested by Thompson and Sharp (1999), the unknown variance of the random-effect model can be computed by an iterative residual (restricted) maximum likelihood process (REML), the Empirical Bayes (EB) method (see also Morris, 1983), or a moment-estimator (MM). The main problem of likelihood methods is that they become computationally intensive and time consuming as the number of studies increases. The benchmark method for estimating the between-study variance is REML. It was developed in order to avoid the biased variance component estimates produced by ordinary maximum likelihood (ML) estimation, because ML estimates of variance components do not take into account the degrees of freedom used in estimating effect size in fixed effects. So, REML avoids downward biased estimates of the between-study variance, underestimated standard errors as well as anticonservative inference (Thompson and Sharp, 1999). The MM estimator, the only non-iterative method, has the advantages of speed and robustness. It does not require numerical maximization or iteration, is not time consuming and performs relatively well in comparison with likelihood methods with both simulated and real data sets. Results are expected to be similar to those obtained by likelihood methods when there is moderate to large heterogeneity. However, ML are often preferred to MM methods as the former have higher probability of being close to the quantities to be estimated (Mavridis and Salanti, 2012). From another point of view, the main advantage of the meta-analysis in a Bayesian framework is that external evidence or information from historical data can be easily incorporated in the model via informative priors. When the number of studies is large, the choice of prior distribution affects the results less, since data play the dominant role. However, when the number of studies is small, priors selection is important. Both REML and EB estimators, being iterative methods, use the MM estimator as starting value.

Finally, since most studies in my sample report more than one regression I estimate my model by OLS with heteroskedasticity cluster-robust standard errors, which allow for error term correlation within each cluster (study)[5], assuming only that they are not correlated across studies (Baum, 2006)[6]. Thus, I relax the usual requirement that the observations are independent. I use this estimation method as a benchmark, because it is the simplest one and is used in many meta-regression works (e.g. Doucouliagos and Stanley, 2009, Effendic et al., 2011), although it is less appropriate for meta-regression analysis compared to the methods described previously. This is because, it does not

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[5] When I build my regression model, I assume that the dependent variable is a linear combination of the independent variables and assume that this function is the correct one to use. Moreover, on the right-hand side of the equation, I assume that I have included all the relevant variables that I should use in the model. So, I employ a link test for cluster data analysis, in order to detect a specification error of the model and as a result, the model appeared correctly specified (see Adam, Kammas and Lagou, 2013, p. 8).

[6] Moreover, with regard to cluster data analysis results, I perform a regression specification error test for omitted variables, namely the Ramsey Reset test, which does not reject the null hypothesis (H_o: the model has no omitted variables), indicating correct specification of the model (see Effendic et al, 2011, p.593).

account for the role of the between-study variance in the estimation of the coefficients in the meta-regression equation, it is likely that observations (education coefficients) are correlated within studies.

Moreover, with regard to cluster data analysis results, I perform a regression specification error test for omitted variables, the Ramsey Reset test, indicating correct specification of the model (see Effendic et al, 2011, p.593). Thus, I relax the usual requirement that the observations are independent. I use this estimation method as a benchmark, because it is the simplest one and is used in many meta-regression works (e.g. Doucouliagos and Stanley, 2009, Effendic et al., 2011), although it is less appropriate for meta-regression analysis compared to the methods described previously. This is because, it does not account for the role of the between-study variance in the estimation of the coefficients in the meta-regression equation. Therefore, from an empirical point of view, I employ cluster data analysis, as well as the REML, EB and MM estimator.

1.6. Meta-regression results

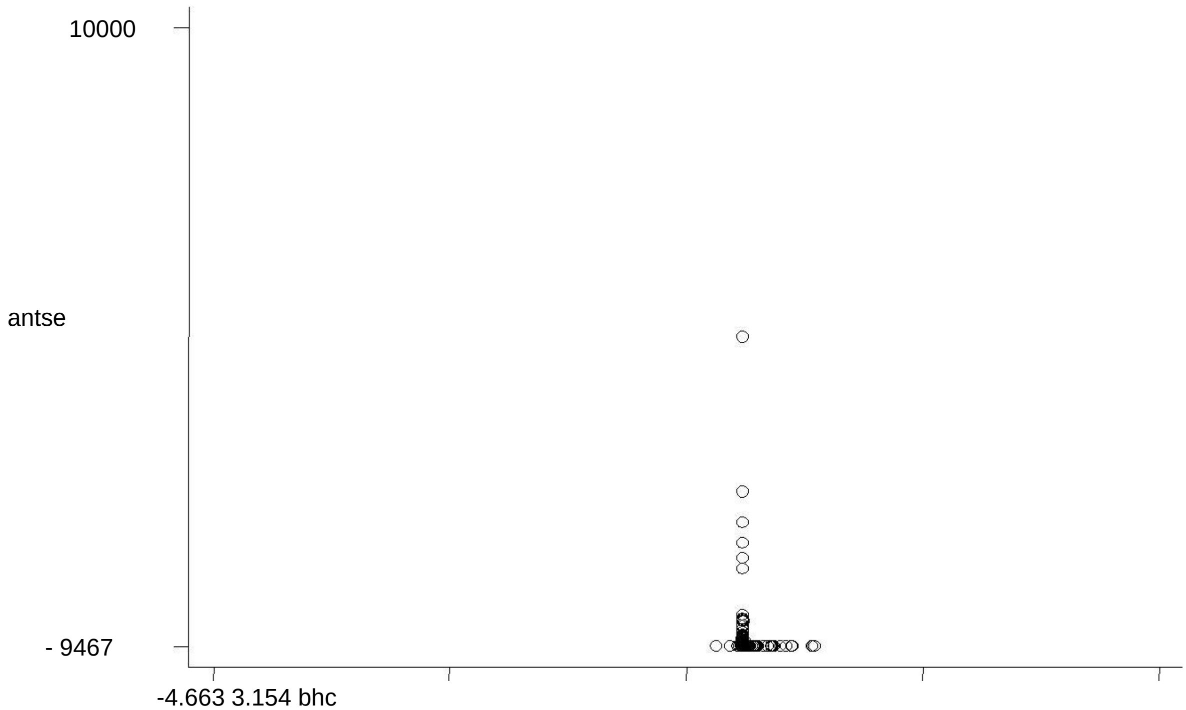
1.6. a). Publication selection

Publication bias has been a primary concern for meta-analysts, as journals are more likely to publish studies reporting statistically significant results. Papers reporting insignificant results are either not submitted for publication or routinely rejected by the editors/referees (Bom and Ligthart, 2008). Thus, the authors treat statistically significant results more favorably, because they are more likely to be published. In light of these, I initially test whether there is publication bias in the education-growth literature.

A first impression on whether the underlying literature is affected by publication bias can be derived by means of a funnel plot. Publication bias is the consequence of a favor for statistically significant results by authors or journal editors. Stanley (2005, 2008) suggests that the degree of this bias can be proxied by the correlation of estimates and their standard errors. To graphically illustrate this relationship Stanley and Doucouliagos (2010) propose to plot estimated coefficients against their precision, where precision is measured by the inverse of coefficients' standard errors. If the underlying literature is not affected by publication bias, estimated adjustment coefficients with high standard errors in the lower part of the plot shall be characterized by high variation around the "true" adjustment coefficient, while estimates with low standard errors in the upper part of the plot should be characterized by low variation around the "true" value. Thus, without publication bias, the plot should take the form of a symmetric inverted funnel. In turn, skewness of the funnel is a hint for publication bias.

Thus, according to Stanley (2005), the simplest method to detect publication selection is a visual examination of a funnel plot, which depicts the estimates of the coefficient in question on the horizontal axis and the inverse of their standard errors on the vertical axis. The expected shape is an inverted funnel, in the absence of publication selection, i.e. estimates should vary randomly and symmetrically around the true population effect. In figure 1, I see that in my case, the funnel graph is asymmetric, as the plot is overweighed on the right side. Thus, I visually inspect the presence of publication selection bias towards positive values of the growth effect of education.

Figure 1: Funnel graph.



Note: The variables bhc and antse represent the education coefficient and the inverse of the standarderror (antse=1/standerror) respectively.

However, graphs are only subjective tests for publication bias. The disadvantage of using funnel plots is that a single "true" effect is assumed for different regions, sectors, time periods, or estimation technique. Hence, possible publication bias within country or regions of reported adjustment coefficients can not be detected with this method (Doucouliagos et al., 2005, Stanley 2005, 2008). In the following, I therefore conduct MRA which provides a more objective analysis than funnel plots.

For this reason, I employ an objective statistical test for modelling publication selection, assuming that all α_k and γ_i are zero (there is no heterogeneity effect), that is the conventional t-test of the intercept of the equation:

$$t_j = \beta_1 + \beta_0 \left(1/se_j\right) + e_j \quad (3)$$

i.e., the Funnel Asymmetry Test or FAT (Egger et al, 1997, Stanley, 2005). If the literature is free of publication bias, the constant term should not be statistically significant (accept H_0: $\beta_1=0$). On the contrary, a non-zero constant term implies upward or downward bias on the effects estimated in the literature. The FAT test confirms the presence of publication bias (Table 3). The constant term is positive and statistically significant for all estimators. Therefore, I confirm the presence of "substantial" upward publication bias, since the estimate of β_1 is between 1 and 2 (Doucouliagos and Stanley, 2013). This model can also be used to test for a genuine effect beyond publication selection. The coefficient on precision, β_0, can be considered an estimate of the empirical effect corrected for publication selection. Applying this precision-effect test (PET), REML and EB results imply a positive genuine impact of education on growth. However, in these cases the growth impact of education is extremely small. On the contrary, cluster data analysis and MM findings do not provide evidence of a genuine education effect on growth.

Table 3: Funnel Asymmetry Test

Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse	0.000610	0.000606	0.000609	0.000606
	(1.34)	(5.26)***	(1.51)	(5.29)***
constant	1.694401	1.707225	1.698321	1.707282
	(6.49)***	(15.59)***	(4.47)***	(15.69)***
R-squared	0.0282	0.0267	0.068	0.027
Ramsey RESET test	F(3,974)=11.26 Prob>F=0.0000 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
a *Cluster data analysis presents the FAT results with cluster-robust standard errors.*
b *The Ramsey reset test rejects the null at all levels of statistical significance, indicating an incorrect specification of the model.*
c *REML presents the FAT results with restricted maximum likelihood.*
d *MM presents the FAT results with the moment estimator.*
e *EB presents the FAT results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

Table 4 presents the empirical results of my complete MRA model with a dummy for publications in academic journals, applying cluster data analysis, REML, MM and EB. Table 5 presents the empirical findings including a dummy for publications in journals listed in Mamuneas et al (2010), while Table 6 presents the empirical evidence of the meta-regression with a dummy for publications in journals listed in ESA. In this way, I check the robustness of the findings to alternative quality measures of the publication outlets.

I proceed by estimating the meta-analysis regression separately with a dummy for publications in academic journals, journals listed in Mamuneas et al (2010) and journals included in ESA, respectively, excluding 5% of the most extreme values of the effect of education on economic growth in Tables 7-9. I do these robustness checks in order to examine the influence of extreme estimates on the findings.

Table 4: Meta-analysis regression with a dummy for publications in academic journals

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.327***	-0.328***	-0.240***	-0.328***
	(-7.043)	(-5.890)	(-2.993)	(-5.928)
sample size				
literacy/se				
enrollment/se	0.00475***	0.00477***	0.00323**	0.00477***
	(4.385)	(4.975)	(2.225)	(5.006)
schooling years/se				
student teacher ratios/se	-0.00152***	-0.00150***	-0.00243***	-0.00150***
	(-5.636)	(-3.057)	(-3.261)	(-3.077)
educational expenditure/se				
scores/se				
real GDP growth/se	-0.00655***			
	(-3.118)			
earliest year/se	9.30e-05***	9.23e-05***	0.000120***	9.23e-05***
	(6.310)	(4.021)	(2.974)	(4.047)
latest year/se	6.82e-05***	6.93e-05***		6.93e-05***
	(3.739)	(2.804)		(2.821)
journal/se	-0.0104***	-0.0104***	-0.00943***	-0.0104***
	(-2.782)	(-6.051)	(-3.064)	(-6.090)
cross/se	0.0198***	0.0199***	0.0153***	0.0199***
	(4.283)	(7.755)	(3.810)	(7.804)
panel/se	0.0178***	0.0179***	0.0152***	0.0179***
	(4.184)	(7.713)	(4.001)	(7.762)
ols/se				
openness/se	-0.00802***	-0.00804***	-0.00667***	-0.00804***
	(-7.098)	(-8.139)	(-4.261)	(-8.191)
political/se				
government spending/se				
population growth/se				
log specification/se	0.00220**	0.00227***		0.00227***
	(2.399)	(3.115)		(3.134)
publication year/se				
constant	1.566***	1.569***	1.560***	1.569***
	(6.400)	(15.09)	(8.185)	(15.19)
R-squared	0.1980	0.1891	0.7778	0.1901
Ramsey RESET test	F(3, 964) = 2.31			
	Prob > F = 0.0748 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*
[b] *The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance, indicating a correct specification of the model.*
[c] *REML presents the MRA results with restricted maximum likelihood.*
[d] *MM presents the MRA results with the moment estimator.*
[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively*

Table 5: Meta-analysis regression with a dummy for publications in journals listed in Mamuneas et al

Moderator Variables	**Cluster data analysis** [a]	**REML** [c]	**MM** [d]	**EB** [e]
antse=1/se	-0.00984***	-0.00983***	-0.00891***	-0.00983***
	(-4.611)	(-6.976)	(-3.404)	(-7.020)
sample size				
literacy/se				
enrollment/se	0.00521***	0.00520***	0.00415**	0.00520***
	(4.120)	(5.485)	(2.357)	(5.520)
schooling years/se				
student teacher ratios/se				
educational expenditure/se				
scores/se				
real GDP growth/se				
earliest year/se				
latest year/se				
Mamuneas et al/se	-0.00372***	-0.00373***		-0.00373***
	(-3.049)	(-4.218)		(-4.245)
cross/se	0.0117***	0.0116***	0.00939***	0.0116***
	(5.082)	(8.117)	(3.599)	(8.168)
panel/se	0.00689***	0.00690***	0.00380**	0.00690***
	(5.273)	(6.471)	(2.552)	(6.511)
ols/se				
openness/se	-0.00708***	-0.00707***	-0.00375***	-0.00707***
	(-5.372)	(-6.914)	(-2.809)	(-6.958)
political/se	0.00359***	0.00359***	0.00308***	0.00359***
	(4.122)	(5.831)	(2.714)	(5.868)
government spending/se				
population growth/se	-0.00124***	-0.00123***		-0.00123***
	(-6.744)	(-3.476)		(-3.498)
log specification/se	0.00620***	0.00619***	0.00507***	0.00619***
	(5.175)	(7.680)	(3.620)	(7.728)
publication year/se				
constant	1.610***	1.623***	1.634***	1.623***
	(6.532)	(15.66)	(8.247)	(15.76)
R-squared	0.1919	0.1830	0.7587	0.1839
Ramsey RESET test	F(3, 964) = 2.32			
	Prob > F = 0.0743 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*
[b] *The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance.*
[c] *REML presents the MRA results with restricted maximum likelihood.*
[d] *MM presents the MRA results with the moment estimator.*
[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

Table 6: Meta-analysis regression with a dummy for publications in academic journals listed in ESA

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.0101***	-0.0101***	-0.00891***	-0.00762***
	(-4.756)	(-7.105)	(-3.404)	(-5.349)
sample size				
literacy/se				
enrollment/se	0.00531***	0.00530***	0.00415**	0.00549***
	(4.222)	(5.589)	(2.357)	(5.778)
schooling years/se				
student teacher ratios/se				-0.00299***
				(-2.847)
educational expenditure/se				
scores/se				
real GDP growth/se				
earliest year/se				
latest year/se				
ESA/se	-0.00392***	-0.00392***		-0.00144**
	(-3.199)	(-4.493)		(-2.253)
cross/se	0.0119***	0.0119***	0.00939***	0.00954***
	(5.259)	(8.252)	(3.599)	(6.554)
panel/se	0.00708***	0.00708***	0.00380**	0.00479***
	(5.393)	(6.666)	(2.552)	(5.065)
ols/se				
openness/se	-0.00728***	-0.00727***	-0.00375***	-0.00507***
	(-5.489)	(-7.122)	(-2.809)	(-5.649)
political/se	0.00367***	0.00368***	0.00308***	0.00361***
	(4.202)	(5.951)	(2.714)	(5.857)
government spending/se				
population growth/se	-0.00127***	-0.00126***		-0.00128***
	(-6.987)	(-3.562)		(-3.641)
log specification/se	0.00635***	0.00634***	0.00507***	0.00381***
	(5.342)	(7.820)	(3.620)	(4.197)
publication year/se				
constant	1.603***	1.616***	1.634***	1.588***
	(6.559)	(15.62)	(8.247)	(15.36)
R-squared	0.1938	0.1850	0.7587	0.1834
Ramsey RESET test	F(3, 964) = 2.23			
	Prob > F = 0.0834 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).

