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**Research Report**

## Adult education and growth

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**Dieter Dohmen, Galiya Yelubayeva**

## **Adult Education and Growth**

**Study as part of the project “ Economic and regional costs, funding  
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Supported by the Federal Ministry of Education and Research**

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## INTRODUCTION

The imperative of growth support was embedded in the core message adopted by the European Commission in the Europe 2020 strategy, which recommends a number of structural reforms in order to boost labour utilisation and productivity growth (European Commission, 2010). The Lisbon Strategy was signed in 2000 with the aim to reach a 12.5 percent benchmark rate of labour participation by 2010, to lower the rate of early school leavers and to increase the rate of adults with tertiary level qualifications (European Commission, 2001). In 2009, these targets were reviewed and adjusted within the strategic framework “Education and Training 2020”. The new benchmark referred to a 15% rate of participation in lifelong learning among the adult population (aged 25 to 64) with a reference period of four weeks. This target is to be achieved by the EU member states by 2020.

The following paper presents an in-depth appraisal of theoretical links between adult education (human capital in general) and macroeconomic growth and provides a summary of the findings in the main empirical macro-studies for European countries. An initial analysis of broad statistics for all EU member states suggests a correlation between investments in adult education (human resources), the working environment and growth, however, clear causal relationships are difficult to establish. The paper also provides a broad historical survey of empirical macro-studies following the theory of human capital growth. To this effect, the paper uses data from various surveys on adult education including LFS, EWCS and CVTS. Surveys and micro-data offer multi-dimensional measures of human capital and are increasingly longitudinal and comparable for European countries. However, rich data on both employee skills and firm performance indicators are rarely combined for the purpose of this study, i.e. to identify output relations. Nonetheless, panel micro-data enable a more systematic approach to identifying the extent of training participation as well as empirical tests for human capital effects.

The purpose of the VoREFFi-WB project was to study the impact of further education. Analysing the adult education-innovation nexus revealed that there is a relationship between the two, however, the direction of their causal link is ambiguous. Yet, controlling for time lag effects of the human capital formation in the model indicated that adult education, in fact, has an impact over time, which supports the idea that adult education affects and drives innovation (Dohmen & Yelubayeva, 2018). Using adult education (human capital formation) as a proxy of innovation, it was possible to reveal the dynamic links between the organisation of work, skills and formal education on the European country level. Although the study was based on macro-data, each country was analysed individually to derive aggregated data in order to improve the efficiency of the parameter estimates in panel data and to identify cross-sectional dependencies.

In the following, this paper examines the impact of adult education on another important macroeconomic output, namely economic growth. The literature on economic growth is vast and the number of policy-oriented studies in particular has increased considerably in the past decade. Yet, there is little agreement on the exact mechanisms linking policy settings to growth. The literature search preceding this analysis revealed no studies that model adult education variables into human capital variables or test the relation of adult education and macroeconomic indicators (except FiBS/CEDEFOP study in 2012). Given the difficulties of measuring adult education as discussed in Dohmen (2018), and the significance of adult education in the context of lifelong learning, closing this research gap is of crucial importance. To this effect, this paper aims to answer the following research questions: (1) What are the various historical antecedents and early conceptualisations of the human capital theory that are useful in understanding the impact of education on economic growth? (2) What is current state of research that

measures this impact econometrically? (3) What is the impact of human capital (determined as adult education) to economic growth? (4) How to consolidate these findings in a systematic way that builds on the theoretical basis of human capital (adult education) theory?

Human capital theory signifies the modern economy focused on the increasing role of human capital in the knowledge-based society. The development of human resources is an important part of all development strategies and has recently been embodied in the policy and reports of most important international institutions: the European Commission and other regional policy institutions (Cedefop, 2011, 2016, 2017b). The theoretical emphasis on human capital is based mainly on the endogenous growth theory as proposed by Becker who was among the first to focus on the role of human capital in the adoption of technology and its impact on economic growth. However, the concept of human capital was fully embodied later, mainly in the works of Romer (1986), Lucas (1988) and Barro (1991). Generally, literature on education and growth is largely based on endogenous growth models, however, education neglects adult education as human capital accumulation and also overlooks working environment through which skills development can influence to output. Besides, the current literature only comprises few studies on human capital and growth on the country or regional level. This calls for further research on the interrelations on the macroeconomic level. Furthermore, due to different scholars using different estimation methods and data, there are currently contradicting findings on the link of human capital and growth. Hence, there is further need for research and discussion in this area that is of distinct theoretical and practical significance.

In the first parts, we define human capital and give a short course on the development of human capital theory. Second part is focused on empirical modelling of human capital. In this part we give overview of key characteristics of human capital applied in recent growth models. Third part describes our analysis, gives methodological framework and discusses the outcomes. The paper ends with conclusion and proposals for future research.

## I DEFINING HUMAN CAPITAL

This part of the paper outlines the theoretical basis and empirical modelling of the human capital theory as well as its interpretation and implications for economic growth. Furthermore, the following chapter integrates contributions from several different strands of the growth literature. The focus is on the first research question as described above: What are the various historical antecedents and early conceptualisations of the human capital theory that are useful in understanding the impact of education impact on economic growth?