[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*

[b] *The Ramsey reset test accepts the null at the 5% and 1% levels of statistical significance, indicating a correct specification of the model.*

[c] *REML presents the MRA results with restricted maximum likelihood.*

[d] *MM presents the MRA results with the moment estimator.*

[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*

, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

Table 7: Meta-analysis regression with a dummy for publications in academic journals, excluding 5% of extreme values

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.325***	-0.325***	-0.240***	-0.325***
	(-7.085)	(-5.782)	(-2.997)	(-5.809)
sample size				
literacy/se				
enrollment/se	0.00472***	0.00475***	0.00325**	0.00475***
	(4.385)	(4.891)	(2.233)	(4.914)
schooling years/se				
student teacher ratios/se	-0.00156***	-0.00154***	-0.00245***	-0.00154***
	(-5.902)	(-3.097)	(-3.274)	(-3.112)
educational expenditure/se				
scores/se				
real GDP growth/se	-0.00611***			
	(-2.956)			
earliest year/se	9.40e-05***	9.33e-05***	0.000120***	9.33e-05***
	(6.545)	(4.029)	(2.978)	(4.048)
latest year/se	6.58e-05***	6.69e-05***		6.69e-05***
	(3.645)	(2.677)		(2.689)
journal/se	-0.0109***	-0.0109***	-0.0100***	-0.0109***
	(-2.855)	(-6.078)	(-3.149)	(-6.106)
cross/se	0.0202***	0.0203***	0.0159***	0.0203***
	(4.407)	(7.781)	(3.892)	(7.818)
panel/se	0.0182***	0.0182***	0.0158***	0.0182***
	(4.274)	(7.721)	(4.078)	(7.757)
ols/se				
openness/se	-0.00801***	-0.00803***	-0.00670***	-0.00803***
	(-7.159)	(-8.035)	(-4.269)	(-8.073)
political/se				
government spending/se				
population growth/se				
log specification/se	0.00221**	0.00228***		0.00228***
	(2.463)	(3.085)		(3.100)
publication year/se				
constant	1.495***	1.497***	1.489***	1.497***
	(6.161)	(13.88)	(7.591)	(13.95)
R-squared	0.2060	0.1971	0.7777	0.1979
Ramsey RESET test	F(3, 914) = 2.07			
	Prob > F = 0.1020 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*
[b] *The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.*
[c] *REML presents the MRA results with restricted maximum likelihood.*
[d] *MM presents the MRA results with the moment estimator.*
[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

Table 8: Meta-analysis regression with a dummy for publications in journals listed in Mamuneas et al, excluding 5% of extreme values

Moderator Variables	Cluster data analysis [a]	REML [c]	MM [d]	EB [e]
antse=1/se	-0.00990***	-0.00989***	-0.00898***	-0.00989***
	(-4.545)	(-6.922)	(-3.417)	(-6.954)
sample size				
literacy/se				
enrollment/se	0.00526***	0.00525***	0.00419**	0.00525***
	(4.114)	(5.480)	(2.370)	(5.506)
schooling years/se				
student teacher ratios/se				
educational expenditure/se				
scores/se				
real GDP growth/se				
earliest year/se				
latest year/se				
Mamuneas et al/se	-0.00376***	-0.00376***		-0.00376***
	(-3.015)	(-4.193)		(-4.213)
cross/se	0.0118***	0.0117***	0.00949***	0.0117***
	(5.037)	(8.085)	(3.620)	(8.123)
panel/se	0.00694***	0.00694***	0.00380**	0.00694***
	(5.175)	(6.396)	(2.536)	(6.426)
ols/se				
openness/se	-0.00717***	-0.00716***	-0.00378***	-0.00716***
	(-5.295)	(-6.860)	(-2.808)	(-6.891)
political/se	0.00357***	0.00357***	0.00309***	0.00357***
	(4.008)	(5.717)	(2.698)	(5.743)
government spending/se				
population growth/se	-0.00126***	-0.00126***		-0.00126***
	(-6.957)	(-3.516)		(-3.533)
log specification/se	0.00628***	0.00627***	0.00515***	0.00627***
	(5.140)	(7.676)	(3.663)	(7.712)
publication year/se				
constant	1.540***	1.552***	1.569***	1.552***
	(6.267)	(14.43)	(7.684)	(14.50)
R-squared	0.1976	0.1898	0.7586	0.1905
Ramsey RESET test	F(3,914) = 1.93			
	Prob > F= 0.1230 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*
[b] *The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.*
[c] *REML presents the MRA results with restricted maximum likelihood.*
[d] *MM presents the MRA results with the moment estimator.*
[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

Table 9: Meta-analysis regression with a dummy for publications in journals listed in ESA, excluding 5% of extreme values

Moderator Variables	**Cluster data analysis [a]**	**REML [c]**	**MM [d]**	**EB [e]**
antse=1/se	-0.0101***	-0.0101***	-0.00898***	-0.0101***
	(-4.693)	(-7.054)	(-3.417)	(-7.087)
sample size				
literacy/se				
enrollment/se	0.00537***	0.00536***	0.00419**	0.00536***
	(4.218)	(5.586)	(2.370)	(5.612)
schooling years/se				
student teacher ratios/se				
educational expenditure/se				
scores/se				
real GDP growth/se				
earliest year/se				
latest year/se				
ESA/se	-0.00397***	-0.00397***		-0.00397***
	(-3.161)	(-4.478)		(-4.499)
cross/se	0.0120***	0.0120***	0.00949***	0.0120***
	(5.218)	(8.224)	(3.620)	(8.262)
panel/se	0.00714***	0.00714***	0.00380**	0.00714***
	(5.290)	(6.599)	(2.536)	(6.630)
ols/se				
openness/se	-0.00738***	-0.00737***	-0.00378***	-0.00737***
	(-5.409)	(-7.076)	(-2.808)	(-7.109)
political/se	0.00366***	0.00366***	0.00309***	0.00366***
	(4.090)	(5.838)	(2.698)	(5.865)
government spending/se				
population growth/se	-0.00129***	-0.00129***		-0.00129***
	(-7.166)	(-3.605)		(-3.622)
log specification/se	0.00643***	0.00642***	0.00515***	0.00642***
	(5.311)	(7.821)	(3.663)	(7.857)
publication year/se				
constant	1.533***	1.545***	1.569***	1.545***
	(6.291)	(14.39)	(7.684)	(14.45)
R-squared	0.2014	0.1919	0.7586	0.1927
Ramsey RESET test	F(3, 914) =1.87 Prob >F=0.1328 [b]			

t-values are reported in parentheses (dependent variable: t-statistic).
[a] *Cluster data analysis presents the MRA results with cluster-robust standard errors.*
[b] *The Ramsey reset test accepts the null at all levels of statistical significance, indicating a correct specification of the model.*
[c] *REML presents the MRA results with restricted maximum likelihood.*
[d] *MM presents the MRA results with the moment estimator.*
[e] *EB presents the MRA results with the empirical Bayes iterative procedure.*
, **, * denote statistical significance at 10%, 5% and 1% levels respectively.*

I have evidence of substantial publication selection in the specific MRA model for the whole sample (Tables 4-6). Applying all techniques, the constant term is positive, large and statistically significant at all levels. However, the constant term itself is no longer a measure of the magnitude of the average publication bias. Rather, publication bias is the combination of the intercept and the *K* variable, i.e. sample size, which, however, is insignificant in all estimations. Therefore, there is strong upward publication selection bias in the education-economic growth literature. This confirms the results obtained from the initial FAT-PET MRA, as well as visual examination of the funnel plot, although the magnitude of the bias is slightly smaller.

Excluding 5% of the extreme values of the effect of education on economic growth (Tables 7-9), the main results remain qualitatively and quantitatively very similar. Using all estimators, the constant term continues to be positive, large and statistically significant at all levels of significance. Moreover, publication bias is the combination of the intercept and the *K* variable (sample size), which is again insignificant in all estimations. Therefore, all findings imply the presence of substantial upward publication selection bias in the education-economic growth literature.

1.6. b). Effects on human capital coefficients

1.6. b). i). Whole sample estimations

In the specific meta-analysis regression of the whole sample with a dummy for publications in academic journals in Table 4, the overall fit of the regression is quite high for a meta-regression (R^2=0.19 approximately). Education effects on growth are the combination of several factors. When all Z-variables are zero[7], in the model with a dummy for publications in academic journals vs. working papers, education is predicted to have a contemporaneous negative and statistically significant effect on growth in all cases.

Additionally, applying all techniques, specifications using education proxies based on enrollment rates increase the education effect on economic growth approximately by 0.004, whereas those using student-teacher ratios reduce it by around 0.001. However, only cluster-data analysis results show that real GDP growth reduces this effect approximately by 0.006.

Regarding publication outlets, according to all findings, research published in academic journals tends to report lower coefficients by about 0.010 compared to research published in working papers. The variation in reported estimates can be also explained by the inclusion of the earliest year of the sample and the type of data employed (cross-section data), as well as openness. The former two variables increase the education effect on growth approximately by 0.0001 and 0.019 respectively, while the latter one reduce it by around 0.008. The OLS variable, though, does not imply different estimates compared to non-OLS (IV) estimation. This seemingly unexpected result is due to the high

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[7] Testing H_0: $\beta_0 = 0$ may provide a valid and powerful test for genuine effect beyond publication selection bias. However, the validity of this test needs to be qualified. Simulations show that PET can be relied upon if the heterogeneity (or the magnitude of misspecification biases) is not too large. If there is large unexplained heterogeneity and a high incidence of publication selection, the above test can suffer from type I error inflation. The failure to reject H_0: $\sigma^2_v \leq 2$ serves as an effective means to limit these potential type I errors (see Stanley 2008), where σ^2_v is the error variance in the MRA model. Regarding cluster data analysis results, I have no evidence of a large amount of unexplained heterogeneity (accept H_0: $\sigma^2_v \leq 2$) at any significance level. As a result, I can rule out a type I error as a likely cause of this significant PET result (see Stanley et al, 2008, p. 282). Thereby, I can rely upon PET to determine genuine effect.

correlation between the OLS and cross-section dummies, because most cross-sectional studies employ OLS. Consequently, the upward bias of the OLS estimates shows up via the positive impact of the cross-section dummy. In addition, panel data, for which IV methods are usually employed, influence positively the education-growth relationship.

Certain aspects of the empirical specification exert an influence on the research findings. In particular, most findings, imply that the inclusion of a log specification and the latest year of the sample as additional variables increase the growth impact of education by around 0.002 and 0.0001 respectively. On the contrary, literacy, schooling years, educational expenditure and scores do not exert any influence on the findings.

Similar results are obtained from the meta-analysis regression of the whole sample with a dummy for publications in journals listed in Mamuneas et al (2010) in Table 5 and ESA (2008) in Table 6. Differences across studies can be attributed to differences in the measurement of education, model specification, publication outlet and the type of data employed. Given that the dummy for cross-section data is still positive (Tables 5 and 6), there exists a smaller positive differential than in the baseline estimations in favor of the education coefficients coming from cross-sectional studies, mostly OLS, relative to estimated parameters from panel studies, mainly IV. Therefore, there is strong evidence, although indirect, of upward bias of OLS relative to IV estimates. On the contrary, the inclusion of the earliest and the latest year of the sample, as well as student-teacher ratios can not explain the variation in reported estimates, while it affected the estimated growth impact of education in the benchmark case. Moreover, political and population growth proxies appear to affect the education-growth nexus, whereas they did not influence the growth effect of education in the benchmark results.

1.6. b). ii). Estimations excluding the most extreme values of the effect of education on growth

If I exclude 5% of the most extreme values of the effect of education on economic growth, the main results remain qualitatively and quantitatively intact for all regressions (see Tables 7-9). In particular, all estimators suggest a significant impact of education on economic growth. In all cases, differences in the measurement of education, model specification, and type of data employed give rise to different findings concerning the effect of education on growth. Moreover, the publication outlet, as well as the inclusion of openness as explanatory variables account for the variation of the empirical evidence. In addition, the estimation method employed in each study does not appear to affect the reported estimates. Finally, when a dummy for publication in the ESA journal list (2008) is employed, the inclusion of population and political measures influences the estimated education coefficients if outliers are omitted from the estimations. The new results, which are robust to outliers, are in line with the findings obtained when publication in the journal list of Mamuneas et al. (2010) is used as indicator of publication quality.

Overall, my findings point toward the presence of a genuine impact of education on economic growth along with a strong upward publication bias in the empirical literature, which examines the education-growth nexus. Moreover, studies employing enrolments are characterized by higher education growth coefficients relative to those using data based on the percentage of working-age population with primary, secondary or tertiary education. On the contrary, the inclusion of openness in empirical research implies a lower estimated education impact on growth. Moreover, the use of cross-section data, partially reflecting OLS estimation bias raises the estimated education coefficients. These findings help explain why early studies, which mainly use cross-section data on school enrollments and OLS methodology, obtain higher estimates of the education impact on growth, relative to recent research, that usually employs panel data on the percentage of the working-age population with a certain education level and IV estimation. Finally, my results are robust to the quality of research outlets and the presence of outliers in the data set.

1.7. Concluding remarks

In conclusion, I have seen that a large body of macroeconomic literature has focused on the relationship between education and economic growth. Empirical findings on this link are controversial. In light of these, I made an attempt to evaluate the empirical literature on the effect of education on growth and explain the wide variation in reported estimates. Specifically, I analyze the findings of 57 empirical studies and apply meta-regression analysis using four estimators, correcting for possible publication selection bias in the relevant literature. I investigate the impact of several factors on the variation of the reported estimates of the growth impact of education. My MRA analysis produces interesting results, which are robust to different estimators, the inclusion of various types of research outlets and the presence of outliers in the data set.

First, I confirm the presence of substantial upward publication selection bias in the education-economic growth literature, while I find no evidence of a large amount of unexplained heterogeneity. Second, all methods indicate a significant genuine education effect on growth after correction for publication selection. Third, differences across studies can be partially attributed to differences in terms of their characteristics. Specifically, the inclusion of enrolment rates tends to make the impact of education on growth, corrected for publication bias, positive. The same is true when cross-section instead of panel data are employed. Here, I should note that the positive bias of the OLS estimations shows up via the impact of the cross-sectional estimates of the growth effect of education. On the contrary, the use of openness and publication outlet tend to lower the estimated growth impact of education.

Thus, it seems safe to conclude that the education-economic growth empirical research, exhibits substantial publication selection toward positive growth effects of education, while the economic growth impact of education after taking into account publication bias depends critically on the specific features of the study. These findings do not necessarily imply that the positive impact of education on growth postulated by theory does not exist. It may well be the case that the problems characterizing empirical research on this question are so severe that they make it impossible to uncover this effect. In any case, my research provides important information for future empirical studies evaluating the role of education in the process of economic growth.

Chapter 2: *Human Capital and Growth: Evidence from a Panel of US States*

2.1. Introduction

The aggregate production function plays a focal role in macroeconomics as it summarizes the connection between inputs and output. It is an extremely useful device for thinking about economic performance, thereby making it attractive for both theoretical and empirical work. In this chapter, I use a panel of U.S. state-level data from 1963 to 2000 to identify the determinants of output level based on a Cobb-Douglas production function. While much of the interest in previous studies lies in yielding estimates of the effect of public capital on regional output, I also examine the decisive role of human capital as an input.

The most relevant example to my study is Dall'erba and Llamossas-Rosas (2012). They estimate a production function in levels for the US states for the years 2000-2008 utilizing spatial econometric specifications proposed by Ertur and Koch (2006, 2007). The relatively short time period might explain their finding that human capital exerts a negative effect on income since educational public investment has long-lasting effects, and thus it takes a longer time for the full impact of this policy to be experienced. In addition, their empirical approach is based on *ad hoc* assumptions concerning the choice of spatial weight matrices. Specifically, they define a spatial weight matrix that captures the degree of connectivity between the states based on their geographical proximity. This, in turn, raises the question of whether a statistically significant spillover variable indeed reflects spillover effects or stems from data dependencies introduced by empirical misspecification of structural heterogeneity across states.

In this research I use a much longer sample period (1963-2000) and employ a more general common factor specification of cross-section dependence. As Costantini and Destefanis (2009) point out "*in the field of regional production functions cross-unit dependence could arise because of spillover effects (trade-, technology-, or policy-determined) that do not bear simple relationships to proximity, or simply reflect the outcome of common shocks*". To this end, I employ recently developed heterogeneous panel data econometric techniques that allow for cross-section dependence and tackle at the same time the issue of parameter heterogeneity across states. Equally important, these techniques allow for modeling non-stationary time series which is not yet the case for spatial dependence models.

The empirical analysis consists of four steps. First, I examine if there is cross-sectional dependence in the panel employing the Pesaran (2004) CD test. Second, I investigate the unit root properties of the panel series through the tests for heterogeneous panels with cross-section dependence proposed by Pesaran (2007). Third, I investigate the existence of a cointegrating relationship among all variables applying the panel cointegration tests developed by Westerlund (2007). The underlying idea is to test for cointegration by determining whether there exists an error correction mechanism for individual panel members or for the panel as a whole. Finally, I employ the Common Correlated Effects Mean Group (CCEMG) estimator (Pesaran, 2006), as well as the Augmented Mean Group (AMG) estimator (Eberhardt and Teal, 2010) in order to estimate the parameters of the US states' production functions. I induce not only cross-section dependence, but also heterogeneity across panel members (i.e. states). These estimators also perform well in terms of bias in panels with non-stationary variables (cointegrated or not).

The empirical results confirm the presence of cross-section dependence and indicate that all variables are I(1), i.e. stationary in first differences, but not cointegrated. Thus, I show that ignoring cross-section dependence and parameter heterogeneity has a serious distorting impact on the estimated results, both qualitatively and quantitatively. The coefficient estimates in levels indicate that private capital has a positive and significant impact on income. In contrast, the income elasticity of public capital is negative or insignificant. When it comes to human capital, the income effects of education are positive whereas the corresponding effects of health are not statistically different from zero. Therefore, it appears that educational capital augmenting policies are effective tools towards narrowing income differences across US states.

2.2. Related literature

Plenty of studies estimate regional production functions in order to identify the determinants of output levels. One of the earliest contributions in the field of production function studies is Ratner (1983). Ratner (1983) examines the impact of public capital on output levels in the USA and finds an elasticity of around 5.7% at the national level over 1949-1973. However, it was not until Aschauer (1989) that studies on this topic received a great amount of coverage. Aschauer (1989) estimates a 39% output elasticity of public capital (larger even than the one for private capital) using aggregate post-war time series data for the USA. These estimates, further supported by Munnell (1990a) and Lynde and Richmond (1993), were severely questioned on the basis of conceptual and econometric deficiencies (Aaron, 1990; Tatom, 1991). To partly overcome time-series problems, a number of studies resorted to the use of state level data. For instance, Munnell (1990b) and Garcia-Milà and McGuire (1992) obtain much lower values for the output elasticity of public capital when estimating state level production functions. Specifically, Munnell's (1990b) elasticity estimates lie between 8% (under the constraint of constant returns to scale) and 15% (without any constraint) over 1970-1986. When considering disaggregated types of public capital (highway, water and sewer), the author obtains significant elasticities equal to 6%, 12% and 1% respectively. Garcia-Milà and McGuire (1992) find a similar elasticity of highway capital (4.5%). However, in a series of latter contributions, the effect of public capital on output or productivity turns to be insignificant (Evans and Karras, 1994; Holtz-Eakin, 1994; Garcia-Milà et al., 1996) or even negative (Moomaw et al., 2002). Even though these studies account for state-specific productivity differences through panel data techniques with state-specific effects, they rest on the assumption of cross-section independence over space. This is an unrealistic and restrictive assumption, especially since states are closely related to each other. Cross-section dependence is usually caused by the presence of common shocks or the existence of local productivity spillover effects. If the independence assumption is indeed violated, then we expect to have biased and inconsistent estimates as well as spurious statistical inference (Andrews, 2005). Dall'erba and Llamossas-Rosas (2012) provide empirical evidence on this issue using state-level cross-section data for the USA. Their results indicate that the spatially augmented version of the production function yields different results from the a-spatial one. Specifically, the coefficient estimates from the traditional production function show that private capital has a positive and significant impact on income while public capital does not. However, when controlling for the presence of dependence across spatial observations they find a significant positive effect of both private and public capital on the income of the region where they are located.

By examining the impact of public capital on output in Japanese prefectures during 1954-1963, Meriman (1990) shows that the output elasticities of public capital range from 0.43 to 0.58. Similar findings are obtained in Yamano and Ohkawara (2000). Their OLS and fixed-effects estimates for Japanese regions show that the output elasticities of public capital range from 0.156 to 0.190. Using LSDV and GMM, Shioji (2001) provides a lower elasticity of output with respect to public infrastructure, around 0.1 to 0.15, among Japanese regions.

Looney and Frederiksen (1981) study the link between income, productivity and public capital for the Mexican states. They disaggregate infrastructure into Economic Overhead Capital (EOC) and Social Overhead Capital (SOC) and group the thirty two states of Mexico into an intermediate and a lagging group. Their 2SLS results show that each measure of EOC (e.g. surfaced road density) examined is statistically significant in explaining variations in GDP in the intermediate group, but not in the lagging group. The reverse findings are obtained for each SOC proxy, such as the number of hospitals and primary schools. In the case of Dutch regions over 1970-1990, Nijkamp (1986) finds an output elasticity of public capital of 0.15.

Other works examine the impact of public infrastructure on regional productivity in Spain. Although such approaches differ in terms of types of public capital and periods considered, most of them illustrate the importance of public capital in explaining the evolution of regional productivity. For instance, Cutanda and Paricio (1994) show via OLS and IV that public infrastructure has a positive and significant impact in accounting for regional income differences across seventeen Spanish regions. By using panel data techniques that control for unobserved state-specific characteristics, this positive influence is confirmed by Mas et al (1996) for infrastructure most directly linked to the productive process (roads, water-sewer facilities, urban structures and ports) across Spanish regions in the period 1964-1991. This impact however does not hold in the case of social infrastructure (education and health). Cantos et al (2005) provide quite similar findings over 1965-1995. By using the IV method, positive and significant effects are obtained in the case of roads and airports (with elasticities of 0.088 and 0.0076 respectively), whereas the influence of ports and railways is not significant. In terms of total public capital, Bajo-Rubio and Díaz-Roldán (2005) report a higher output elasticity of 0.09 via GMM during 1965-1995.

Fewer studies investigate the role of human capital on the US state economies. The results provide conflicting evidence. On the one hand, Garcia-Milà and McGuire (1992) report significant educational capital elasticity ranging from 7.2% to 16.5%, depending on the specification. On the other hand, Dall'erba and Llamossas-Rosas (2012) conclude that the impact of educational public investment on US state income levels is negative even after controlling for spatial effects. The authors argue that this may be due to the counter-cyclical nature of this type of investment and the high degree of mobility of US workers who have recently graduated.

Turning the focus on regional human capital policies in Spain, Rivera and Currais (2004) employ the Least Squares Dummy Variables (LSDV) estimator and find that health spending is relevant when it comes to explaining productivity, while the coefficient of education expressed as the percentage of the working age population with secondary education, appears to be insignificant among seventeen Spanish regions over 1973-1993. By employing the same educational measure in a fixed effects model, Gumbau-Albert and Maudos (2006) reveal the importance of education in explaining differences in productivity among seventeen Spanish regions in the period 1986-1996. These controversial results motivated Ramos et al (2010) to examine the differential impact of education in terms of different levels of schooling. Using spatial panel techniques for a larger data set of fifty Spanish provinces between 1980 and 2007, tertiary and secondary average schooling years appear to exert a significant and positive influence on productivity, while primary education plays no role.

In the case of Italy, DiGiacinto and Nuzzo (2006) show via the LSDV estimator that regional productivity differences are traced back to differences in human capital endowments. This result is reinforced by Bronzini and Piselli (2009) who report a strong human capital influence on regional productivity between 1980 and 2001, using

Pedroni's cointegration tests and Fully Modified OLS (FMOLS). By incorporating cross-section dependence issues, Costantini and Destefanis (2009) find through FMOLS that neglecting this hypothesis can have a strong impact on the estimated long-run positive human capital elasticity among Italian regions during 1970-2003. Considering the differences in the effect of human capital between Northern and Southern Italian regions, Di Liberto (2008) finds, using 2SLS, that primary education is important in the

South, while a negative impact of tertiary schooling is found for Northern regions. Marrocu and Paci (2010) reinforce these findings. Through the IV method, they confirm that human capital is more productive in the Southern regions of Italy over 1996-2003.

By examining the impact of human capital on output per worker among Chinese provinces between 1979 and 1989, Gundlach (1997) reports through OLS and IV an estimate of 0.46. This finding is further supported via IV by Zhang and Zhang (2003). Among the production factors considered in their estimation, the elasticity of education (0.9) has the largest effect on productivity among twenty eight Chinese provinces over the period 1986-1998. In the presence of cross-section dependence, Fleisher et al (2010) provide lower estimates for the elasticity of education (0.39) during 1985-2003 among twenty eight Chinese provinces using the CCEP (Common Correlated Effects Pooled) estimator. When considering the role of knowledge capital in German regions, Audretsch and Keilbach (2004) suggest that this type of capital expressed as the number of employees engaged in R&D in the public and the private sectors is important in determining output and productivity.

Therefore, although, human capital constitutes a primary source of economic activity in the theoretical literature (Lucas, 1988; Stokey, 1991), the empirical findings provide mixed results stemming either from the methodology employed and/or the measure of human capital. In this chapter, I assume that human capital is a fundamental determinant of regional economic activity in the US. To this end, I consider both education and health in the formation of human capital. Both forms of human capital are considered as production factors, the accumulation of which affects regional (state) income. For empirical purposes, I adopt a production function approach and estimate the impact of human capital (education and health) on output using data for the 48 contiguous US states while addressing at the same cross-sectional dependence and parameter heterogeneity.

2.3. The model

In this study, I attempt to explore the relationship between output, labor, physical capital, education, health as well as R&D and public capital using regional (state) data for the US. I adopt a Cobb-Douglas production function with Hicks-neutral technical progress in the basic specification:

$$Y_{it} = T_{it} L_{it}^{a_l} K_{it}^{a_k} \qquad (1)$$

where: *i=1, …, 48* denotes states , *t=1963,…, 2000* is a time index, *Y* is real personal income, *T* is Total Factor Productivity (TFP) representing technical change, *L* is the labor input and *K* is private physical capital stock.

I follow the literature which emphasizes the role of educational human capital and R&D activities in driving technical progress, and thus productivity (Romer, 1990). Regarding R&D, theory postulates that technological knowledge, accumulated and implemented through R&D activity, boosts the production and diffusion of innovations, stimulating productivity and output. Some studies examine the strategic complementarities between R&D and human capital. For instance, Redding (1996) provides an endogenous growth model in which the presence of strategic complementarities between human capital accumulation and R&D investment may affect output and economic growth. Individual human capital investments by workers depend on the expected investments by firms in R&D activity. At the same time, firm R&D investments depend on the expected private human capital investments. Consequently, productivity is determined by both human capital and R&D investments.

Based on the theoretical literature outlined above, plenty of empirical papers employ R&D and human capital as primary determinants of productivity (Coe et al, 1997; Engelbrecht, 1997, 2002; Frantzen, 2000). In light of this, I assume that both R&D and educational human capital affect TFP. To this end, I specify the empirical model by augmenting a standard aggregate production function with a technological progress function driven by educational and R&D capital. I employ the following technological progress function:

$$T_{it} = A E_{it}^{a_e} P_{it}^{a_p} \tag{2}$$

where E is educational human capital stock, P is research and development capital and A is exogenous technical progress.

Substituting Equation (2) into Equation (1), I get:

$$Y_{it} = A E_{it}^{a_e} P_{it}^{a_p} L_{it}^{a_l} K_{it}^{a_k} \tag{3}$$

In addition, I convert variables into natural logs in order to estimate elasticities. So, equation (3) can be written in log form, where lower-case variables denote logarithms:

$$y_{it} = a_e e_{it} + a_p p_{it} + a_l l_{it} + a_k k_{it} + u_{it} \qquad (4)$$

where u_{it} is a stochastic error term, $u=ln(A)$.

Equation (4) represents the baseline empirical specification. I impose no constant returns to scale to all inputs. This is because factors affecting output may generate positive externalities, which make their social marginal benefits greater than their private as measured by the rewards they earn. This is particularly true for public capital and R&D, but it also holds for human capital (Acemoglu and Angrist, 2001).

While most studies focus on education, they tend to ignore health as a core component of human capital and output determinant. The population's health may affect output through productive efficiency, life expectancy, learning and inequality (Howitt, 2005). For instance, health status affects the probability of future survival, therefore the returns to human capital accumulation and output. For this reason, I extend the analysis by taking into account human capital in terms of health as a production factor. The introduction of human capital in a broad sense by including both education and health in the production function, gives me the ability to obtain more accurate estimates of the model's parameters. Thus, my fifth empirical specification takes the following form:

$$y_{it} = a_e e_{it} + a_h h_{it} + a_p p_{it} + a_l l_{it} + a_k k_{it} + u_{it} \qquad (5)$$

Other approaches focus on public capital and its contribution in stimulating output, as it raises the availability of resources and enhances the productivity of existing ones (Aschauer, 1989). Public capital may also stimulate output through private capital accumulation by raising its returns. Equations (4) and (5) ignore the impact of public capital on production. Thus, for completeness, I proceed by including public capital in the production function. I split public capital into different categories in order to examine the contribution of its different types to output. The rationale is similar to Munnell (1990a) who uses production function analysis in order to study the impact of public capital spending on productivity and economic activity.

Specifically, I now assume that TFP is driven by educational and health human capital stocks, as well as by R&D and public capital. In the robustness analysis, I provide results using alternative measures of public capital. Public capital is measured by three different proxies: total public capital stock (pc_1), public capital stock in terms of highways, water and sanitation (pc_2) and public capital stock in terms only of highways (pc_3). I choose to concentrate on these critical subcomponents, as they have a direct impact on productivity, and thus on economic performance (Garcia-Milà and McGuire, 1992).

Thus, my sixth, seventh and eighth empirical specifications take the following forms respectively:

$$y_{it} = a_e e_{it} + a_h h_{it} + a_{pc_1} pc_{1it} + a_p p_{it} + a_l l_{it} + a_k k_{it} + u_{it} \quad (6)$$

$$y_{it} = a_e e_{it} + a_h h_{it} + a_{pc_2} pc_{2it} + a_p p_{it} + a_l l_{it} + a_k k_{it} + u_{it} \quad (7)$$

$$y_{it} = a_e e_{it} + a_h h_{it} + a_{pc_3} pc_{3_{it}} + a_p p_{it} + a_l l_{it} + a_k k_{it} + u_{it} \quad (8)$$

As a further robustness check, I consider alternative specifications. So, I ignore health human capital and assume that TFP is driven by R&D, educational human capital stocks and public capital stocks as captured by the three aforementioned measures. Thus, Equations (5) - (8), as well as those obtained without the health variables represent the empirical specifications used in robustness analysis.

2.4. Data and methodology

I start the analysis with a brief description of the data set. The sample consists of the 48 contiguous US states over 1963-2000. The dependent variable is state personal income in millions of real (2000) dollars (lrpim). To construct this variable I simply divide nominal state personal income (obtained from the Bureau of Economic Analysis-BEA) by the state consumer price indices provided by Berry et al (2000). My choice of the education human capital variable is dictated by the relevant literature. I employ the most reliable and commonly used human capital measure, i.e. average years of schooling (lschoolyears). This metric is viewed by the literature as the most reliable and accurate measure of existing human capital stock (Benhabib and Spiegel, 1994; Engelbrecht, 1997; Bassetti, 2007). This is because average schooling years take into account the total amount of formal education acquired by the workforce, that is, they proxy more accurately the existing stock of human capital (Bassetti, 2007; Benhabib and Spiegel, 1994; Engelbrecht, 1997).

Moreover, I use labor force (lnlabor) as a proxy for labor. Data on education and labor are provided by Tamura et al (2006). Data for private capital stock (lprivatecapital) are obtained from Garofalo and Yamarik (2002) and Yamarik (2013). For public capital stock, I employ three alternative measures, namely (i) total public capital stock, (ii) public infrastructure stock (highways, water and sanitation), and (iii) highway capital stock. In particular, for public capital stock, I employ data on total public capital stock (lkgpublic), public capital stock in terms of highways, water and sanitation (lkgcorepublic), as well as public capital stock in terms only of highways (lkghwpublic). The public capital data cover the 1970-2000 period. All public capital data are obtained from Christ and Islam (2012), while R&D is proxied by the number of patents (lpatents) taken from the US Patent and Trademark Office (2013).

Regarding my health proxy (lbeds), I use decennial data for community hospital beds per 1000 resident population from the CDC database. I only have data for one year per decade, thus I interpolate missing data using the corresponding average annual state-specific percentage change. I would have been keen to use other health data (i.e. life expectancy), since hospital beds is a measure of the quantity of health services, and do not capture neither the quality of such services nor the health status of the population, but unfortunately they are not available for a long time-horizon. Details on the data can be found in the Appendix of this chapter.

In Table 1, I present the descriptive statistics for the variables in levels over 1963-2000. I convert all series to raw numbers, which are easier for the reader to understand. The average value of real personal income is 104,432.50 and Texas, the most spacious state, is the state with the highest value. Regarding schooling years, they are equal on average to 11.97. New Hampshire exhibits the highest education level, while South Dakota presents the lowest. Labor force shows maximum and minimum values of 171,000.00 and 130,716.00 in California and Nevada respectively, which mainly reflect the population size of the corresponding states. In addition, private capital is on average 126,043.50, but displays huge variation across states, ranging from 5,750.731 in Vermont to 136.666,80 in California. With respect to R&D capital, patents show maximum and minimum values of 174,91 and 17 observed in California and Nevada respectively, which is expected given the high concentration of the US high technology firms in the former state. The variation among states is also huge in terms of health services, since the corresponding beds per 1000 inhabitants vary between 1.746 and 7.400 in Virginia and Illinois respectively. Finally, as far as public capital values are concerned over 1970-2000 (see Table 6), there are differences among states. According to Table 6, this variable exhibits its minimum in Vermont and its maximum in New York state. This finding is a result of various factors that affect the composition of public spending, such as population density, trade openness, income inequality and ethnic fractionalization (Shelton, 2007).

Table 1: Descriptive statistics for variables in levels (1963-2000)

Variable	Mean	Max	Min	Median	Standard deviation
rpim	104432.5	1000000	4484.63	65917.15	122686.6
schoolyears	11.97047	14.14101	8.876521	12.09063	1.112115
labor	2214076	1.71E+07	130716	1513695	2384442
privatecapital	126043.5	1366668	5750.731	71637.89	161520.5
patents	1021.477	17491	17	417	1519.372
beds	3.88721	7.4	1.746	3.793	1.026392

These descriptive statistics refer to the sample of 48 US states. All variables are expressed in raw numbers.

Given that I use a panel data set for 48 US states, the empirical analysis starts with the examination of the cross-section independence hypothesis, which has received increasing attention in the emerging panel time-series literature (Eberhardt, 2011). Violation of this hypothesis, can lead to inconsistency and incorrect inference in standard panel econometric approaches (Pesaran, 2006). Cross-section dependence can arise due to spatial/spillover effects and unobserved (or unobservable) common factors (Baltagi and Pesaran, 2007). In the context of my state-level production functions, this type of correlation may be due to US-wide shocks with possibly heterogeneous impact across cross-sectional units (i.e. states), such as the 1970s oil crises. Alternatively, it can be the result of local spillover effects between states (trade, technology or policy-determined). Given that the observed variables are likely to be correlated across states, it is natural to expect that the unobservables contained in the error term, may also be correlated across states. Thus, the need of testing for cross-section dependence in the estimation of my production functions at the US state level is obvious.

To this end, I use Pesaran's CD test (2004), which detects the presence of correlation in the error terms across different cross-sections. The null hypothesis is that residuals are uncorrelated. The Cross-section Dependence test statistic is based on the average of pair-wise correlation coefficients (ρ_{ij}) of the OLS residuals, obtained from the individual Augmented Dickey Fuller (ADF) regressions[8]. The CD statistic is given by:

[8] The applicability of this CD test along with other similar tests is discussed in Hoyos and Sarafidis (2006).

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right) \qquad (9)$$

where i,t index the cross-section and time series dimensions respectively. Under the null hypothesis of cross-section independence, the CD statistic converges to a normal standard distribution. The CD statistic has mean zero for fixed values of T and N, under a wide range of panel-data models, including homogeneous/heterogeneous dynamic models and non-stationary models. The CD test is robust to non-stationarity, parameter heterogeneity or structural breaks and is shown to perform well even in small samples.

I proceed by testing whether my series are stationary or not. In particular, I examine the stationarity properties of my series, by employing the t-test for unit roots in heterogeneous panels with cross-section dependence, proposed by Pesaran (2007).

Parallel to Im, Pesaran and Shin's (IPS, 2003) test, this test is based on the mean of individual DF (or ADF) t-statistics of each unit in the panel. The null hypothesis assumes that all series are non-stationary. To eliminate the cross-section dependence, the standard DF (or ADF) regressions are augmented with the cross-section averages of lagged levels and first-differences of the individual series (CADF statistics) which are asymptotically similar (Baltagi and Pesaran, 2007). A truncated version of the CADF statistics is also considered, which has finite first- and second-order moments. The exact critical values of the t-bar statistic are given by Pesaran (2003). The critical values and summary statistics of the individual t are also given in the aforementioned paper, so the Z[t-bar] statistic is distributed as standard normal under the null hypothesis of non-stationarity.

Moreover, I examine whether the production process is representative of a cointegrating relationship between output and inputs in the context of non-stationary variable series. In this context, I test the cointegration hypothesis by carrying out the procedure developed by Westerlund (2007) which allows for cross-section dependence. Since my cross sectional units are suspected to be correlated, I obtain robust critical values through bootstrapping. The underlying idea is to test for the absence of cointegration by determining whether there exists error correction for individual panel members or for the panel as a whole. In particular, I implement four panel cointegration tests. The Ga and Gt test statistics test the null hypothesis of no cointegration for all cross-sectional units against the alternative that there is cointegration for at least one cross-sectional unit. Thus, rejection of H_0 according to the *Ga* and *Gt* statistics is taken as evidence of cointegration of at least one of the cross-sectional units. The *Pa* and *Pt* test statistics pool information over all the cross-sectional units to test the null of no cointegration for all cross-sectional units against the alternative of cointegration for all cross-sectional units. Therefore, rejection of H_0 according to the *Pa* and *Pt* statistics is taken as evidence of cointegration for the panel as a whole.