### I.1 Adult education as a basis of Human capital

Due to the diversity of definitions and issues of validity, there are various perspectives involved in the discussion of how to measure human capital. In this paper, adult education is proposed as a basis of human capital. The rationale behind this approach is explained in the following chapter.

In general, education is positively associated with a range of other individual and societal benefits such as, for example, a healthier life-style, active political involvement, lower propensity to commit crime and richer social networks. Especially adult education can help to find a job, and jobs in turn can highly level up the government budget in terms of taxation and opportunity cost of social benefits towards unemployed people. From an economic efficiency point of view, spending on adult education may have more immediate effects compared to spending on primary and secondary education, which in turn gives viable results in the short term and therefore raises accountability of decision makers. In the following analysis, human capital is considered to be limited to adult education. Yet, it is important to point out that earlier stages of education – primary and secondary education – as well as subsequent education – higher education – also make up a viable part of human capital in a broader sense. Furthermore, these early stages of education can underpin the further participation in education, as higher educated people tend to get into skills-intensive jobs in knowledge-intensive sectors, where they are given opportunities to acquire skills continuously and participate more in training possibilities. It is widely confirmed via collected surveys that higher educated people tend to participate more in adult education.

The following analysis assumes there to be different types of training (formal, non-formal and informal training) without making any attempts to go into further detail on training technology and instructional variety. Even in European countries training programs remain non-systematic. Moreover, there are no national training systems or central databases that could serve as a basis of classification. There is no central training authority and no information about the qualifications of teachers working in the adult education system. The development and effectiveness of training programs is also beyond the scope of this paper. Additionally, the overall limitations for composition of questions in surveys as well as other quality assurance, sample coverage, error issues for surveys apply (Dohmen et.al, 2019). This paper is focused on the correlation of growth rates and training participation, which is modelled using panel data for the years available. The way of proxying human capital and using data on participation in further education may provide insights about attitudes towards lifelong learning where individuals seek to constantly expand their competencies. From the analysis of adult education in Europe, the overall grouping of countries and analysis of contextual factors such as, for example, competitiveness, innovation and equity, there appears to be a correlation between a country's state of development, i.e. better equity, higher innovation and competitiveness rankings, and the rate of participation in adult education, further analyzing the demand and supply issues of further education (Dohmen et.al, 2019).

Adult education can influence economic growth in various ways. Accumulated knowledge and skills

acquired through adult education directly impact a person's employability and skills match to work, which in turn increases labour productivity and facilitates technological progress and innovation. Moreover, especially adult learners can in turn initiate changes in the wider sense by affecting the home/family, work, and community contexts they engage in (Schuller & Desjardins, 2010).

### **The overall issues of participation in adult education**

Reasons of participation in adult education are defined variously in many studies, where participation is treated as the result of a complex chain of responses such as personal attitudes (Cross, 1981) or monetary and non-monetary expectations (Baert, De Rick, & Van Valckenborgh, 2006). Motivation specialists have tried to link the motivation and attitude of adults to their participation in training (early researchers include Houle, 1961; Boschier, 1971; Bourges, 1971; Morstain and Smart, 1974; recent researchers are (Gorges, Maehler, Koch, & Offerhaus, n.d.)). Others have related adult education participation with the social psychology theory in early studies (Boshier, 1973; Cross, 1981; Darkenwald and Merriam, 1982) and more recently (Gorges & Kandler, n.d.; Rammstedt, Danner, & Clemens, 2017). Thus, measuring the motivation of adults appears to be a fruitful approach to understanding the processes of why they participate in further education. Recent studies have found that a combination of several factors that vary by target groups influence adults in their decision to undertake (Dohmen, 2016).

The paper then moves to the topic of drop-out from adult education. According to Silva et al. (2017) who examined drop-out from adult education in six European countries (2016-2017 period), drop-out is not systematically registered due to the flexible, modular organisation of adult education. However, according to estimates the drop-out rate ranged from 15-25% in these countries. It was found that students drop out due to lack of certain skills, organisational issues or for personal reasons (Silva M. et.al, 2017).

There are various sources of information on adult education participation including surveys such as AES, LFS or CVTS which different approaches to the topic (for overview see Dohmen et.al, 2019). A recent FiBS study gives an overall descriptive comparison of these surveys at the country level (Orr & Cristóbal López, 2016).

Adult education is complex and diversified than formal higher education. Training providers are also more heterogeneous and more dispersed. There are considerable pitfalls of making generalisations and aggregations on the national level without taking a more systematic look at national policies and regulations. A variety of training schemes as presented in a project conducted by Ecorys has shown that there are no centralised data collection centres, so the information on funding and participation as well as the effectiveness of schemes is scattered or even unrepresented. Furthermore, when computing unit costs, rate of return or benefits, scholars often have no choice but to draw on proxies as made available by the data and which often suffer from biases. Indeed, the current statistical databases provide no clear indication on the sources and means of investments in human capital (Andriescu, et al. 2019). Moreover, training is interdisciplinary in nature, and there is no institutionalised or pedagogical training for further education instructors. Therefore, the surveys mentioned above use methodology and thus definition and types of adult education differently and calculate the participation on certain types of training. When comparing these surveys of adult education CVTS, AES and LFS, it is also important to keep in mind that some of these surveys have seen changes in their methodological framework between different waves (Dohmen et.al, 2019).