Conventional panel estimators such as fixed or random effects can result in misleading inference and even inconsistent estimators, depending on the extent of cross-sectional dependence and on whether the source generating cross-sectional dependence (such as an unobserved common shock) is correlated with the regressors (Sarafidis and Robertson, 2009). Also, using OLS to estimate relationships among non-stationary series or among series of different orders of integration can result in spurious outcomes.

Rather than making the data fit the requirements of the estimators, as practiced in Pedroni (2007) for the non-stationary panel econometric approach, I postulate the use of estimation methods which are robust to potential non-stationarity. In fact, over the last years, there has been a rapid development in panel estimation methods, resulting in many different estimators. For example, in order to take account of heterogeneous parameters within a stationary panel data framework, Pesaran and Smith (1995) propose a Mean Group (MG) estimator which is in its simplest form equivalent to the average of parameters from each panel. Furthermore, they consider other estimation procedures for dynamic models of heterogeneous panels allowing for cross-section dependence without imposing a priori homogeneity restrictions.

In addition, Pesaran (2006) proposes the Common Correlated Effect estimator (CCE) which treats a common factor as the cross-section average of dependent and independent variables, and then develops an MG estimator for the CCE, namely the CCEMG, in order to allow for heterogeneous slopes. This is similar to the Common Correlated Effects Pooled (CCEP) estimator, which can be derived under the a priori assumption of parameter homogeneity.

Given these considerations, I implement panel time-series estimators which allow for heterogeneous slope coefficients and correlation across panel members (cross-section dependence). Specifically, in order to estimate the parameters of my production functions, I employ the Pesaran's (2006) CCEMG estimator (Common Correlated

Effects Mean Group), which is a generalization of the MG (Mean Group) estimator of Pesaran and Smith (1995) adapted for the possibility of cross-section correlation by

Pesaran (2006). The Pesaran's (2006) CCEMG estimator allows for an empirical setup, which induces cross-section dependence and heterogeneous impact across panel members, by using OLS to estimate an auxiliary regression for each cross-section in which the (weighted) cross-sectional averages of the dependent variable and the individual-specific regressors are added. I use this particular estimator, because according to Monte Carlo simulations (Eberhardt and Bond, 2009), it performs well in panels with non-stationary variables (cointegrated or not) and multifactor error terms (cross-section dependence). I employ robust CCEMG regressions that estimate the outlier-robust mean of parameter coefficients across states in order to provide resistant (stable) results in the presence of outliers.

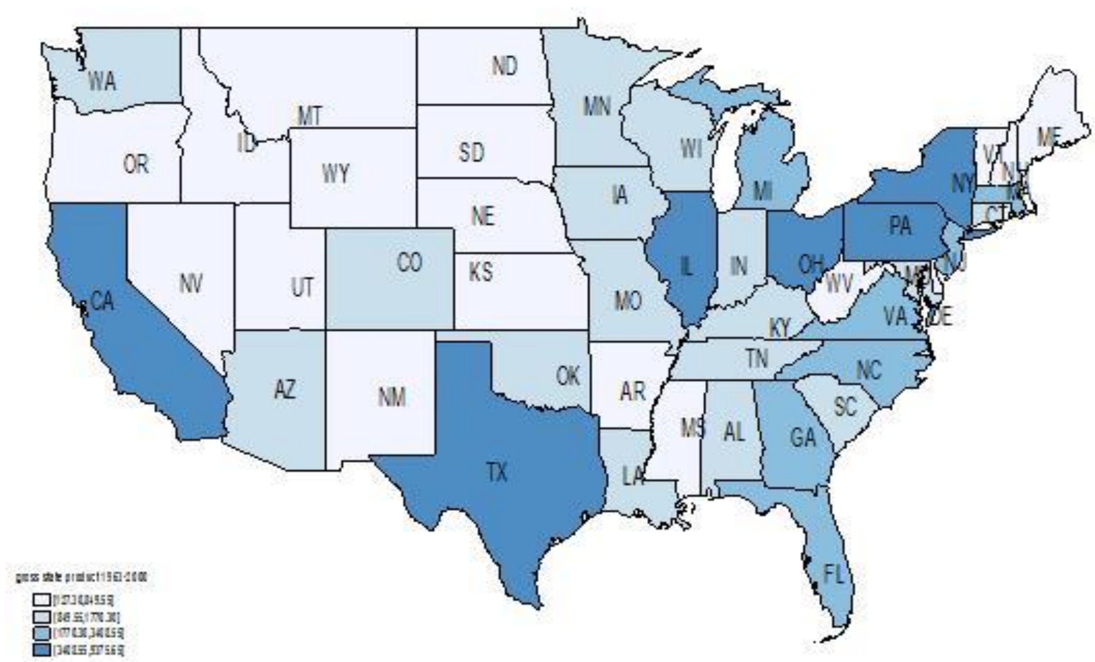
In addition, I test for the robustness of my results, by employing an alternative method, namely the Augmented Mean Group (AMG) estimator introduced in Eberhardt and Teal (2011). This estimator allows for cross-section dependence in the panel and performs well in panels with non-stationary variables (cointegrated or not). The AMG estimator is a method conceptually similar to the Pesaran (2006) Common Correlated Effects (CCE) estimator in the Mean Group version and accounts for cross-section dependence by the inclusion of a common dynamic effect in the cross-section regression. The AMG procedure is implemented in three steps. First, a pooled regression model augmented with year dummies is estimated in first difference form by OLS and the coefficients on the (differenced) year dummies are collected. These coefficients represent an estimated cross-group average of the evolution of unobservable TFP over time referred to as common dynamic process (cdp). The cdp is a globally common, unobserved factor or factors, which can be interpreted as common TFP evolution or an average of state-specific evolution paths of omitted variables. Second, the group-specific regression model is augmented with this estimated TFP process: either as an explicit variable or imposed on each group member with unit coefficient by subtracting the estimated process from the dependent variable. I impose the unit coefficient restriction after having tested and verified its validity. Third, similarly to the CCEMG procedure, the group-specific model parameters are averaged across the panel (Hamilton, 1991). Specifically, I perform AMG robust regressions, which estimate outlier-robust means of parameter coefficients across states putting less emphasis on outliers while computing the average coefficients.

2.5. Empirical results

Following the recent literature (e.g. Costantini and Destefanis, 2009), I first examine if there is cross-sectional dependence in my panel data set as the assumption of cross-section independence is unlikely to hold in regional/state-level data. At first, I use a relevant map in order to examine whether I have visual evidence of cross-section dependence.

In particular, Map 1 below presents the division of the 48 US states according to real personal income, showing states separated into clusters with different colors, through the use of their average real personal income value during 1963-2000, i.e. the sample period. In general, high-income states have common borders with other high-income states, while low income states share borders with other low income states. Map 1 generally uncovers patterns of clustering for the dependent variable, generating differentiated areas of high and low income. Thus, I have at least visual evidence of cross-section dependence across US states.

Map 1: Average real personal income over 1963-2000 for US states



To further explore the spatial pattern of the data, I employ the Pesaran's (2004) CD test to formally examine the presence of correlation in the error terms across different cross-sections over 1963-2000. The test statistics (reported in Table 2) verify my previous conjecture and provide strong evidence of cross-section dependence for all variables. The test statistics (reported in Table 2) provide strong evidence of cross-section dependence for all variables both in levels and first differences.

Table 2: Cross-section dependence - CD test results (1963-2000)

Variables in levels	CD	Variables in 1st differences	CD
lrpim	202.370***	dlrpim	35.090***
	(0)		(0)
lschoolyears	205.810***	dlschoolyears	70.640***
	(0)		(0)
lnlabor	203.200***	dlnlabor	201.560***
	(0)		(0)
lprivatecapital	199.440***	dlprivatecapital	57.730***
	(0)		(0)
lpatents	118.870***	dlpatents	62.340***
	(0)		(0)
lbeds	199.000***	dlbeds	66.000***
	(0.007)		(0.004)

*Pesaran CD statistics refer to the 48 US states. Under the null hypothesis, (H_0: cross-section independence), the CD statistics converge to a normal standard distribution. P-values are in parentheses. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively.*

Next, I test for the unit root properties of the data employing the *t-test* proposed by Pesaran (2007) which accounts for heterogeneous panels with cross-section dependence. This test examines the null hypothesis of non-stationarity against the alternative of stationarity. According to Table 3, the tests clearly reject the null hypothesis of non-stationarity for all variables in first difference form, thus, all variables are found to be stationary in first differences over 1963-2000, i.e. they are I(1).

Table 3: Pesaran's CADF panel unit root tests (1963-2000)

Variables in levels	CADF test	Variables in 1st differences	CADF test
lrpim	-2.296	dlrpim	-4.283***
	(0.636)		(0)
lschoolyears	-2.227	dlschoolyears	-2.652***
	(0.570)		(0)
lnlabor	-2.110	dlnlabor	-2.377***
	(0.390)		(0)
lprivatecapital	-1.940	dlprivatecapital	-2.555***
	(0.106)		(0)
lpatents	-1.275	dlpatents	-13.835***
	(0.999)		(0)
lbeds	-1.265	dlbeds	-2.868***
	(0.999)		(0)

*Pesaran's unit root test statistics for the 48 US states. P-values are in parentheses. The null is H_0: non-stationarity. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively.*

I then investigate the existence of a cointegrating relationship among the variables of interest using the Westerlund (2007) procedure. Since the cross sectional units are correlated, I calculate robust critical values through bootstrapping (1,000 replications). I use the AIC to choose optimal lag and lead lengths for each series and I set the Bartlett kernel window width equal to $4(T/100)^{2/9} \approx 3$ (Persyn and Westerlund, 2008).

The results (reported in Table 4) show that the variables are not cointegrated across alternative specifications over the full sample period (1963-2000). All test statistics fail to reject the null hypothesis, apart from the *Gt* statistic for the first specification which confirms the presence of a cointegrating relationship at the 10% significance level.

Table 4: Panel cointegration results (1963-2000)

Variables	**(1)**	**(2)**
Gt	-2.829*	-2.733
	(0.099)	(0.121)
Ga	-5.217	-2.701
	(0.974)	(0.999)
Pt	-16. 760	-11.121
	(0.189)	(0.887)
Pa	-5.159	-2.676
	(0.845)	(0.997)

*Panel cointegration test statistics by Westerlund (2007) using the AIC to choose optimal lag and lead lengths. N= 48 US states. The null is H_0: no cointegration. Robust p-values through bootstrapping with 1000 simulations are in parentheses. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively. The Ga and Gt test statistics test the null hypothesis against the alternative that there is cointegration for at least one cross-sectional unit. The Pa and Pt test statistics test the null against the alternative of cointegration for all cross-sectional units.*

In light of the results of the unit root and cointegration tests, I estimate the aggregate production function specifications in levels using the CCEMG and AMG estimators which are robust to the presence of I(1) non-cointegrated variables. First, I employ the Common Correlated Effects Mean Group (CCEMG) estimator introduced by Pesaran (2006). Coakley, Fuertes, and Smith (2006) show that the CCEMG procedure stands out as the most efficient and robust among alternative estimators for linear heterogeneous panels with unobserved common (correlated) factors.

According to columns 1 and 2 of Table 5, the estimated coefficients for labor and private capital are positive and highly significant across all specifications over 1963-2000. So, my results support earlier findings which are in favor of a positive effect of these factors on regional income. At first, my findings are in line with Hulten and Schwab (1984) who conclude that labor and capital differences across regions explain positively most of the regional differences in output. However, while these findings certainly do not contradict the conclusions of earlier studies, they point to an additional factor, namely educational human capital. In this way, I support the results obtained by Garcia-Mila and McGuire (1992) which indicate the positive output effects of education. In other words, I support the hypothesis that human capital has a direct role in production through the generation of worker skills.

Table 5: CCEMG, AMG and AMG impose robust estimation results (1963-2000)

Method	*CCEMG*		*AMG*		*AMG impose*	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
lschoolyears	0.482**	0.400*	0.634***	0.609***	0.696***	0.637***
	(0.041)	(0.079)	(0)	(0)	(0)	(0)
lnlabor	0.272**	0.226*	0.448***	0.459***	0.462***	0.472***
	(0.019)	(0.097)	(0)	(0)	(0)	(0)
lprivatecapital	0.381***	0.395***	0.298***	0.294***	0.291***	0.288***
	(0)	(0)	(0)	(0)	(0)	(0)
lpatents	0.00297	0.00660	-0.00545	-0.00410	-0.000885	-0.00497
	(0.655)	(0.290)	(0.119)	(0.217)	(0.879)	(0.306)
lbeds		0.00328		-0.0108		-0.000580
		(0.831)		(0.444)		(0.970)
constant	1.406**	1.139*	-0.577*	-0.521*	-0.650*	-0.470
	(0.0201)	(0.0870)	(0.0924)	(0.0994)	(0.0529)	(0.126)
cdp			0.995***	0.983***		
			(0)	(0)		
CD	0.050	0.700	-0.180	0.350	-0.720	-0.740
	(0.246)	(0.486)	(0.245)	0.725	(0.471)	(0.459)
test cdp=1			(0.886)	(0.614)		

*Dependent variable: lrpim. CCEMG, AMG and AMG impose robust estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively. All variables are in logarithms. The cross-section dependence CD statistic (Ho: cross-section independence) is based on the residuals from these CCEMG, AMG and AMG impose robust regressions.*

As regards their magnitude, I find larger coefficients for human and private capital, while labor force has a smaller coefficient. According to my findings, a 1-standard deviation of the education variable by 1% is expected to raise income by approximately 0.40%. The same percentage increase in the private capital stock or in labor force boosts regional income by around 0.38% and 0.23% respectively.

In contrast, the impact of health and patents on real personal income is insignificant (Table 5). Health, measured by hospital beds, may not influence economic activity, since this proxy measures the quantity, rather than the quality, of the provided health services (Benos and Karagiannis, 2010). In addition, the insignificant impact of patents on income is not a surprising result, since patents may exert indirect effects on economic activity via their impact on factor accumulation. For instance, patents may indirectly affect income by stimulating the accumulation of physical and human capital. The intuition behind this assumption is that patents do not directly affect the technical efficiency of production, and subsequently output, but rather the environment in which research, innovation and investment can take place (Park, 1999). Thus, patents alone may not exert a direct economic impact on income.

Next, I examine the regression residuals for cross-sectional dependence. The CD tests suggest that CCEMG yields cross-sectionally independent residuals in all specifications. Thus, my estimated specifications appear to be correctly specified in all cases. I check the robustness of my results employing two variants of the AMG estimator. Specifically, in Table 5 I report the results from the unrestricted AMG estimator, as well as the corresponding AMG results after imposing the restriction of a unitary common dynamic process (Hamilton, 1991). As such, the results in Table 5 are less sensitive to the presence of outliers. I impose the restriction of the common dynamic process after having tested and verified its validity.

According to columns 3 and 4 of Table 5, the AMG results appear to be in line with the findings obtained through the CCEMG method. The AMG findings during 1963-2000 confirm the positive influence of education, labor and private capital on income. The income effects of health (and at a lesser extent those of patents) are statistically insignificant. As regards the magnitude of the AMG estimates, I find larger coefficients for education and labor, but smaller for private capital in comparison with those obtained via the CCEMG method. A rise of the education variable by 1% is expected to raise income by about 0.60%. The same percentage increase in the private capital stock or in labor force, would raise regional income by 0.29% and 0.45% respectively. Finally, the CD test results show that AMG provides cross-sectionally independent residuals across all specifications.

The results from the restricted AMG estimator in columns 5 and 6 of Table 5 further verify my main outcomes. Again, the estimated coefficients bear similar signs, magnitudes and statistical significance regarding the main determinants of regional income. The CD test results show that the null hypothesis of cross-section independence is accepted for all specifications.

Similar results are obtained for the 1970-2000 sub-period. Descriptive statistics for this shorter sample are reported in Table 6. Cross-section dependence is confirmed (Table 7) and all variables appear to be stationary in first differences (Table 8). The cointegration test statistics reject the presence of a cointegrating relationship across most specifications (Table 9). Moreover, the CCEMG and AMG estimates confirm the positive impact of education, labor and private capital on income (Tables 10, 11 and 12). The income effects of health and patents are statistically insignificant, as before, while public capital is negatively or insignificantly associated with regional income. In addition, I find larger coefficients for education, labor and private capital via the AMG method than those obtained during the 1963-2000 period. Regarding public capital, I report larger coefficients through the AMG method. A 1% increase in the total public capital stock, decreases regional income via the CCEMG and AMG estimators by around 0.35% and 0.10% respectively. The same percentage increase in the other two proxies of public capital, would also decrease output by 0.19% or 0.23%, according to the CCEMG findings. Moreover, the CD test results suggest that CCEMG and AMG yield cross-sectionally independent residuals in most specifications (the results indicate misspecification problems in 6 out of 24 specifications - see Tables 10, 11 and 12).

Table 6: Descriptive statistics for variables in levels (1970-2000)

Variable	Mean	Max	Min	Median	Standard deviation
rpim	111539.3	1000000	5465.92	72161.5	128539.7
schoolyears	12.2939	14.14101	9.332555	12.41168	0.917744
labor	2355808	1.71E+07	132819	1647338	2495994
privatecapital	138107	1366668	7816.658	83176.35	171623.6
patents	1032.796	17491	17	440.5	1539.178
beds	3.889452	7.4	1.746	3.804	1.012393
kgpublic	63032.33	457480.5	5263.173	44288.9	68202.06
kgcorepublic	30951.68	158180.1	3492.906	23353.25	28807.63
kghwpublic	24246.46	108411.5	2972.995	18867.08	21070.8

These descriptive statistics refer to the sample of 48 US states. All variables are expressed in raw numbers.

Table 7: Cross-section dependence - CD test results (1970-2000)

Variables in levels	CD	Variables in 1st differences	CD
lrpim	181.79***	dlrpim	94.61***
	(0)		(0)
lschoolyears	185.19***	dlschoolyears	64.35***
	(0)		(0)
lnlabor	180.62***	dlnlabor	179.07***
	(0)		(0)
lprivatecapital	173.58***	dlprivatecapital	54.48***
	(0)		(0)
lpatents	122.74***	dlpatents	111.46***
	(0)		(0)
lbeds	120.30**	dlbeds	103.12***
	(0.042)		(0.002)
lkgpublic	183.62***	dlkgpublic	42.88***
	(0)		(0)
lkgcorepublic	182.23***	dlkgcorepublic	56.30***
	(0)		(0)
lkghwpublic	180.48***	dlkghwpublic	52.74***
	(0)		(0)

*Pesaran's CD statistics refer to the 48 US states. Under the null hypothesis, (H_0: cross-section independence), the CD statistics converge to a normal standard distribution. P-values are in parentheses. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively.*

Table 8: Pesaran's CADF panel unit root tests (1970-2000)

Variables in levels	CADF test	Variables in 1st differences	CADF test
lrpim	-2.193	dlrpim	-2.216***
	(0.876)		(0)
lschoolyears	-2.259	dlschoolyears	-2.333***
	(0.739)		(0)
lnlabor	-2.495	dlnlabor	-2.313***
	(0.111)		(0)
lprivatecapital	-2.321	dlprivatecapital	-2.366***
	(0.560)		(0)
lpatents	-2.398	dlpatents	-2.979***
	(0.323)		(0)
lbeds	-1.100	dlbeds	-2.289**
	(0.999)		(0)
lkgpublic	-2.349	dlkgpublic	-2.938***
	(0.472)		(0)
lkgcorepublic	-2.033	dlkgcorepublic	-2.417***
	(0.992)		(0)
lkghwpublic	-2.106	dlkghwpublic	-2.212***
	(0.967)		(0.001)

*Pesaran's unit root test statistics refer to the 48 US states. P-values are in parentheses. The null is H_0: non-stationarity. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively.*

Table 9: Panel cointegration results (1970-2000)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gt	-3.198***	-2.743*	-6.467	-15.823*	-9.957	-2.277	-1.963	-2.217
	(0.003)	(0.089)	(0.274)	(0.077)	(0.156)	(0.114)	(0.402)	(0.158)
Ga	-2.054	-0.771	-0.202	-0.335	-0.365	-1.811	-1.763	-1.682
	(0.999)	(0.999)	(0.999)	(0.914)	(0.854)	(0.984)	(0.994)	(0.997)
Pt	-12.660	-10.944	-9.502	-10.518*	-10.023*	-11.714	-8.065	-6.456
	(0.548)	(0.501)	(0.159)	(0.064)	(0.064)	(0.197)	(0.719)	(0.917)
Pa	-1.679	-0.827	-0.312	-0.386	-0.325	-1.425	-1.370	-1.199
	(0.990)	(0.999)	(0.650)	(0.559)	(0.282)	(0.900)	(0.908)	(0.963)

*Panel cointegration test statistics by Westerlund (2007)using the AIC to choose optimal lag and lead lengths. N= 48 US states. The null is H_0: no cointegration. Robust p-values through bootstrapping with 1000 simulations are in parentheses. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10% , 5% and 1% significance levels respectively. The Ga and Gt test statistics test the null hypothesis against the alternative that there is cointegration for at least one cross-sectional unit. The Pa and Pt test statistics test the null against the alternative of cointegration for all cross-sectional units.*

The negative and significant income elasticity of both total public capital stock and its subcomponents may seem economically unreasonable, but it is not new in the public capital productivity literature. A number of empirical studies suggest that the marginal return of public capital is virtually zero and often negative, especially when either state or both state and time-effects are controlled for (Baltagi and Pinnoi, 1995; Garcia-Milà et al., 1996; Holtz-Eakin, 1994).

This confusing result may arise from public sector efficiency issues (Adam et al, 2011), as the relationship between public capital and economic activity depends explicitly on the efficiency of the public sector (socio-economic and political elements may influence public sector efficiency). In addition, the public capital-output relationship turns negative above a certain public capital threshold. For example, maintaining and/or expanding the existing capital stock may require high (and potentially distortionary) tax rates, which would reduce economic activity, all else being equal (Aschauer 1998; Barro 1990). In this case, the impact of public capital on regional income depends on the initial stock of public capital and its negative sign stems from neglected nonlinearities in the production process (Kalyvitis and Vella, 2015). Alternatively, the negative coefficient on public capital may be to indirect effects. Public capital may affect output either directly as an additional input in the production function or indirectly via its effects on private inputs, such as private capital and labor. In this study, however, I focus only on the direct impact of production factors on output, leaving the analysis of the indirect effects for future research[9].

Table 10: CCEMG robust estimation results (1970-2000)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
lschoolyears	0.454*	0.055*	0.143*	0.173*	0.235*	0.390*	0.060*	0.135*
	(0.073)	(0.098)	(0.070)	(0.057)	(0.082)	(0.062)	(0.087)	(0.085)
lnlabor	0.203**	0.105**	0.139**	0.245**	0.214**	0.204*	0.127**	0.118**
	(0.043)	(0.048)	(0.021)	(0.035)	(0.011)	(0.069)	(0.032)	(0.036)
lprivatecapital	0.450***	0.425***	0.418***	0.434***	0.427***	0.430***	0.446***	0.442***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
lpatents	0.00459	0.00592	0.00380	0.00421	0.00709	0.000168	0.00262	0.00298
	(0.543)	(0.419)	(0.520)	(0.471)	(0.243)	(0.978)	(0.687)	(0.611)
lbeds		-0.0370	-0.0380	-0.0166	-0.0358			
		(0.147)	(0.121)	(0.482)	(0.129)			
lkgpublic			-0.381***			-0.342***		
			(1.17e-05)			(1.54e-05)		
lkgcorepublic				-0.193**			-0.131	
				(0.0278)			(0.141)	
lkghwpublic					-0.231***			-0.121
					(0.00765)			(0.122)
constant	0.686	0.401	0.681	-0.0595	-0.344	-0.0198	-0.399	-0.730
	(0.285)	(0.613)	(0.512)	(0.947)	(0.668)	(0.980)	(0.591)	(0.236)
CD	1.470	1.500	2.510**	3.740***	3.240***	2.150**	4.680***	4.710***
	(0.143)	(0.113)	(0.012)	(0)	(0.001)	(0.032)	(0)	(0)

*Dependent variable: lrpim. CCEMG robust estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively. All variables are in logarithms. The cross-section dependence CD statistic (Ho: cross-section independence) is based on the residuals from these CCEMG regressions.*

[9] The constant term is positive and highly significant in all specifications. However, I do not report a group-specific trend term, representing the long-term movement in time series data after other components have been accounted for, since it appears insignificant in all specifications.

Table 11: AMG robust estimation results (1970-2000)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lschoolyears	0.686***	0.637***	0.899***	0.767***	0.677***	0.925***	0.905***	0.841***
	(0)	(0)	(0)	(3.01e-10)	(9.25e-	(0)	(0)	(0)
lnlabor	0.446***	0.456***	0.508***	0.475***	0.444***	0.507***	0.484***	0.451***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
lprivatecapital	0.305***	0.303***	0.330***	0.305***	0.311***	0.329***	0.297***	0.307***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
lpatents	-0.00284	-0.00106	0.00398	0.00107	0.00203	0.00347	-9.46e-05	-0.000443
	(0.547)	(0.819)	(0.328)	(0.815)	(0.684)	(0.437)	(0.984)	(0.930)
lbeds		-0.00905	-0.0146	-0.00809	-0.0107			
		(0.649)	(0.526)	(0.693)	(0.625)			
lkgpublic			-0.118*			-0.0971*		
			(0.0696)			(0.0725)	-0.0802	
lkgcorepublic				-0.0582			(0.259)	
				(0.496)				
lkghwpublic					-0.0400			-0.0771
					(0.623)			(0.229)
cdp	1.041***	0.985***	1.025***	1.000***	1.014***	1.053***	1.063***	1.069***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
constant	-0.613*	-0.671**	-1.124***	-0.994***	-0.588	-1.047***	-1.243***	-0.933***
	(0.0588)	(0.0308)	(0.00127)	(0.00533)	(0.106)	(0.000248)	(0.000494)	(0.00938)
CD	0.940	1.450	1.410	1.470	1.330	1.320	1.520	1.290
	(0.346)	(0.149)	(0.161)	(0.183)	(0.200)	(0.191)	(0.121)	(0.222)
test cdp=1	(0.139)	(0.682)	(0.520)	(0.996)	(0.728)	(0.998)	(0.143)	(0.132)

*Dependent variable: lrpim. AMG robust estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively. All variables are in logarithms. The cross-section dependence CD statistic (Ho: cross-section independence) is based on the residuals from these AMG regressions.*

Table 12: AMG impose robust estimation results (1970-2000)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lschoolyears	0.670***	0.630***	0.906***	0.775***	0.676***	0.880***	0.812***	0.773***
	(0)	(0)	(0)	(0)	(6.76e-	(0)	(0)	(0)
lnlabor	0.453***	0.450***	0.498***	0.458***	0.431***	0.502***	0.459***	0.447***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
lprivatecapital	0.324***	0.315***	0.328***	0.311***	0.316***	0.332***	0.311***	0.311***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
lpatents	0.00330	-0.000391	0.00535	0.00192	0.00332	0.00920	0.00487	0.00561
	(0.548)	(0.945)	(0.296)	(0.736)	(0.599)	(0.127)	(0.411)	(0.375)
lbeds		-0.00305	-0.00180	-0.00248	-0.00155			
		(0.876)	(0.934)	(0.907)	(0.938)			
lkgpublic			-0.131**			-0.0726		
			(0.0175)			(0.174)		
lkgcorepublic				-0.0407			-0.00762	
				(0.539)			(0.897)	
lkghwpublic					-0.0140			-0.0181
					(0.827)			(0.741)
constant	-0.689**	-0.537*	-0.890***	-0.783**	-0.454	-0.927***	-1.120***	-0.972***
	(0.0329)	(0.0840)	(0.00668)	(0.0153)	(0.190)	(0.00156)	(0.000912)	(0.00228)
CD	1.320	0.990	1.100	1.290	1.200	1.430	1.470	1.040
	(0.189)	(0.323)	(0.245)	(0.196)	(0.230)	(0.165)	(0.113)	(0.304)

*Dependent variable: lrpim. AMG impose robust estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively. All variables are in logarithms. The cross-section dependence CD statistic (Ho: cross-section independence) is based on the residuals from these AMG regressions.*

Finally, in Table 13 I report the state-specific coefficients for R&D, health and total public capital. I focus on these three variables as my analysis provides confusing results and suggests that the income effects of these capital proxies are either insignificant or negative. The results of this exercise show that the state-level estimates of R&D, health and public capital differ substantially in terms of sign, magnitude and statistical significance. Specifically, the results indicate a negative or weak influence of public capital on regional income. Thus, the public capital-output nexus remains an open issue which merits further investigation.

Table 13: CCEMG, AMG and AMG impose robust results by state

	CCEMG	**CCEMG**	**CCEMG**	**AMG**	**AMG**	**AMG**	**AMG impose**	**AMG impose**	**AMG impose**
State	lpatents	lbeds	lkgpublic	lpatents	lbeds	lkgpublic	lpatents	lbeds	lkgpublic
Alabama	-0.045*** (0.002)	-0.015 (0.492)	-0.026 (0.944)	-0.022 (0.245)	-0.064** (0.028)	0.218 (0.506)	0.021 (0.155)	-0.074*** (0)	0.210 (0.548)
Arizona	0.046 (0.412)	-0.027* (0.067)	0.271 (0.129)	-0.016 (0.634)	0.171** (0.014)	0.286* (0.086)	-0.032 (0.184)	0.082* (0.051)	0.331* (0.054)
Arkansas	0.009 (0.676)	-0.053 (0.311)	-0.606 (0.402)	0.009 (0.622)	-0.036 (0.330)	-0.245 (0.538)	0.006 (0.709)	-0.013 (0.632)	-0.242 (0.536)
California	0.085* (0.087)	0.045 (0.365)	-0.087 (0.879)	-0.049** (0.015)	0.088* (0.068)	-0.338 (0.127)	-0.021** (0.044)	0.037 (0.415)	-0.385 (0.106)
Colorado	0.065 (0.130)	-0.021 (0.271)	-0.162 (0.665)	0.050*** (0.001)	0.026 (0.102)	-0.334 (0.164)	0.038*** (0.001)	0.018* (0.056)	-0.247 (0.225)
Connecticut	0.103** (0.044)	-0.038 0.357	-1.165*** (0)	-0.008 (0.826)	-0.012 (0.736)	-0.590*** (0)	-0.060 (0.151)	0.023 (0.594)	- 0.637***
Delaware	0.009 (0.598)	-0.044** (0.046)	0.116 (0.687)	-0.011 (0.623)	0.033 (0.237)	0.395*** (0)	-0.004 (0.845)	0.036 (0.143)	0.367*** (0)

Florida	0.092** (0.010)	0.056 (0.334)	0.106 (0.731)	0.049*** (0.004)	0.059 (0.300)	0.054 (0.542)	0.029*** (0.003)	0.075* (0.088)	0.017 (0.818)
Georgia	0.026 (0.369)	0.147*** (0)	0.312 (0.226)	0.001 (0.964)	0.140*** (0)	0.105 (0.371)	0.054*** (0.001)	0.177** (0)	0.172 (0.160)
Idaho	0.033* (0.069)	-0.301** (0.010)	-1.725*** (0.001)	0.035** (0.027)	-0.273*** (0)	0.097 (0.772)	0.004 (0.580)	-0.297*** (0)	-0.024 (0.927)
Illinois	0.153 (0.555)	0.009 (0.521)	-0.191 (0.489)	0.001 (0.975)	-0.009 (0.452)	0.086 (0.513)	-0.001 (0.982)	-0.008 (0.453)	0.076 (0.551)
Indiana	-0.085*** (0.001)	-0.091 (0.153)	-0.255 (0.342)	-0.024 (0.212)	-0.054 (0.179)	0.129 (0.503)	0.008 (0.590)	0.030* (0.079)	0.228 (0.263)
Iowa	-0.014 (0.667)	-0.042 (0.526)	-1.168 (0.258)	-0.021 (0.380)	-0.017 (0.745)	-1.223** (0.010)	-0.032* (0.028)	-0.017 (0.504)	-0.571 (0.146)
Kansas	-0.019 (0.314)	-0.033 (0.621)	0.318 (0.373)	-0.016 (0.138)	-0.076** (0.037)	0.360 (0.135)	-0.036*** (0)	-0.061*** (0)	0.410* (0.082)
Kentucky	-0.007 (0.818)	-0.061 (0.139)	-0.222 (0.595)	0.003 (0.803)	0.031 (0.433)	0.651* (0.064)	0.025* (0.061)	0.063* (0.051)	0.733** (0.024)
Louisiana	-0.094*** (0.001)	-0.022 (0.611)	-0.381 (0.340)	-0.057** (0. 033)	0.222* (0.067)	0.625** (0.049)	-0.068*** (0.007)	0.136 (0.238)	-0.309 (0.303)
Maine	0.007 (0.665)	0.239*** (0)	-0.920*** (0.001)	0.005 (0.744)	-0.016 (0.833)	-0.451*** (0.006)	-0.048*** (0.005)	-0.211** (0.010)	- 0.515***
Maryland	-0.028 (0.513)	0.087 (0.374)	-0.746*** (0.002)	0.042 (0.110)	-0.214** (0.003)	-0.079 (0.645)	0.024 (0.363)	-0.233*** (0.002)	-0.341** (0.020)
Massachusetts	0.013 (0.807)	0.010 (0.860)	-0.395** (0.046)	-0.027 (0.157)	0.043*** (0)	-0.084 (0.503)	-0.040** (0.024)	0.045** (0)	-0.131 (0.290)
Michigan	0.018 (0.760)	0.025 (0.355)	-0.741** (0.036)	-0.013 (0.656)	-0.087*** (0.006)	-0.383 (0.501)	-0.035 (0.128)	-0.088*** (0.006)	-0.333 (0.300)
Minnesota	0.028 (0.515)	-0.017 (0.596)	-0.486 (0.147)	0.017 (0.469)	0.009 (0.659)	-0.799*** (0)	0.032* (0.024)	0.005 (0.803)	-0.499** (0.018)
Mississippi	-0.007 (0.824)	0.011 (0.589)	-1.074** (0.032)	-0.007 (0.779)	-0.733*** (0)	0.078 (0.768)	0.056*** (0.002)	-0.456*** (0)	-0. 114 (0.685)
Missouri	-0.034 (0.175)	-0.619*** (0.001)	0.040 (0.925)	-0.027*** (0.005)	-0.102** (0.021)	-0.132 (0.105)	-0.010 (0.131)	-0.093*** (0.001)	-0.102 (0.177)

Montana	-0.015	-0.108**	0.180	-0.012	0.024	-1.344*	-0.036**	0.085**	-1.278**
	(0.258)	(0.038)	(0.561)	(0.483)	(0.762)	(0.029)	(0.011)	(0.038)	(0.021)
Nebraska	0.023	-0.015	-0.627	0.016	0.231**	-0.309	0.015	0.104	-0.461
	(0.365)	(0.864)	(0.331)	(0.410)	(0.015)	(0.437)	(0.278)	(0.104)	(0.172)
Nevada	0.324***	0.178	0.929	-0.016	-0.068	-0.029	-0.013	-0.109*	0.101
	(0)	(0.474)	(0.147)	(0.305)	(0.261)	(0.853)	(0.430)	(0.063)	(0.339)
New	-0.025	-0.009	0.149*	-0.028	0.103*	-0.189	-0.075***	0.182***	0.021
Hampshire	(0.462)	(0.993)	(0.092)	(0.176)	(0.086)	(0.333)	(0.001)	(0)	(0.901)
New Jersey	0.108**	0.196*	-0.472*	0.108***	0.006	-1.296***	0.109***	0.002	-
	(0.026)	(0.067)	(0.087)	(0)	(0.821)	(0)	(0)	(0.900)	1.281***
New Mexico	-0.014	0.001	-1.054***	-0.005	0.051	0.074	-0.019*	0.057	-0.022
	(0.588)	(0.927)	(0)	(0.786)	(0.248)	(0.569)	(0.065)	(0.161)	(0.771)
New York	-0.082	0.001	-0.013	-0.009	-0.252***	-0.311**	0.041	-0.231**	-0.328**
	(0.182)	(0.998)	(0.966)	(0.678)	(0)	(0.033)	(0.001)	(0)	(0.024)
North Carolina	0.046	-0.224**	-0.342	0.018	-0.014	0.127***	0.141***	-0.041**	0.099
	(0.135)	(0.010)	(0.104)	(0.254)	(0.175)	(0.005)	(0)	(0.028)	(0.130)
North Dakota	-0.004	-0.011	0.010	-0.006	-0.852**	-3.678**	-0.027	-0.758**	-2.378**
	(0.955)	(0.511)	(0.960)	(0.992)	(0.022)	(0.016)	(0.606)	(0.040)	(0.032)
Ohio	-0.039	-1.408*	-2.525	0.002	0.023	-0.535***	0.040**	0.030*	-0.460**
	(0.487)	(0.066)	(0.223)	(0.901)	(0.122)	(0)	(0.020)	(0.054)	(0.010)
Oklahoma	0.012	0.018	-0.965**	-0.018	-0.050**	-0.229*	-0.032	-0.113***	-0.244**
	(0.655)	(0.204)	(0.015)	(0.214)	(0.040)	(0.070)	(0.150)	(0)	(0.012)
Oregon	0.018	-0.143***	-0.461***	0.001	-0.080	-1.186***	-0.019	-0.065*	-
	(0.662)	(0.004)	(0)	(0.997)	(0.124)	(0)	(0.159)	(0.077)	1.139***
Pennsylvania	-0.139***	-0.300***	-0.934**	-0.019	0.298***	-0.195	0.017	0.160***	0.185
	(0.006)	(0)	(0.014)	(0.445)	(0)	(0.440)	(0.482)	(0)	(0.490)
Rhode Island	-0.013	0.298***	0.443	-0.010	-0.005	-0.431	-0.017	-0.006	-0.314
	(0.741)	(0)	(0.178)	(0.623)	(0.824)	(0.183)	(0.253)	(0.652)	(0.299)
South Carolina	-0.020	-0.005	-1.325**	0.006	-0.026	0.100	0.023**	0.056***	0.092
	(0.376)	(0.848)	(0.020)	(0.601)	(0.754)	(0.217)	(0.025)	(0.007)	(0.254)
South Dakota	0.002	0.173***	0.034	-0.027	0.036*	-0.303	0.005	0.065*	-0.040
	(0.925)	(0.009)	(0.891)	(0.229)	(0.069)	(0.615)	(0.762)	(0.067)	(0.947)