#### Infobox 1

##### Adult education surveys

The Adult education survey (AES) is a self-contained survey referring to “all learning activities, i.e. intentional learning, undertaken throughout life, with the aim of improving knowledge, skills and competences, within a personal, civic, social, and employment related perspectives” (Eurostat AES metadata). This includes formal and non-formal activities, while informal learning activities, such as self-learning, are not considered. Learning activities are covered within the last twelve months prior to the conduction of the survey, whereas LFS only captures activities in the previous four weeks.

The Continuing Vocational Training Survey (CVTS) reviews learning activities in enterprises employing 10 or more staff. Here, participation rates refer to the percentage of employees participating in continuing vocational training courses (all enterprises). Thus, learning activities refer particularly to non-formal training, while informal learning is neglected and persons who are not employed are also excluded.

The European Working Conditions Survey surveys workers (employees and self-employed) and refers to participation as activities (education and training) covered within the last twelve months prior to the conduction of the survey. There are no types defined, generally referring to training, and specifying it further by on-the-job training and other forms of training.

The Programme for the International Assessment of Adult Competencies (PIAAC) also covers information on participation of respondents in training of both a formal and informal nature over the 12 months prior to the interview.

Sources: CVTS 5 manual, 2016, “Skilled for Life? KEY FINDINGS FROM THE SURVEY OF ADULT SKILLS,” n.d.; Eurofound, 2015; Eurostat, 2014.

## 1.2 The development of the human capital theory

In his work "Wealth of Nations" (1776), Adam Smith was the first classical economist to include human capital in the definition of capital. More precisely, he considered the skills of a nation's population as part of its capital stock and argued that more skills would lead to an increase in the wealth of both the society and individuals. According to economist David Ricardo, economic growth is also the result of capital accumulation, where an increase in productivity leads to an increase in wealth per capita. In 1691, William Petty included the monetary value of labour in the calculation of national wealth and provided an analysis of rents. He capitalised the wage bill to perpetuity at the market interest rate, where wage bills are defined by deducting property income from national income.

Following the income-based approach, human capital is calculated as the total income generated by an individual in the labour market throughout their lifetime (Le, Gibson, & Oxley, 2003). Farr (1853) further developed this approach and proposed a calculation model, which dominated in the first half of the 20th century (De Foville 1905; Barriol 1910; Dublin and Lotka 1930) before the cost-based approach came into play in the 1940s (Leeuwen, n.d.). This approach dates back to 1883, when Ernst Engel proposed the estimation of the monetary value of human capital based on a cost of production procedure. He argued that calculating the value of human as the costs incurred by parents in raising their children would provide a more grounded value, which in turn could be applied to measure the monetary value of human capital. He also modified the approach of Petty to allow for only a limited number of years, i.e. the time that an individual may be employed, to be included in the analysis. Early studies of Petty and Engel did not take into consideration the costs of maintaining the level of human capital, neither were issues of depreciation. There are also other issues due to oversimplification issues, which make the approach taken in these early studies implausible (Kiker, 1986). In the 1960s, Engel's approach was further developed by Schultz (1961), Machlup (1962) and Becker (1964). They attempted to calculate expenditures as human capital stock (Le, Gibson, and Oxley 2003). Kendrick (1976) following these ideas and used the opportunity costs of education as foregone income by students to calculate investments in education. However, he did not include the returns from these investments in educations (Jorgenson, 1995).



Further influential advancements of the human capital theory were driven by Becker, who developed a theoretical basis for the importance of investments in human capital (Becker, 1975). Important aspects of his work involved differentiating transferability, specifying general and firm-specific skills and proposing the rationale of costs: firm-specific training is preferably born by employer, while general skills training is to be covered by the employee. Over the last decade, the literature has defined a variety of skill variations, including digital skills (FiBS, 2017), soft skills in management theories (Wheeler, 2016) and learning how to gain skills. According to human capital theories, technical skills become obsolete faster and returns on investments in technical training are lower. Furthermore, wage effects on training were found to be lower compared to other types of training (Groot & Oosterbeek, 1995). Other authors believe that general and specific types of training are complementary in enhancing one's skills. In fact, a recent study found that individuals learning to play a musical instrument also showed increased cognitive skills and better performance at work (Cedefop, 2017a).

Other studies have taken different approaches and while these estimates enhance the topic's importance and show some improvements compared to earlier works, they are still limited in their theoretical approach and data analysis. Another approach draws on the theory of the screening model, which proposes that education serves as a way of "screening" students in the process of matching them to a workplace, while education itself does not bring any value to society (Arrow, 1973; Stiglitz, 1975; Wiles, 1974) While this theory was initially strongly supported in the academic work, it has seen little revival in recent times.

### **1.3 Empirical modelling of human capital**

This part of the paper gives an overview of the literature on definitions of human capital in econometric models. The existing literature comprises a variety of different conceptual rationales and approaches to modelling human capital in growth models. Taking these issues into consideration, the following section examines the second of the research questions: What work has been done to econometrically measure the impact of education on economic growth?

The neo-classical growth models proposed by Solow in the mid-20th century placed no importance on human capital (Solow, 1956). According to these models, physical capital contributes to the growth of GDP, and the unexplained residual - called total factor productivity (TFP) - provided an explanation for economic growth in the long run. However, the growing popularity of human capital theories saw the inclusion of human capital variables in the analysis of growth and lead to further discussions of modelling these variables as part of empirical growth models. Economic studies attempted to reveal the driver of the "residual" (TFP), which is the unexplained part of economic growth as modelled by changes in capital stock and labour in terms of numbers and hours. In these models, human capital reduced TFP and was significant factor for a country's growth.

In early studies of human capital modelling, human capital was included in growth models that differentiated by individuals' age and education (Attiyah & Denison, 1969). These studies involved considerable shortcoming in terms of data availability, which resulted in short time periods of observation and a lack of cross-country analyses. However, with the introduction of large-scale statistics collections, it became possible to perform cross-country analyses. Studies making use of these large-scale databases measure human capital through proxies such as school enrolment ratios, adult literacy ratios, weighted averages of the population in primary, secondary and higher education, etc. (Azariadis & Drazen, 1990; Romer, 1989). Before the 2000s, the most commonly used measures of human capital were the level of educational attainment or the average years of schooling among the population over 25

years of age and enrolment rates, i.e. the proportion of adults enrolled in secondary education (Barro, 1991). During the years when no censuses was conducted, Barro and Lee (1991) constructed a widely used dataset by estimating the educational attainment through enrolment rates using a perpetual inventory method. From the analysis of 98 countries in the period 1960-1985, they concluded that the growth rate of real GDP per capita was positively related to a country's human capital as proxied by the national rate of school enrolment in 1960 (Barro, 1991). Barro and Lee further extended their dataset to cover the years of 1950-2010 in 5-year intervals for a total of 146 countries (Barro & Lee, 2011). This dataset was used by many authors as a proxy of human capital. Mulligan and Sala-i-Martin (1995) outline the drawbacks of using schooling data, –such as the heterogeneity of workers, and different productivity outcomes by the impact of an additional schooling year. Barro also states that the school quality has a positive impact in increasing country's growth: by measuring primary and secondary teacher-student ratios in 1960, he found that higher ratios have a significant negative impact.

At the micro level, the human capital theory suggests that education is an investment that increases the productivity of workers which in turn increases the income of workers. Some authors use a wage premium as a proxy, such as for example the modified Mincer regression (Heckman & Klenow, 1997), or wage difference between educated and uneducated people (Pritchett et al., n.d.), while other authors combine variables of individual income and educational attainment (Maria Serena, 2001) or shares of people in certain knowledge-intensive sectors, such as the number of people in private sector R&D (Izushi and Huggins, 2004), shares of graduates in the general labour force (Baldwin (1971) and Outreville (1999)) or the share of specific STEM graduates in the labour force, and linking the idea that the technological sector plays a role in production.

The measures of estimating human capital outlined above can be summarised as follows:- education stock, prospective and retrospective methods (Leeuwen, n.d.). Le et.al (2003) give a general description of two approaches to measuring human capital: the (prospective) income-based approach and the (retrospective) cost-based approach. The (retrospective) cost-based approach involves calculating all expenses occurring to develop human capital and includes the calculations of costs of every aspect of human capital such as spending on education, food, health, etc. One major shortcoming of this approach is that it excludes social costs and depreciations (or appreciations) of human capital investments. Moreover, the income-based approach is considered to produce higher estimates than the cost-based approach, as it includes all extra earnings that can be generated by abilities of human capital in the calculation. However, it is doubtful that all income is generated purely by the individuals' abilities. Furthermore, higher levels of input do not necessarily guarantee a higher quality of output (in cost approach) and wage differentials do not necessarily reflect human productivity as suggested by the income-based approach (Le et al., 2003). Similarly, Kwon (2009) argues that there are three approaches to measuring the value of human capital: the output-based, the cost-based and the income-based approach. In terms of the output-based approach, he identifies the stock of human capital through indicators such as school enrolment rates as in Barro (1991) and Barro and Lee (1993), accumulated years of schooling as in Nehru et.al (1993) and (Nehru, Swanson, & Dubey, 1993), and average years of schooling as in Psacharopoulos et al. (1986) and (Psacharopoulos & Arriagada, 1986). The cost-based approach calculates the value of human capital as the sum of investments in human capital while taking into consideration depreciations of these investments following the approach of Kendrick (1976). The income-based approach involves calculating the returns of educational investments from the labour market; the indicators used in this approach include, for example, the sum of quality adjustment of each individual's labour force as used in Mulligan & Sala-i-Martin (1995).