Tennessee	0.068***	0.023	-1.062	0.041**	-0.015	0.280**	0.118***	0.076***	0.234**
	(0.004)	(0.836)	(0.345)	(0.025)	(0.316)	(0.035)	(0)	(0)	(0.050)
Texas	-0.003	0.038**	0.343	-0.030*	-0.058	-0.102	-0.036***	-0.007	-0.108
	(0.942)	(0.044)	(0.336)	(0.083)	(0.284)	(0.231)	(0)	(0.532)	(0.155)
Utah	-0.009	-0.002	-0.523***	-0.016	-0.157	0.066	0.009	-0.064	0.088**
	(0.702)	(0.936)	(0.004)	(0.202)	(0.142)	(0.259)	(0.250)	(0.274)	(0.023)
Vermont	-0.028	-0.048	0.127	-0.001	0.002	-0.283*	-0.020	0.022	-0.293**
	(0.112)	(0.559)	(0.300)	(0.910)	(0.816)	(0.072)	(0.255)	(0.824)	(0.043)
Virginia	-0.003	0.494***	-0.422**	-0.015	-0.066	0.066	0.016*	0.005	0.071
	(0.988)	(0.005)	(0.038)	(0.185)	(0.119)	(0.314)	(0.090)	(0.652)	(0.264)
Washington	-0.035	0.010	-0.142	-0.019	-0.049	0.066	-0.026*	-0.066	-0.013
	(0.369)	(0.342)	(0.388)	(0.412)	(0.337)	(0.546)	(0.071)	(0.111)	(0.879)
West Virginia	0.035*	-0.082	0.120	0.028*	-0.007	-1.494**	0.017	0.033	-1.687**
	(0.054)	(0.134)	(0.479)	(0.073)	(0.924)	(0.015)	(0.302)	(0.479)	(0.010)
Wisconsin	-0.049	0.093	-1.603***	0.128	-0.237	-0.547***	0.022***	-0.027*	-
	(0.154)	(0.207)	(0.007)	(0.441)	(0.104)	(0)	(0.008)	(0.577)	0.395***
Wyoming	0.013	-0.341**	-0.398	0.020	-0.178	-0.646***	0.025	-0.182	-
	(0.540)	(0.037)	(0.266)	(0.275)	(0.232)	(0)	(0.169)	(0.143)	0.590***
CD	0.050	0.700	2.510**	-0.180	0.350	2.410**	-0.720	-0.740	2.000**
	(0.960)	(0.486)	(0.012)	(0.860)	(0.725)	(0.016)	(0.471)	(0.459)	(0.045)

*Dependent variable: lrpim. Robust estimates by state. Estimates are obtained over 1963-2000, apart from those employing public capital proxies as explanatory variables that refer to the 1970-2000 period. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively. All variables are in logarithms. The CD statistic (Ho: cross-section independence) is based on the residuals from these regressions.*

Patents (hospital beds) carry a statistically significant positive coefficient in nine (five) states and a negative one in seven (eight) states. In the remaining states, the income effect of both patents and hospital beds is insignificant, thereby verifying the baseline results.

2.6. Concluding remarks

Conclusively, this chapter employs a production function approach and examines simultaneously the impact of different factor of production (labor, private and public capital, human capital and R&D) on the US states' income accounting at the same time for parameter heterogeneity and cross-section dependence.

The empirical analysis consists of four steps. First, I test for cross-section dependence among the US states. Second, I apply unit root tests allowing for cross-section dependence. Third, I test for cointegration after allowing for cross-section dependence. Fourth, I estimate the models using the CCEMG and AMG estimators.

The results of the analysis of cross-section correlation indicate substantial interdependence among all variables. Furthermore, all variables appear to be I(1), i.e. stationary in first differences, but not cointegrated. The CCEMG and AMG estimates suggest that education, labor and private capital are positively associated with regional income, whereas public capital, health and R&D are negatively or insignificantly related to output. I focus my attention on educational human capital which exerts the strongest direct effect on regional income. This qualifies education as a suitable and effective instrument for regional policies aiming at narrowing income gaps across the US states.

Appendix of Chapter 2

The definitions of all variables used in Chapter 2 along with the sources and their measures are presented in the following table:

Variable	Source	Definition/Measure
real personal income	BEA regional accounts, CPI US state data of Berry et al (1960-2007 extended dataset)	real personal income in millions of chained 2000 dollars
schooling years	Tamura et al (2006)	average schooling years in the labor force
labor force	Tamura et al (2006)	persons aged 16 years and older
private capital	Garofalo-Yamarik (2002), Yamarik (2013)	net private capital stocks in millions of chained 2000 dollars
patents	US Patent and Trademark Office	number of patents
beds	CDC database	community hospital beds per 1000 resident population
total public capital stock	Christ and Islam (2012)	total public capital stock measured in millions of chained 2000 dollars
public capital stock in terms of highways, water and sanitation	Christ and Islam (2012)	public capital stock in terms of highways, water and sanitation measured in millions of chained 2000 dollars
public capital stock in terms only of highways	Christ and Islam (2012)	public capital stock in terms only of highways measured in millions of chained 2000 dollars

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Chapter 3: Spatial variations in life expectancy among US states

3.1. Introduction

Human capital plays an important role in the economic development of countries and regions. In fact, aggregate human capital at national or regional level has been a recurrent variable in economic growth models (Barro, 1991, 1996; Barro and Lee, 1993; Benhabib and Spiegel, 1994; Islam, 1995). However, despite of the wide scholarly agreement of its impact on economic growth there is little consensus on the exact contributions of the different measures and indicators of human capital to economic development (Levine and Renelt, 1992). Another important issue related to human capital and economic development and far less studied is the role the economic geography of a country or a region plays with respect to this relationship. At this point the fairly new branch of the spatial economics has emerged as a new theory.

Spatial or neighbouring aspects on regional economic analysis are important things that can not be ignored because inter-regional interaction exists in certain. The mobility of production factor, trade relations and geographical overflow (such as technology deployment) influences the economic development of an area, which is affected by its neighbours. Spatial aspects are important in explaining economic growth. Countries can interact with each other through channels such as trade, technological diffusion, capital flows, political, economic and social policies. Spatial externalities can spill over across borders between countries, which contribute in explaining economic growth. Technology diffusion between neighbouring countries is also very important.

Recently, maintaining, expanding, and improving the health of human populations is considered as one of the key policies for sustainable development in developing countries. Health is a basic form of human capital and as a result, one of the most significant development issues facing the world today. The study of the health status of a population is important for the evaluation of economic development of a country. Thus, the examination of the sources of life expectancy can offer useful information for policy decisions towards development. Besides, in the last decades, life expectancy has significantly increased, but with cross-section variations according to particular development conditions.

The investigation of relevant measures of the health status is an important step in order to assess and compare country performances and establish targets for health policies. In addition, it is also necessary to distinguish the determinants behind cross-section differences in health performance. From this point of view, macro level studies find plenty of factors that are associated with the overall health status. However, actual knowledge on the determinants of health outcomes of populations, at the level of countries, suffers from the partiality of models and frameworks used in empirical investigation.

Moreover, a methodological shortcoming for most of this literature is the lack of accounting for spatial autocorrelation across regions or states. In such approaches the issue of spatial autocorrelation has not been addressed in a systematic way. Spatial interdependence may occur if one country strategically mimics neighboring health policies, for example by adopting the same vaccine to prevent the diffusion of a contagious disease (Baltagi et al, 2012). Therefore, life expectancy can be used for spatial studies (comparison between countries or regions of a country), temporal analyses, or space-time studies with the purpose of identifying if the recorded life expectancy has different tendencies in different locations (Jen et al, 2010).

This, in turn, requires an approach, which investigates potential explanations for the relative impact of various sources on health outcomes. Following these considerations, the analysis of this chapter seeks to build upon previous studies by employing a wider set of medical and non-medical factors. In particular, the aim of this research is to examine the main determinants of life expectancy among US states by using a spatial process and give some appropriate and efficient health policy designs in order to raise life expectancy. To my knowledge, there exists no previous study that estimates empirically the determinants of US life expectancy on the basis of state-level data under a spatial framework.

According to previous studies, the sources of life expectancy are grouped into three main categories: resources of the health system, factors related to lifestyle and socio-economic measures (Joumard et al, 2008). The first category refers to health expenses (public and private spending) and to material resources of the healthcare system. The determinants connected to lifestyle consist of individual behaviors that determine health (smoking, alcohol consumption and physical activity) and eating habits (consumption of fats, sugar, fruits and vegetables or obesity indexes). The third category includes income per capita, education, poverty and unemployment proxies, as well as the ethnic structure of the population, environment measures and the degree of air pollution.

In order to quantify the relative impact of each factor (namely health spending, life style and socio-economic proxies) on health outcomes, I adopt a production function, using state-level data for the US over the period 1995-2007. I assume that life expectancy is related to health spending, education, income and some life-style measures (e.g. alcohol consumption, smoking, physical exercise and obesity). The empirical model is then estimated via the Instrumental Variables (IV) estimator in order to explore the main factors behind US state differences in longevity. The instrumental IV procedure suggested by Kelejian and Prucha (1998) relates to the parameters of a spatial first order autoregressive model with first order autoregressive disturbances, where instruments are given by the spatial lags of the included regressors, and is based on a Generalized Moments (GM) estimator of a parameter in the disturbance process. The Kelejian and Prucha (1998) procedure does not require specific distributional assumptions.

A priori, one would expect a positive relation between health care spending and health status if increasing resources implies an improvement in the quality of health services supplied to the population. In addition, it would appear reasonable to argue that there is a positive association between income and health. Higher income results in higher consumption of goods that have a direct impact on the quality of life, such as food, housing, schooling, etc. However, empirical studies over the past years have given contradictory results on these relationships (Auster et al, 1969; Rodgers, 1979; Wilkinson, 1996; Christiansen, 1994).

Regarding life-style variables, previous approaches argue that populations that are less likely to exercise, smoke, have excessive intakes of alcohol or be overweight, are more likely to have health insurance coverage and access to health care, thus higher life expectancy (Thornton and Rice, 2008). Education also appears to be an important determinant of health in most empirical papers, irrespective of the output measure used and even when differences in income are controlled for (Auster et al, 1969; Silver, 1972; Grossman, 1972; Valkonen, 1988). Several explanations have been given for the influence of education on health. In summary, education seems to determine many of the decisions, which affect the quality of life: choice of job, ability to select a healthy diet and avoid unhealthy habits, efficient use of medical care, etc. Education, thus, affects both health behaviors and health status.

In this direction, my empirical results reinforce some of these aforementioned aspects. According to the obtained estimates, health spending plays a primary role in increasing longevity. Other factors, such as education also appear to have positive influence on life expectancy. On the contrary, cigarette smoking has a substantial adverse impact on the dependent variable. Therefore, US state health policies towards longevity should mainly focus on increasing the amount of spending devoted to health care and educational systems.

For robustness analysis, I also use health spending as well as education criteria, apart from the geographical. In the former case, states with similar health expenditure are "neighbors" and affect in turn positively the life expectancy process. In the latter one, if education is applied together with geographic proximity, the spatial correlation is insignificant, thus education neighbors do not affect the life expectancy process.

3.2. A brief literature review

Regarding empirical research into the production of health, there are only few studies that employ time-series data (Katsouyanni et al, 1997; Woodruff et al, 1997; Samet et al, 2000; Schmueli, 2004, Lichtenberg, 2004/2006 and Halicioglu, 2011). For example, Lichtenberg's (2004) maximum likelihood results imply that increases in US life expectancy during the period 1960-2001 are driven by pharmaceutical innovation and public health care expenditure, rather than health care expenditure and nonmedical determinants, such as real per capita GDP, which are found to be insignificant. When considering social determinants or life style measures as sources of life expectancy, Halicioglu (2011) shows through the ARDL cointegration approach that nutrition, food availability and health expenditure are the main positive factors for improving longevity in Turkey over 1965-2005, whereas smoking and illiteracy exert a negative impact.

However, such studies do not examine the issue of spurious regression due to its relevance to time-series analysis. This problem is important, because it may relate health status to medical or nonmedical inputs, when no links exist. In this direction, Accoyunlu et al (2009) apply the bounds testing procedure to Lichtenberg's (2004) estimates and find that they are not the result of spurious correlation, but they likely reflect an effective relationship, at least for the United States.

As a result, other approaches employ cross-sectional data. From this point of view, Kenkel's (1995) OLS estimates indicate that schooling and practices such as smoking, drinking and exercising, but not eating breakfast, are positively related to US health status. This evidence is further supported by Thornton (2002) who suggests via 2SLS that socioeconomic and life style factors are the most effective instruments for improving life expectancy in the US. By distinguishing life expectancy determinants by age (40, 60 and 65 years) and gender across 19 OECD countries, Shaw et al (2005) report similar results. Through a nonparametric jackknife technique, they find that decreasing tobacco consumption or increasing fruit and vegetable consumption, as well as health spending and pharmaceutical expenditure have a positive effect on longevity at various ages for females and males.

Employing a larger data set of 33 SSA (Sub-Saharan Africa) countries during the 1990-2000 period, Fayissa and Gutema (2005) reinforce some previous results. In particular, their GLS estimates reveal that an increase in food availability and literacy rate, as well as a decrease in alcohol consumption has a significant positive effect on life expectancy, while health expenditure exerts a negative influence, which possibly arises from the inefficient health service provision systems. Nixon and Ulmann (2006), though, report opposite findings among 15 European countries over 1980–1995. Using OLS, they conclude that health expenditure and the number of physicians have a significant contribution to improvements in life expectancy across EU areas.

In a different analysis, Thornton and Rice (2008) apply a Three-Stage Least Squares (3SLS) estimation procedure and report relatively strong evidence of higher levels of healthcare spending in the US for state populations with higher income, less education, fewer uninsured residents, less healthy lifestyles, larger proportion of elderly residents and greater availability of medical care providers. In order to determine the probability of a country to be in one of the following groups: low, medium and high life expectancy, Kabir (2008) employs probit regressions for 91 developing countries and concludes that socioeconomic factors like income, education, health expenditure, access to safe water and urbanization can not always be considered to be influential in determining life expectancy of developing areas. Turning the focus on international medical technology diffusion, Papageorgiou et al (2007) construct a set of measures of flows of medical R&D originating from advanced economies, which are directed to the "non-frontier" countries and conclude that technology diffusion is an important determinant of life expectancy in "non-frontier" areas.

In the case of panel data applications that investigate the sources of life expectancy, Crémieux et al (1999) use homogeneous province-specific Canadian data and show through the Generalized Least Squares (GLS) estimation method with provincial fixed effects that lower health care spending is associated with a statistically significant decrease in life expectancy. When examining the relationship between a country's openness to international trade and health status, Owen and Wu (2007) report Fixed Effects (FE) estimates on 139 countries and show that increased openness is associated with higher average life expectancies, especially in developing countries. Via the same estimation technique, Bayati et al (2013) indicate that income, education, food availability, level of urbanization and employment ratio exert a positive influence on life expectancy across 21 EMR (East Mediterranean Region) countries over 1995-2007, whereas CO_2 emission and health expenditure do not exert a significant impact.

In a different approach of studying life expectancy in the US, Hall and Jones (2007) develop a model of endogenous health spending and argue that one can generate the growth in health spending and the resulting change in life expectancy as a result of income growth (Grossman, 1972). Instead of modeling other changes simultaneously, they show that with reasonable parameter estimates and implied value of longevity gains, one can generate the rise in health spending and life expectancy, assuming it is an optimal response to the income growth.

However, all aforementioned studies account only for within-area correlation and disregard between-area dependency. Not taking cross-section/spatial patterns in the empirical models into account means that the geographical units are statistically independent. This assumption might be misleading and as a result some approaches recognize cross-section or spatial dependence as an important characteristic of health data (Freeman, 2003; Carrion-i-Silvestre, 2005; Chou, 2007).

In fact, a recent subfield of the health economics literature explicitly focuses on spatial dependence in health, health care and health care spending. From this point of view, Baltagi and Moscone (2010) use a panel data framework controlling for both cross-section dependence and unobserved heterogeneity in order to examine the relationship between health care expenditure and income in 20 OECD countries over 1971–2004. They model cross-section dependence through a common factor model and spatial dependence, while they handle heterogeneity via fixed effects in a panel homogeneous and heterogeneous model. Their FE, spatial MLE (Maximum Likelihood Estimation) and CCEP (CCE Pooled) estimation results suggest that health care is a necessity rather than a luxury, with an elasticity much smaller than that estimated in other studies.

Similarly, Baltagi et al (2012) use a health production function across OECD countries during 1960-2007 and assume that life expectancy depends on health, social spending, lifestyle variables and medical innovation. Their FE results show that health spending has a significant, but mild effect on longevity, even after controlling for medical innovation. Moreover, they find significant spillover effects in life expectancy that point to the existence of interdependence across countries in technology adoption.