The historical timeline of the literature on endogenous growth shows that initially human capital was proxied by literacy rates and data on enrolment as this was the only comparative data available. In terms of data on enrolment, scholars used data on different levels of education such as, for example, enrolments in primary education or enrolments by field of education (Law, engineering, etc.) (Murphy, Shleifer, & Vishny, 1990), enrolments in primary and secondary education (Barro, 1991), data on education attainment (Gemmell, 1996) or data on both enrolment and literacy rates (Levine & Renelt, 1992). However, the issue in this respect was that the notions of ‘flow’ and ‘stock’ of human capital were used interchangeably, while it is, in fact, important to distinguish between these two terms. Human capital can be defined as ‘stock’ (level of education achieved), which is often measured as educational attainment or average years of schooling, or as ‘flow’ (process of education), which is measured by enrolment data. These proxies, however, involve some conceptual weaknesses.

As it is seen various underlying variables are used to define human capital, and the following paragraphs revise statistical approaches that are varied even using the same set of variables and countries. For example, Cohen and Soto (2007) had the access to the recent education data and applied the backward extrapolation to calculate the years of schooling for earlier dates. They also used the information on educational attainment by age in constructing Human capital and accounted for mortality across age groups, which Barro and Lee (1993) did not. The issue of different country compositions in the dataset as well as the presence of outliers further add to the inconsistency of results, as was criticised by a number of scholars (D. Cohen & Soto, 2007; de la Fuente & Doménech, 2000; Krueger & Lindahl, 2000). For example, Temple (2000) showed that when removing some countries in the dataset of Benhabib and Spiegel (1994), the variable of years of schooling turned from being statistically insignificant to statistically significant (Temple, 2000). Furthermore, the transparency and provision of information in the data used for growth regressions posed another problem as pointed out by De la Fuente and Domenech (2006) in reference to the data of Benhabib and Spiegel (1994) and Pritchett (2001). The above-mentioned differences lead to noticeable discrepancies in the regression results and subsequent divergence in the estimation of the impact of education on economic growth.

Moreover, data on school enrolments and educational attainment cannot be used immediately to study the impact of education on growth as it covers basic education level, which is not directly impacting economic production and does not include skills changes after formal schooling. There are many ways to improve one’s skills, for example through informal learning (learning from colleagues or learning from doing), as presented in detail for the ESJS survey and PIAAC data. Another approach that has recently met with growing attention involves learning from open educational resources such as online courses or badge systems which may be regarded as a form of non-formal learning (Berge, 2016). By default, the disadvantage of this skills-based approach is that a person’s skills are related to their specific type of job, and do not necessarily match in an alternative context (Cedefop, 2017a). Furthermore, there is still constraints in defining and data collection of non-formal and informal learning in terms of numbers, hours, costs, work-related or non- work-related types.

The current literature is increasingly focused on studies of skills levels to reflect human capital. In reference to PIAAC data, a person’s personality and competences are considered the essential factors defining their life outcomes, as they have a high impact on life satisfaction and health and, to a lesser extent, on educational attainment, employment status and income (Rammstedt et al., 2017). Many economists believe that skill-biased technological progress is another main cause of increasing skill premia, and a widening dispersion of earnings in many OECD countries (OECD Publishing, 2017).

Nowadays, skills nowadays are mainly assessed using PISA and PIAAC data, which show both increases

and decreases in the skills levels of different countries. For example, comparison of the rankings of countries by the skills of the birth cohort of 1985 who participated in the 2000 PISA test at the age of 15, and in the 2012 PIAAC test at the age of 27 reveals considerable improvements in the ranking of countries with strong continuous vocational education and training systems, they showed improvements in skills in PIAAC and thus scored better in the countries ranking in PIAAC (Dohmen, 2017). However, there are many general limitations of the comparison of PISA and PIAAC, as the two studies have not been designed to be linked psychometrically and the results are presented on separate scales. They differ in their target population, sampling and administration procedures, as well as in the definition and organisation of the skill domains they assess. Moreover, there are no established links between PISA and PIAAC for the same birth cohort; therefore, comparing the two surveys is not advisable when attempted to explain trends in the development of skills (Borgonovi, Pokropek, François, Gauly, & Paccagnella, 2017). PIAAC test scores remain highly significant in defining individual earnings and overall mismatch (Hanushek, Schwerdt, Woessmann, & Zhang, 2017; Perry, Wiederhold, & Ackermann-Piek, 2014). Some researchers tried to mediate the impact of PIAAC scores by studying the impact of non-cognitive skills (Anghel, Pau Balart, Balart, & Cat, 2017).

#### Infobox 1

The Programme for International Student Assessment (PISA) is a triennial international survey which aims to evaluate education systems worldwide by testing the skills and knowledge of 15-year-old students.