By studying regional differences in health via methods from spatial econometrics, Costa-Font and Pons-Novell (2007) examine the determinants of public health expenditure within Spanish regions/states. Their OLS and maximum likelihood results with spatial error autocorrelation show that the key determinants are income, the number of doctors and beds, as well as some institutional variables. Furthermore, they provide evidence of positive spatial interactions among regional health systems of Spain. Later, Moscone and Tossetti (2010) investigate the association between health care expenditure and income across 49 US states during 1980-2004. Specifically, they assume that the error term is the sum of a multifactor structure and a spatial autoregressive process, which capture global shocks and local spillovers in health expenditure. Their Common Correlated Effects (CCE) results suggest that health care is a necessity rather than a luxury. Also, they find significant spatial spillovers, though with a smaller intensity than that detected in other studies on spatial concentration of US health spending.

Most recently, Yu et al (2013) use a spatial Durbin model with spatial and time fixed effects to examine the determinants of public health expenditure in 31 Chinese provinces covering the period 1997–2008. Via the Generalized Spatial two-Stage Least Squares (GS2SLS) and the two-step System Generalized Method of Moment (SYS-GMM) estimation procedures, they report strong evidence of spatial interaction in public health expenditure across provinces. Specifically, a provincial government appears to decrease its own health spending as a response to the rise of health spending of its neighboring provinces, which supports the expenditure externality hypothesis.

Benos et al. (2015) incorporate geographical, economic and technological effects in two seminal growth models in order to test for the existence and magnitude of interregional externalities. Their findings show that spillovers are important for European regional growth, regardless of the measure of proximity. Moreover, they underline the need for coordinated EU policies aiming at higher physical and human capital accumulation, taking into account regional synergies.

Among these studies that have been carried out, it is not uncommon to find contradictory results, depending on the model and the indicators used, concerning the impact of different factors on health outcomes, such as health expenditure. As a result, I follow this strand of literature and study the spatio-temporal variations in health productivity using state-level data on life expectancy in the US over 1995-2007. In particular, I estimate a production function where life expectancy depends on health spending, income, education and some lifestyle measures.

3.3. The health production function model

This section develops a basic health production function in order to investigate factors that determine health status variations among US states. In the widest sense, a health production function describes the relationship between combinations of medical and non-medical inputs and the resulting output (Smith, 1993). My output measure is a proxy of population's health status i.e. life expectancy across males and females, while inputs consist of health care expenditure, income, education and some life style factors.

Following Baltagi et al (2012), I employ a simple Cobb-Douglas production function model with physical capital and labor inputs, where the dependent variable le_{it} is a proxy of my health outcome, i.e. life expectancy, in state i=1, 2,…,N at time t=1, 2,…,T:

$$lnle_{it} = lnb_{it} + \beta_K \, lnK_{it} + \beta_L \, lnL_{it} \quad (1),$$

where b_{it} represents the level of medical technology in state i at time t, while L_{it} and K_{it} denote labor and capital inputs in the health sector in state i at time t respectively.

With respect to medical innovation b_{it}, I adopt Ertur and Koch's (2007), as well as Frischer's (2010) approach and argue that these technologies are driven by the following spatial process:

$$lnb_{it} = s_i + t_t + \sigma \sum_{j=1}^{N} w_{ij} \, lnb_{jt} + \kappa lnK_{it} \quad (2),$$

where s_i is a state-specific effect that expresses heterogeneity at the state level, t_t is a time-specific impact representing the stock of medical knowledge common to all states and w_{ij} are elements of a known $N \times N$ spatial weights matrix, which is row normalized, i.e. $\sum_{j=1}^{N} w_{ij} = 1$. The σ coefficient captures the strength of interdependence in medical technological innovation among neighboring states. I assume that $0 \leq \sigma < 1$. The parameter κ denotes the strength of home externalities generated by physical capital accumulation. Next, I substitute Equation (2) in Equation (1) and obtain the following specification:

$$lnle_{it} = s_i + t_t + \sigma \sum_{j=1}^{N} w_{ij}\, lnb_{jt} + (\kappa + \beta_K) lnK_{it} + \beta_L\, lnL_{it} \quad (3)$$

In order to avoid the spatial lag of technology, I subtract the spatial lag $\sigma \sum_{j=1}^{N} w_{ij}\, lnle_{jt}$ from both sides of Equation (3) to obtain the following Equation (4):

$$lnle_{it} = s_i + t_t + \sigma \sum_{j=1}^{N} w_{ij}\, lnle_{jt} + (\kappa + \beta_K) lnK_{it} + \beta_L\, lnL_{it} - \beta_K \sigma \sum_{j=1}^{N} w_{ij}\, lnK_{jt} - \beta_L \sigma \sum_{j=1}^{N} w_{ij}\, lnL_{jt} \quad (4)$$

where the coefficient attached to the spatial lag in Equation (4) measures how the health outcome in one state is correlated with health outcomes in neighboring states due to technological diffusion.

Similar to Skinner and Staiger's (2009) study, I use total per capita health spending as a proxy for factor inputs (i.e. hsp), rather than capital and labor separately. Furthermore, given a large body of literature in economics, I analyze the effect of health spending, lifestyle and socio-economic factors on health outcomes. Specifically, my independent variables consist of health expenditure, obesity, smoking, drinking, exercise, income and education as significant determinants of longevity.

3.4. Data and empirical specification

Following the above considerations and Equation (4), I employ the following empirical framework:

$$lnle_{it} = s_i + t_t + \sigma lnsle_{it} + \beta_1 lnperhsp_{it} + \beta_2 lnalc_{it} + \beta_3 lntob_{it} + \beta_4 lnob_{it} + \beta_5 lninc_{it} + u_{it} \quad (5),$$

where s_i and t_t are country-specific and year-specific effects respectively, le_{it} is life expectancy of males and females at birth in years, $pershsp_{it}$ is total personal health care spending measured in millions of dollars, alc_{it} is the number of binge drinkers i.e. adults who have had at least one/ five or more drinks of any alcoholic beverage, tob_{it} represents adults who are current smokers, ob_{it} denotes the number of overweight persons according to the weight classification by the Body Mass Index (BMI) and inc_{it} is total personal income divided by total midyear population in millions of dollars. The variables for obesity, smoking, drinking and health spending are normalized, i.e. divided by state population, and as a result they are comparable across states. The variable $lnsle_{it}$ is the spatial lag of the dependent variable of Equation (5).

I also follow the literature which examines the role of education and physical exercise in explaining life expectancy. In particular, plenty of studies find that education ($educ_{it}$) has a large effect on health at the individual, state and national level. For example, Grossman (2000) suggests that years of schooling is the most important factor of explaining the increase in health status and this conclusion is robust to different measures of health, as well as the level of aggregation of the analysis. Moreover, evidence suggests that levels of physical exercise (exc_{it}) among older adults also play some role in U.S. life expectancy trends, but the degree is difficult to quantify (Steptoe and Wikman, 2010). As a result, I expand my baseline model (equation 5) with these two inputs and employ the following specifications:

$$lnle_{it} = s_i + t_t + \sigma lnsle_{it} + \beta_1 lnhsp_{it} + \beta_2 lnalc_{it} + \beta_3 lntob_{it} + \beta_4 lnob_{it} + \beta_5 lninc_{it} + \beta_6 lneduc_{it} + u_{it} \quad (6)$$

and

$$lnle_{it} = s_i + t_t + \sigma lnsle_{it} + \beta_1 lnhosp_{it} + \beta_2 lnalc_{it} + \beta_3 lntob_{it} + \beta_4 lnob_{it} + \beta_5 lninc_{it} + \beta_6 lneduc_{it} + \beta_7 lnexc_{it} + u_{it} \quad (7),$$

where $educ_{it}$ is captured by the proportion of the educated population with at least secondary education and exc_{it} denotes the number of people that participated in any physical activities during the past month. The variable for exercise is normalized, i.e. divided by state population in order to be comparable across states.

The empirical analysis focuses on a panel of the 48 contiguous U.S. states spanning the period 1995-2007 due to data availability. In particular, there are no data on CPI at the state level after 2007. Moreover, obesity, alcohol, smoking and exercise data by state are available only from 1995 onwards. I also employ an economic spatial weights matrix based on the income level across states. Other geographical metrics can be used, such as the inverse distance expressed in kilometers between states or social proximity (e.g. Baicker, 2005).

In order to estimate my model, I first examine the cross-section dependence hypothesis, which is unlikely to hold in my state-level data set. Violation of this hypothesis can lead to inconsistent and incorrect inference in panel econometric approaches (Pesaran, 2006). Cross-section dependence may arise from spatial/spillover effects and unobserved common factors (Baltagi and Pesaran, 2007). In the context of my analysis, cross-section dependence may stem either from nationwide shocks which exert a heterogeneous impact on US states or from local, interstate, spillover effects (trade, technology or policy-determined). To this end, I use Pesaran's CD test (2004), which detects the presence of correlation in the error terms across different cross-sections. The null hypothesis is that residuals are uncorrelated. The Cross-section Dependence test statistic is based on the average of pair-wise correlation coefficients (ρ_{ij}) of the OLS residuals, obtained from the individual Augmented Dickey Fuller (ADF) regressions. The CD statistic is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \right) \qquad (8),$$

where i ,t index the cross-section and time series dimensions respectively. Under the null hypothesis of cross-section independence, the CD statistic converges to a normal standard distribution. The CD statistic has mean zero for fixed values of T and N, under a wide range of panel-data models, including homogeneous/heterogeneous dynamic models and non-stationary models. The CD test is robust to non-stationarity, parameter heterogeneity or structural breaks and is shown to perform well even in small samples. Next, I estimate the model using the Instrumental Variables (IV) estimator.

3.5. Empirical findings

Table 1 below shows some descriptive statistics on the variables included in the model. In US states, mean male life expectancy at birth is 73.8 years, ranging from 69 to 78 years between 1995 and 2007, whereas mean female life expectancy at birth is higher (79.2 years). Moreover, per capita health spending ranges from 1,750 to 174,562.6 dollars. The average value of real per capita personal income is 36,188.5 dollars ranging from 26,704.6 to 48,923.3 dollars. The percentage of people with at least high-school education varies from 44.9 to 62.9. Obesity share ranges between 10.1% and 32.6%, while the maximum and minimum value of smoking prevalence is 9.1% and 32.6% respectively. Finally, the mean share of binge drinkers is almost 15%, whereas exercise shares vary between 48.7% and 85.8%.

Table 1: Descriptive statistics for variables in levels

Variable	Mean	Standard deviation	Median	Max	Min
malelifexpectancy	73.83333	1.764946	74	78	69
femalelifexpectancy	79.27244	1.220271	80	82	76
realhealthspending	31557.38	32837.83	120000	174562.60	1749.62
realpcincome	36188.47	3778.307	35900.70	48923.27	26704.64
education	0.550604	0.036441	0.557362	0.628655	0.448777
obese	0.2086656	0.04243795	0.208	0.326	0.101
currentsmokers	0.221703	0.035251	0.224	0.326	0.091
bingdrinkers	0.1478898	0.03496722	0.150	27	0.053
exercise	0.746762	0.05529451	0.754	0.858	0.487

These descriptive statistics refer to the sample of 48 US states. All variables are expressed in raw numbers.

Table 2 reports the results of the Pesaran's cross-section dependence test. This test examines the null hypothesis of cross-section independence against the alternative of cross-section dependence. According to the obtained findings, the null hypothesis of cross-section independence is rejected in all cases. All test statistics provide strong evidence of cross-section dependence for all variables used in the model. In addition, I estimate the production function, by using spatial techniques such as the IV approach, where instruments are given by the spatial lags of the included regressors (Kelejian and Prucha, 1998).

Table 2: Pesaran's cross-section dependence test

Variable	CD-test
lnmalelifexpectancy	101.94
	(0.001)***
lnfemalelifexpectancy	116.47
	(0)*
lnrealhealthspending	113.71
	(0.005)***
lnbingdrinkers	24.73
	(0.001)***
lncurrentsmokers	55.44
	(0.003)***
lnobese	112.52
	(0)***
lnrealpcincome	91.74
	(0.002)***
lneducation	86.63
	(0.006)***
lnexcercise	48.44
	(0.009)***
lnsle	79.93
	(0)***

*Pesaran's cross-section dependence test statistics for the 48 US states. P-values are in parentheses. The null is H_0: cross-section independence. Superscripts *, **, *** indicate rejection of the null hypothesis at the 10%, 5% and 1% significance levels respectively.*

I present evidence that supports my hypothesis on the role of externalities across states in life expectancy by estimating my empirical counterpart. I use male as well as female life expectancy as a proxy of the dependent variable and the aforementioned explanatory variables to capture the fundamental considerations of the theoretical models which I test. When selecting these conditioning variables, I had in mind that observations for each one of them do not differ markedly across nearby states, so that their inclusion can be considered as a test of robustness for the hypothesis on the role of externalities. This is so, because the spatial lag of life expectancy captures the effect of omitted factors within each state which are spatially or economically correlated depending on the connectivity measure used. Furthermore, I test the model at state level. State level estimations (Tables 3-4) allow me to study neighboring effects and provide evidence in relation to the life expectancy dynamics in each state separately.

By employing the base and the base spatial lag model, the spatial IV findings show that the impact of neighboring male life expectancy is significant, positive and substantial in magnitude across all sample states, presented in Table 3. Differences in human capital formation (education) reveal as the main source of the observed gap in male life expectancy. Specifically, education enters as the most important determinant of male life expectancy with a positive sign. A 1% increase in education is expected to raise male life expectancy by around 0.25%. However, I should note that education seems to have a stronger effect on male life expectancy than male life expectancy spillovers. Moreover, health spending has a modest positive effect on male life expectancy in all examined states. A 1% increase in health spending boosts male life expectancy by approximately 0.15%. Among the lifestyle variables examined, alcohol has a positive, but small in magnitude effect on male life expectancy, whereas smoking exerts a strong negative impact. Obesity, income and exercise on the other hand, bear an insignificant influence on male life expectancy. Thus, stronger neighbor male life expectancy has a sizeable impact on male state life expectancy, i.e. positive inter-state externalities exist. The spatial spillovers are stronger when neighbors are defined according to human capital, i.e. education, in all states. These IV results also hold when using both the spatial lag model and the economic lag model.

Table 3: Spatial and Economic Models - IV results (male)

Variables	Base model	Base Spatial lag model				Spatial lag model	Economic lag model
laglnmalelifexpectancy		0.111*	0.105*	0.097*	0.092*	0.094*	0.168*
		(0.055)	(0.054)	(0.044)	(0.043)	(0.044)	(0.089)
lnrealhealthspending	0.171*	0.143**	0.151*	0.149*	0.136*	0.138*	0.129*
	(0.087)	(0.057)	(0.081)	(0.082)	(0.065)	(0.069)	(0.058)
bingdrinkers	0.004*			0.005*	0.004*	0.003*	0.003*
	(0.002)			(0.003)	(0.002)	(0.002)	(0.002)
currentsmokers	-0.242**				-0.301**	-0.158*	-0.096*
	(0.107)				(0.102)	(0.078)	(0.051)
obese	-0.003				-0.001	-0.004	-0.006
	(0.221)				(0.115)	(0.575)	(0.774)
lnrealpcincome	0.011		0.021	0.018	0.032	0.029	0.047
	(0.645)		(0.471)	(0.876)	(0.552)	(0.306)	(0.201)
education	0.216*		0.304**	0.264*	0.243*	0.221*	0.227*
	(0.109)		(0.103)	(0.143)	(0.131)	(0.099)	(0.095)
exercise	0.002					0.003	0.002*
	(0.167)					(0.055)	(0.001)
R-squared	0.598	0.581	0.643	0.649	0.675	0.681	0.705

*Dependent variable: lnmalelifexpectancy. IV estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively*.

When using female life expectancy as the dependent variable of the base and the base spatial lag model, the obtained estimates remain approximately the same (Table 4). The impact of neighboring female life expectancy on state female life expectancy is found to be significantly positive and even larger that the corresponding one across males, coupled with a substantial magnitude, in line with my previous estimations. So, I conclude that the economic dynamics of each state's neighborhood seems to influence the female life expectancy prospects of the state in question regardless of the underlying structural model. Education is estimated to have a modest positive effect on female life expectancy, which is consistent with the male estimates, although is it slightly higher in magnitude in the case of females. In particular, a 1% increase in education is expected to raise female life expectancy by around 0.31%. Also, alcohol has a positive, but smaller in magnitude effect on female life expectancy, whereas smoking bears a strong negative influence. Obesity, income and exercise do not appear to affect female life expectancy, since the corresponding coefficients are insignificant.

Table 4: Spatial and Economic Models - IV results (Female)

Variables	**Base Model**	**Base Spatial lag model**				**Spatial lag model**	**Economic lag model**
laglnfemalelifexpectancy		0.152*	0.159*	0.147*	0.141*	0.127*	0.168*
		(0.075)	(0.074)	(0.069)	(0.073)	(0.058)	(0.089)
lnrealhealthspending	0.187*	0.163**	0.174*	0.189*	0.179*	0.166*	0.009*
	(0.091)	(0.064)	(0.089)	(0.075)	(0.078)	(0.082)	(0.004)
bingdrinkers	0.003**			0.006*	0.005	0.007	0.007
	(0.001)			(0.003)	(0.006)	(0.005)	(0.006)
currentsmokers	-0.277**				-0.281*	-0.247*	-0.059*
	(0.125)				(0.147)	(0.126)	(0.032)
obese	-0.007				-0.002	-0.003	-0.003
	(0.481)				(0.547)	(0.902)	(0.742)
lnrealpcincome	0.018		0.049	0.027	0.059	0.074	0.089
	(0.681)		(0.806)	(0.708)	(0.671)	(0.741)	(0.351)
education	0.175*		0.405*	0.361*	0.349*	0.287*	0.227*
	(0.86)		(0.195)	(0.172)	(0.182)	(0.154)	(0.109)
exercise	0.002					0.018	0.038
	(0.159)					(0.259)	(0.337)
R-squared	0.622	0.602	0.624	0.638	0.642	0.651	0.683

*Dependent variable: lnfemalelifexpectancy. IV estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.*

This section analyzes both structural models estimates across the same US states incorporating economic in addition to geographical proximity. For robustness purposes, I also use health spending as well as education criteria, apart from the geographical. When both geographical criteria and health spending are used (Tables 5 and 6), the life expectancy effect of adjacent regions is positive and significant, and the respective influence of neighbors with similar health spending appears stronger pointing to the distinct roles of geographical and health expenditure proximity in the life expectancy process. However, whether the economic neighbor is defined on the basis of health spending across males and females, the spatial correlation coefficient remains always positive and significant, implying robust geographical spillovers. Thus, states with similar health expenditure are "neighbors" and affect in turn positively the life expectancy process. If education is applied instead of health spending together with geographic proximity (Tables 5 and 6), the spatial correlation is insignificant compared with the previous case, thus education neighbors do not affect life expectancy across males or females. Furthermore, alcohol and smoking affect male and female life expectancy only when both health spending and geographical proximity criteria are used. Alcohol exerts a positive, but small in magnitude influence on male and female life expectancy, whereas smoking bears a strong negative impact. This confirms the results of the state-level estimations, although the range of estimates is once more narrower. Accordingly, obesity, income and exercise have an insignificant impact on male and female life expectancy in the whole sample. Thus, all results are approximately the same for males and females.