The Programme for the International Assessment of Adult Competencies (PIAAC) is an OECD-coordinated internationally comparative survey that directly measures people's (aged 16 to 65) skills in literacy, numeracy, and problem-solving in technology-rich environments (OECD, 2013).

In light of the limited availability of comparable data, test scores from internationally comparable skills tests are most frequently used to measure the formation of human capital. Both Hanushek and Kimbo (2000) and Hanushek and Woessmann (2007) find human capital as proxied by indicators on the quality of education from PISA and TIMSS tests to have a positive impact to economic growth. Furthermore, Hanushek and Schultz (2012) showed that a positive deviation of 100 points in the PISA test results may lead to an increase of 2 percentage point in annual growth rate of GDP per capita. However, the study has been criticised for assuming test scores to implicitly describe both the quality and the quantity of schooling. On the other hand, Breton (2011) argues the assumption to be valid by pointing to high correlations between these variables. Yet, he criticises the approach of Hanushek and Schultz (2012) in their regression calculations (Breton, 2011). Furthermore, some scholars argue that long-term projections of growth rates should include another two exogenous variables: population growth and the growth of joint factor productivity (Kreps & Wallis, 2003; Mankiw, Romer, & Weil, 1992).

Hanushek and Woessman (2012) identified positive links between the cognitive skills of school students - measured as math and science results of international test results - and economic growth by applying the instrumental variables estimation and difference-in-differences approach. Their base model which covers 50 countries showed that a change of one standard deviation in the individual students' performance translates into changes in annual growth rates of 1.2–2.0 percentage points difference. When adding additional variables such as the quality of teachers or school attainment, the effect of cognitive skills is always highly significant and variations are limited (Hanushek & Woessmann, 2012). However, their analysis does not take into account skills acquired at a later stage in life.

## 1.4 Endogenous econometric growth models

The following section reviews some of the major empirical works on economic growth with a special focus on studies that analyse the impact of education. The availability of data on education across different countries and statistical methods advancements are among the key drivers of the increased amount of work on models of human capital models. However, scholars have taken different approaches to modelling that led to a variety of conclusions which are discussed in more detail below.

In a comprehensive study, Durlauf et al. (2004) divide statistical growth models into three main categories: 1) Studies investigating the impact of different variables on cross-country differences in growth (e.g. Levine & Renelt, 1992; Mulligan & Sala-i-Martin, 1995), 2) studies focusing on reasons for the heterogeneity in growth between countries (e.g. S. Durlauf, Kourtellos, & Minkin, 2001; Mamuneas, Savvides, & Stengos, 2006) and 3) studies examining non-linearities in the growth process (e.g. S. N. Durlauf, Johnson, & Temple, 2004; Graham & Temple, 2006). A number of other studies find schooling to have a negative impact on economic growth (e.g. Pritchett 2001; Benhabib and Spiegel 1994; Spiegel 1994; Lau et al. 1991; Jovanovic et al. 1992; Bils and Klenow 2000). Pritchett (2001) brings forward several explanations for this finding including the adverse institutional environment that directs skilled labour towards relatively unproductive activities and, thus, hindering the growth in some of the less developed countries, the decrease of marginal returns of educated labour and the decreased quality of an additional year in education which fails to increase human capital. Krueger and Lindahl (2001) propose that there might be an inverted U-shaped relation between the years of schooling and labour output. The authors determine the turning point to be at 7.5 years of schooling, after which there is a decreasing marginal effect of education on growth. They conclude that human capital has a positive effect on economic growth which, however, varies by country due to differences in the quality of education and institutional arrangements.

Mostly, human capital is considered as a separate factor from technological capital. However, some authors argue that human capital, in fact, drives technological capital by facilitating technological catch-up. This approach was first introduced by Nelson and Phelps (1966), who argued that treating human capital only as an input variable would lead to misspecifications of the interrelationship of variables. According to them, human capital (proxied by educated people) help to develop and adapt technology, therefore separating human capital and technology and including as separate variables are not valid. Following a different approach, Benhabib and Spiegel (1994) made analysis of a structural specification for cross-sectional heteroskedasticity to study other mechanisms through which human capital affects growth. While their study gave no indication of human capital impacting growth, they found human capital to cause a decrease in TFP, which is in line with the findings of Nelson and Phelps (1966) that human capital enhances the benefits of using capital stock. The authors conclude that education has an indirect positive effect on economic growth through technological progress. Furthermore, Engelbrecht (2003) examined structural equations for the OECD countries and found that there is a small contribution of human capital to economic growth. He developed a hybrid model that reflects the combined level and accumulation effect of education on growth which, however, he found to lack statistical significance. The impact of workplace organization to macroeconomic output (innovation) was proposed by Lorentz et al. (2005), they categorised by four types: discretionary, Taylorism, lean and simple working environments and found correlations of discretionary working environment and innovation level of 15 European countries. With the use of these classification and approach to classify, the paper of Dohmen and Yelubayeva (2018) found that a discretionary working environment has a positive impact on a country's level of innovation, whereas a simple organisation of work had a significant negative effect on innovation (Dohmen and Yelubayeva 2017).