Table 5: Robustness Analysis (male)

Variables	Base lag model-health			Base lag model-education		
laglnmalelifexpectancy	0.189*	0.173*	0.394*	0.558	0.775	0.844
	(0.045)	(0.037)	(0.042)	(0.974)	(0.865)	(0.906)
lnrealhealthspending	0.111*	0.099*	0.305*	0.299*	0.265*	0.219*
	(0.051)	(0.052)	(0.052)	(0.073)	(0.053)	(0.089)
bingdrinkers			0.015*			0.017*
			(0.004)			(0.009)
currentsmokers			-0.116*			-0.478*
			(0.082)			(0.031)
obese			-0.009			-0.001
			(0.774)			(0.947)
lnrealpcincome		0.063	0.119		0.842	0.086
		(0.913)	(0.388)		(0.739)	(0.285)
education		0.248**	0.152*		0.397*	0.342*
		(0.002)	(0.077)		(0.071)	(0.081)
exercise			0.179			0.012*
			(0.659)			(0.044)
R-squared	0.592	0.658	0.671	0.649	0.584	0.629

*Dependent variable: lnmalelifexpectancy. IV estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.*

Table 6: Robustness Analysis (female)

Variables	Base lag model-health			Base lag model-education		
laglnfemalelifexpectancy	0.286*	0.211*	0.192*	0.189	0.156	0.131
	(0.057)	(0.056)	(0.073)	(0.903)	(0.412)	(0.852)
lnrealhealthspending	0.186*	0.156*	0.103*	0.542*	0.411*	0.377*
	(0.043)	(0.049)	(0.086)	(0.085)	(0.073)	(0.064)
bingdrinkers			0.038*			0.159*
			(0.051)			(0.083)
currentsmokers			-0.075*			-0.088*
			(0.041)			(0.075)
obese			-0.942			-0.829
			(0.553)			(0.995)
lnrealpcincome		0.309	0.493		0.531	0.485
		(0.909)	(0.748)		(0.994)	(0.658)
education		0.168*	0.088*		0.207*	0.192*
		(0.038)	(0.089)		(0.092)	(0.085)
exercise			0.749			0.039*
			(0.988)			(0.052)
R-squared	0.624	0.641	0.659	0.618	0.624	0.648

*Dependent variable: lnfemalelifexpectancy. IV estimates for the 48 US states. P-values are in parentheses. Superscripts *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.*

Thus, according to the obtained results, education as well as health spending plays a primary role in increasing US state longevity. On the contrary, cigarette smoking bears a substantial negative impact on life expectancy, whereas other life-style factors, such as obesity or exercise do not affect longevity. Therefore, health policies should focus on improving the amount of spending devoted to health care and educational systems. Also, a combination of economic and educational policies should be implemented in order to reduce smoking habits.

With respect to health expenditure and its positive effect on life expectancy, my findings are in line with those reported in earlier approaches. As expected, states that spend more on health care would have longer life expectancy. By contrast to other studies which conclude that states with higher levels of income would probably have a better standard of living, which in turn affects positively longevity, in my case, income has no effect on health status.

Regarding education, I also verify past results. A better educated population is likely to be better informed about their health and should contribute to higher life expectancy. Besides, the more educated persons, are less likely to smoke, to drink or be overweight and are more likely to have health insurance coverage and access to care, so higher longevity. The better educated also are substantially less likely to report that they are in poor health. However, a potential explanation of the obtained estimates representing the insignificant influence of income, obesity and physical exercise on life expectancy can be found in the lifestyle factors of people that include: more stress due to more complex responsibilities at work, bad nutrition habits, long working hours, etc that are excluded from my approach.

Furthermore, in all regressions, the estimated spatial lag coefficients of the dependent variable are positive. These values may capture the indirect effects of unobservable neighboring variables across states, such as environmental factors, which are obviously excluded from my model due to data availability and may affect my health outcome, i.e. life expectancy.

Additionally, when both geographical criteria and health spending are used, the life expectancy effect of adjacent regions is positive and significant, and the respective influence of neighbors with similar health spending appears stronger pointing to the distinct roles of geographical and health expenditure proximity in the life expectancy process. However, if education is applied instead of health spending together with geographic proximity, the spatial correlation is insignificant compared with the previous case, thus education neighbors do not affect life expectancy.

3.6. Concluding remarks

In conclusion, this chapter examines the spatial variations in health status using state-level data on life expectancy in the US over 1995-2007. I employ an approach based on a spatial process and a production function model, where life expectancy depends on health spending, lifestyle measures, income and education. The obtained findings show that health spending has a large positive effect on health outcomes. Other factors, such as education, also bear a positive effect on the dependent variable, whereas smoking exerts the most negative influence.

The results of this chapter provide some new evidence on the determinants of US state life expectancy and raise a number of important issues for policy designs. Similar to what has been suggested by other authors (e.g. Halicioglu, 2011), there appears to be a significantly positive relation between health expenditure and longevity for males and females. At the same time, my findings strongly reinforce previous estimates that imply an insignificant effect of income on health outcomes (Kabir, 2008). I also verify the beneficial impact of education on health outcomes given the policy debate about the appropriate role of the educational sector in healthcare provision. Individuals with higher levels of education have higher sensitivity and awareness about their health status, and as a result, they try to improve the quantity and quality of their health (Fayissa and Gutema, 2005). Moreover, the results strongly suggest that life style factors, such as smoking, exert a negative influence in life expectancy. The negative impact of smoking may be minimized through a number of financial and nonfinancial policies. “Public education about adverse health effects of smoking may be more effective in reducing consumption and less regressive on consumer’s income than raising the price of cigarettes” (Tansel, 1993). For example, a complete cigarette smoking ban in public places across US states may cause a positive contribution on longevity.

Therefore, my findings indicate that health care expenditure and education present basic health determinants, since they exert a strong positive impact on US state life expectancy. Overall, I find relatively strong evidence of higher levels of life expectancy for US state populations with better education, less healthy lifestyles and greater availability of healthcare spending. Thus, health policies should mainly focus on increasing the amount of spending devoted to health care and educational systems.

Moreover, the estimated spatial lag coefficients of the dependent variable are positive. This finding may arise from the indirect effects of unobservable neighboring variables, such as environmental factors, which are obviously excluded from my approach. In other words, the positive sign of the spatial coefficients can be attributed to the presence of unobserved common factors that affect my health outcome, i.e. life expectancy.

When both geographical criteria and health spending are used, the life expectancy effect of adjacent regions is positive and significant. However, whether the economic neighbor is defined on the basis of health spending across males and females, the spatial correlation coefficient remains always positive and significant, implying robust geographical spillovers. Thus, states with similar health expenditure are "neighbors" and affect in turn positively the life expectancy process. If education is applied together with geographic proximity, the spatial correlation is insignificant, thus education neighbors do not affect life expectancy.

The obtained estimates robustly demonstrate that inter-state externalities do matter for US states. Geographical and economic linkages imply strong cross-regional spillovers. Also, findings exhibit a strong positive influence of education on life expectancy. A number of policy implications can be drawn from the above findings. State-level development policies should consider externalities among neighboring economies. As a consequence, coordinated policies aiming at higher human capital investment in lagging states should take priority, taking into account state-level synergies. These policies would maximize the potential growth benefits, given the scarcity of the available funds in the present era of fiscal consolidation. The evidence taken as a whole, in turn, justifies the need for harmonized US policies, which embody a strategic coordination for life expectancy aiming at economic and social cohesion across US states.

In conclusion, my findings should be interpreted with care, due to data availability and the limited set of variables included in my analysis. Limitation of my research is the short period of observations and not including other variables such as environmental proxies, nutrition habits or other variables that represent life quality in the model, due to the lack of available and comparable state-level data. Therefore, although the results of this chapter suggest that health outcomes across states can be modeled and useful policy conclusions drawn from this kind of quantitative evaluation, further work is clearly called for.

Appendix of Chapter 3

The definitions of all variables used in Chapter 3 along with the sources and their measures are presented in the following table:

Variable	Source	Definition/Measure
male lifexpectancy	http://vizhub.healthdata.org/us-health-map/#/publications-presentations/publications	life expectancy of males-females at birth (years)
female lifexpectancy		
personal healthcare	http://www.cms.gov/NationalHealthExpendData/downloads/provider-state2009.zip	total personal health care spending in millions of dollars
obese	http://apps.nccd.cdc.gov/brfss/	obese weight classification by Body Mass Index (BMI)
current smokers	http://apps.nccd.cdc.gov/brfss/	adults who are current smokers
binge drinkers	http://apps.nccd.cdc.gov/brfss/	binge drinkers (males having five or more drinks on one occasion-females having four or more drinks on one occasion)
exercise	http://apps.nccd.cdc.gov/brfss/	during the past month, did you participate in any physical activities?
personal per capita income	http://www.bea.gov/regional/index.htm	per capita personal income is total personal income divided by total midyear population
CPI	http://mailer.fsu.edu/~wberry/garnet-wberry/a.html (Berry et al, 2000)	Consumer Price Index
education	http://www.shsu.edu/~eco_mwf/inequality.html	the proportion of the population with at least secondary education

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Conclusions

Many theoretical contributions to the growth literature emphasize the role of human capital in the process of economic growth. Human capital theory is primarily about the role of human capital in the production process and about the incentives to invest in skills, including labor market investments, in the form of schooling, and on-the-job investments, in the form of training. This approach emphasizes the productivity-enhancing role of human capital. There are, also, other important connections between human capital and economic growth, especially related to its effect on technological progress, possibly through improving a country's capacity to generate new knowledge or imitate and implement new technologies from more advanced countries.

In this context, this dissertation, at first, conducts a theoretical literature review with regard to the relationship between human capital and economic growth. As far as this relationship is concerned, theoretical growth models can be divided into two main categories: exogenous and endogenous growth models. Exogenous growth models include the Solow-Swan model as well as its extensions. Endogenous growth models can be distinguished into three subcategories: growth models in which human capital is an accumulation factor, growth models in which human capital is an important stock variable in the process of technological progress and growth models in which human capital is a threshold variable in the economic growth process. In addition, growth models with a specific form of human capital accumulation, health, are examined as a separate category. Growth models with health can be distinguished into three groups:

growth models with health and human capital accumulation, growth models with health and human capital stocks, as well as growth models with health and threshold effects.

Exogenous growth models and the first two subcategories of endogenous growth models, imply a linear relationship between human capital and economic growth. On the contrary, growth models emphasizing threshold effects and multiple equilibria are consistent with a nonlinear treatment of human capital in the process of economic growth. Regarding growth models with health human capital, these also include both linear and nonlinear specifications.

According to such theoretical approaches, the channels through which human capital may affect output growth include direct productivity effects and indirect effects due to externalities, technological adoption or enhanced productivity of R&D activities. In addition, higher human capital is associated with a higher investment rate. Thus, part of the positive effect of human capital on growth is transmitted via increased investment in physical capital, rather than through enhanced productivity of labor. As far as health is concerned, it constitutes an important form of human capital investment, the improvement of which, ceteris paribus, enhances workers' productivity, hence wages and earnings, as healthier people are better workers, work harder and longer. In this way, good health leads directly to higher income. Health, also, contributes to economic growth through its indirect effects on labor supply and market participation, investments in human capital, savings available for investment in physical and human capital, individual fertility choices and population growth. Thus, growth theories as a whole, incorporate human capital not only in terms of education, but also health as important determinants of economic growth.

Turning the focus on the empirical literature examining the relationship between human capital and growth, two main categories of empirical approaches are distinguished: those that refer to cross-section estimation techniques and those that use panel estimation techniques. The first category explains the cross-country differences in growth, while the second examines both the cross-country differences in growth as well as the evolution of the performance over time. Both categories are divided into growth accounting exercises and growth regressions.

However, the empirical literature on human capital and growth is subject to a number of methodological problems, such as the underlying data and the techniques with which these data are analyzed. While poor data quality may be responsible for some results, there are also some important econometric issues, such as methods of estimation, the inadequacy of empirical human capital proxies and reverse causality, which may limit the generality of findings as well. Overall, therefore, there seems to be a tendency of empirical results to the amount of data's variation.

In addition, by taking studies as a whole, empirical results imply a prominent role for human capital in explaining differences in growth rates across countries. Specifically, they indicate that education and health affect positively and significantly the accumulation of human capital, and thus, they can foster economic growth. In this way, I suggest that a concerted effort should be made by policy makers to promote educational and health investments in order to facilitate the process of human capital accumulation, which in turn, would lead to higher economic growth.

Thus, I have seen that a large body of macroeconomic literature has focused on the relationship between education and economic growth. Empirical findings on this link, however, are controversial. Their interpretation must take into account several conceptual and methodological problems. Most importantly, educational attainment, commonly used in empirical studies, is a crude measure of human capital, since the education quality varies widely across countries. Also, low data quality for educational attainment as well as important econometric issues, such as omitted variables bias, parameter heterogeneity, reverse causality and non-linearity, are factors responsible for the non-robustness of the results. In light of these issues, I make an attempt to evaluate the empirical literature on the effect of education on growth and explain the wide variation in the reported estimates.

Specifically, I analyze the findings of 57 empirical studies and apply meta-regression analysis using four estimators, correcting for possible publication selection bias in the relevant literature. I investigate the impact of several factors on the variation of the reported estimates of the growth impact of education. My MRA analysis produces interesting results, which are robust to different estimators, the inclusion of various types of research outlets and the presence of outliers in the data set.

First, I confirm the presence of substantial upward publication selection bias in the education-economic growth literature, while I find no evidence of a large amount of unexplained heterogeneity. Second, all methods indicate a significant genuine education effect on growth after correction for publication selection. Third, differences across studies can be partially attributed to differences in terms of their characteristics. Specifically, the inclusion of education enrollment, the use of cross-section or panel data instead of time series and log specification, tend to make the impact of education on growth corrected for publication bias more positive. On the contrary, the use of student-teacher ratio, openness and publication in a high-quality journal tend to make the growth impact of education more negative. However, only in the case of research published in academic journals vs. working papers, alternative economic growth measures are found to explain the heterogeneity of the research findings.

Thus, it seems safe to conclude that the education-economic growth empirical research, exhibits substantial publication selection toward positive growth effects of education, while the economic growth impact of education after taking into account publication bias depends critically on the specific features of the study. These findings do not necessarily imply that the positive impact of education on growth postulated by theory does not exist. It may well be the case that the problems characterizing empirical research on this question are so severe that they make it impossible to uncover this effect. In any case, my MRA analysis provides important information for future empirical studies evaluating the role of education in the process of economic growth.

Afterwards, given the empirical literature on the relationship between education and growth and the sources of the wide variation in previous research findings, I employ panel cointegration techniques to study the particular relation. Specifically, I examine the association between growth, TFP growth, labour productivity growth and physical capital, education, health as well as R&D, using state level data for the US. In particular, I use a Cobb-Douglas production function to analyze the determinants of income levels across the U.S. states. Contrary to earlier studies in the field, I adopt a flexible and efficient panel estimation approach, controlling for parameter heterogeneity, cross-section dependence and non-stationarity. My empirical methodology is based on mean-group estimation and multifactor modelling, making use of the approaches proposed by

Pesaran (2006) and Eberhardt and Bond (2009), i.e. the CCEMG estimator and the AMG estimator, respectively. My results indicate that the two conventional factors of production (labor and private capital) exert a positive and significant effect on income. The impact of educational human capital is also found to be positive. In contrast, health does not seem to be a significant determinant of income level. This may stem from the relative inappropriateness of the specific indicator I use (number of hospital beds) in characterizing the health status of the population. Further investigation on the role of health as human capital is left for future research, once improved data become readily available. Finally, I find robust evidence for the negative elasticity of income with respect to both total public capital stock and its infrastructure components. The strong (positive) income effects of years of schooling indicate that educational human capital is a suitable and effective instrument for promoting state economic activity.

In addition, I use spatial econometric methods to study the probability of US states falling into a specific income class depending on their characteristics, e.g. human capital, physical capital, proximity to other states with regard to geographic, social and economic characteristics. For this reason, I examine the factors affecting life expectancy across US states over the period 1995–2007 under a spatial model. In particular, I employ a production function where life expectancy depends on health expenditure, income, education and lifestyle variables (alcohol, smoking, obesity and exercise). Empirical results through the IV estimator, suggest that education and health expenditure are the main positive determinants for improving longevity, whereas smoking seems to bear a strong negative influence. For robustness purposes, I also use health spending as well as education criteria, apart from the geographical ones. In the first case, states with similar health expenditure are "neighbors" and affect in turn positively the life expectancy process. If education is applied instead of health spending together with geographic proximity, the spatial correlation is insignificant, thus education neighbors do not affect life expectancy.

My estimates robustly demonstrate that geographical and economic linkages imply strong inter-state spillovers. Also, the obtained findings imply a strong positive effect of education on longevity. Regarding policy implications, I suggest that state-level development policies should consider externalities among neighboring areas. Thus, coordinated policies aiming at higher life expectancy in lagging states should take priority, taking into account state-level synergies. The evidence taken as a whole, in turn, justifies the need for harmonized US policies, which embody a strategic coordination for life expectancy aiming at economic and social cohesion across US states.

However, such findings should be interpreted with care, due to data availability and the limited set of variables included in the analysis. Specifically, limitation of my research is the short period of observations and the exclusion of variables such as environmental proxies or other indicators that represent life quality in the model, due to the lack of available and comparable state-level data. Therefore, although my results suggest that health outcomes across states can be modeled and useful policy conclusions drawn from this kind of quantitative evaluation, further work is clearly called for.

Finally, it is also noteworthy to enrich the analysis of human capital by accounting for more indicators that comprise different levels and forms of human capital. Further measures may be added and new proxies can be developed that enable an improved approximation of human capital, by incorporating the dimensions of both space and time in the analysis, because history and geography matter.

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