## 2 ANALYSIS

While the previous chapter provides a reference framework of the current research on adult education, i.e. human capital formation, as an engine of economic growth, the following chapter is focused on growth accounting models which are based on production models. As outlined in the previous chapter, there is an alternative modelling approach that calculates total factor productivity (TFP). These models see the factors of production incorporated in the aggregate production function, and that TFP defines the impact of education by the state of the residual. Considering the wide range of independent variables, however, the TFP approach is not the model of choice. Instead, this paper makes use of the growth accounting model. The following section provides a discussion of the selected variables.

The empirical work on growth accounting models comprises different econometric models, most of which involve ordinary least squares (OLS) regression. As more comprehensive datasets based on cross sectional and time series approaches have become available, some authors have attempted to use panel data analysis and to apply instrumental variables estimations. Empirical studies of economic growth often produce contradictory results due to weaknesses in the data (Atkinson & Brandolini, 2001; de la Fuente & Doménech, 2000) or due to the inclusion of different sets of variables. Regarding the extensive variety of the variables used to study drivers economic growth, Durlauf et al. (2004) present a literature review which finds close to 145 different variables to be statistically significant in at least one study (S. N. Durlauf et al., 2004). While it is not possible to include all these variables in this paper's model, it will include the most robust variables describing education and skills.

This part of the paper deals with the third research question: What is the importance of human capital in the form of adult education to economic growth?

### 2.1 Methodological framework

The challenge of econometric modelling is to account for both the theoretical specifications of the model and the empirical problems encountered in previous studies on economic growth. For example, Romer (1990) regresses the growth of GDP on the level of human capital, while Lucas (1988) regresses the growth of GDP on the growth of human capital. Also, the effect of human capital on economic growth strongly depends on the empirical specifications, of which an overview is provided in this paper. Furthermore, including a high number of variables may increase the explanatory power of the R-square statistic, while structurally lowering the regression coefficient of human capital. The majority of empirical works use the growth of GDP per capita to study the impact of human capital. Furthermore, some studies such as Benhabib and Spiegel (1994) consider GDP per capita as technological frontier level.

Another issue of econometric modelling is concerned with the modelling of non-linear terms. The approach taken in this paper is to include an interaction term of the level of human capital and the workplace environment. Initially, each variable is tested using the augmented Dickey-Fuller (ADF) test, which is a unit root test, in order to avoid spurious correlations. Other econometric pitfalls such as autocorrelation, multicollinearity issues and heteroskedasticity should also be avoided and the model was tested accordingly. Multicollinearity reduces the precision of the model in estimating regression coefficients and may lead to statistically insignificant effects of human capital formation on economic growth. However, multicollinearity has no impact on inference as it causes no bias in the regression coefficients and standard errors. Therefore, multicollinearity may not pose a problem as long as the coefficients' reported standard errors are small. Nonetheless, it is important to keep in mind that multicollinearity can be an issue when coming with the measurement error (Mankiw 1995).



The augmented growth model developed in this paper is based on the current literature on growth models as discussed in the previous chapter. The growth of real GDP per capita constitutes the dependent variable of the model as it accounts for nominal changes as well as differences in the population, which allows for cross-country comparisons. The panel dataset covers the years 2005, 2010 and 2015 according to the survey waves of EWCS and CVTS. All other variables also refer to these years. Panel data analysis accounts for country heterogeneity and allows to control for aspects such as differences in the organisation of work and (adult) further education (FE) practices between countries. Furthermore, panel data analysis allows to control for unobserved heterogeneity; hence, omitting variables from the model will not lead to a bias in the estimates (Durlauf et al. 2004; Islam 1995; Temple 2000). The model developed in this paper accounts for various variables capturing framework conditions such as GDP per capita, the share of tertiary educated people, R&D expenditure and PISA numeracy test scores. Both GDP per capita and the PISA numeracy test scores are included as log values in order to make the results more comparable as has been done in previous works on growth accounting models.

The majority of studies on economic growth that use panel data apply fixed effects (within-group) regression rather than random effects regression. That way, any omitted variables that are constant over time will not bias the estimates, even if they are correlated with the explanatory variables (Durlauf et al. 2004). The base model developed in this paper involves 5-year interval regression of panel data with country random effects and different framework controls:

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + u_{it} + \varepsilon_{it}$$

$Y_{it}$  Growth rate of real GDP per capita of country  $i$  at the time  $t$

$X_{2it}$  Human capital formation

$X_{3it}$  Organisation of work factor – discretionary learning environment (WO1)

$X_{4it}$  Organisation of work factor – Taylorism (WO2)

$X_{5it}$  Organisation of work factor – Lean production (WO3)

$\beta_6 X_{6it}$  Organisation of work factor – Simple or Traditional working environment (WO4)

$\beta_7 X_{7it}$  GDP per capita of country  $i$

$u_{it}$  Between-country error;

$\varepsilon_{it}$  Within-country error;

$\beta$  Regression coefficient

In the panel data analysis, the change in real GDP per capita is used as the dependent variable, while the variables on the organisation of work, human capital formation, GDP per capita, the share of tertiary educated adults, the share of recent graduates in STEM and R&D expenditure and the PISA test scores are used as independent variables. In the following, the data and methodology of the empirical analyses are described in more detail.

In the 2012 study conducted by FiBS and CEDEFOP, participation in adult education was found to have a positive impact on economic growth in European countries. The results are shown in Table 1. The rates of participation in adult education were derived from the AES dataset. Applying panel regression to the data from AES 2007, 2011 and subsequent years shows that the participation in adult education has a statistically significant positive effect on economic growth both in fixed effects and random effects models. The explanatory power of the models (R-square) is high. Furthermore, the models are extended

to control for income levels and to include time lagged participation rates in order to estimate also lagged effects of adult education on economic growth, i.e. whether currently participating in adult education has an impact on economic growth over time. The results show that the impact of participation remains positive and statistically significant in both fixed effects and random effects models.

	FE1	FE2	RE1	RE2
AES participation	0.827***	1.048***	0.569**	0.542**
Time lag of AES participation (participation rate in previous year)		0.274**		0.355***
GDP per capita	3.248*	1.142	-0.389*	-0.477
Year dummy	Yes	Yes	Yes	Yes
N	44,000	37,000	44,000	37,000
R-square	0,627	0,731	0,489	0,609
Standardized Beta Coefficients. Significance levels: *p<0,10, **p<0,05, ***p<0,001				

Table 1 Fixed effects estimation results of AES participation on growth. Years 2007 and 2011.

## 2.2 Data

The variables constructed come from the basis of the extant literature. The data used in this paper are secondary data collected through European surveys and statistical offices of the European Union. The methodological approach is focused on minimising the extent of extrapolations in order to keep the data as close as possible to those directly available from European surveys. There are several advantages of international data with respect to understanding the determinants of innovation. Firstly, all data are derived from standardised European surveys which makes for more comparable data and reliable cross-country time series. Secondly, these survey data provide systematic heterogeneity across countries. However, aggregated data are poorly suited to deal with the question of causality: does human capital cause economic growth or does economic growth lead to human capital formation? The paper also investigates the possibility of reverse causality in explaining the empirical relationship of human capital formation and economic growth. The geographical scope of the analysis covers the EU-28 countries (see Table 2 for a country list).

The econometric model is described in the equation in the previous section. It draws on a sample of up to 28 countries and up to three five-year periods between 2005 and 2015, which results in 72 possible observations. For the empirical analysis, most of the data is derived from the EWCS, Eurostat and CVTS surveys.

The dependent variable– the change in the growth rate of a country’s GDP per capita - is derived from Eurostat where data on an annual basis instead of averages over time are available, as is often the case in cross-country empirical studies. However, it must be kept in mind that year-to-year variations in output include cyclical components.

The EWCS survey provides information on human capital at the firm level. However, it covers no worker-specific information on education and skills. In this respect, the following analysis draws on Dohmen & Yelubayeva (2018) who derive estimates of human capital by drawing on different micro-datasets to link surveys with human capital information. More precisely, the authors use data from the AES, LFS and CVTS surveys to estimate the human capital formation of different classes of employees, which are combined with other information to develop new control variables as well as new panel estimates for human capital

at the macro level.

The dependent variable of the model is **the change in the growth rate of real GDP per capita**, which is in line with the current literature. The variable refers to real changes in GDP.

#### Infobox 2

##### Real GDP per capita

Chain linked volumes, percentage change on previous period, per capita (definition by Eurostat)

The indicator is calculated as the ratio of real GDP to the average population of a specific year. GDP measures the value of total final output of goods and services produced by an economy within a certain period of time. It includes goods and services that have markets (or which could have markets) and products which are produced by general government and non-profit institutions. It is a measure of economic activity and is commonly used as a proxy for the development in a country's material living standards. However, it is not a complete measure of economic welfare. For example, GDP does not include most unpaid household work. Neither does GDP take account of negative effects of economic activity, like environmental degradation.

While the literature frequently refers to the role of human capital, there is a general lack of consensus regarding a common definition of human capital and its operationalisation. **Human capital** is defined according to the variable of human capital formation in FiBS/CEDEFOP study (2012) that captures different variation factors of adult education (participation rate, costs, and hours in further education). The variable of human capital formation comprises participation rate in adult education, mean hours spent on further education, costs and share of enterprises providing training as % of total. We also realize the limitations in the use of human capital concept and including it as a separate and independent variable from initial levels of education, from skills and workplace environment, however that would help us see the impact of separate factors that constitute human capital.

Likely, there is also an interrelationship between innovation and economic growth, as innovation plays a key role in the rapid growth of emerging economies, whereas many countries that lack innovations show a lag in economic growth (OECD, 2009). The model developed in this paper draws on the **innovation index** derived from the UIS database where statistical data that measure and benchmark the level of innovation in European countries are published on an annual basis. Following the approach of FiBS/CEDEFOP study (2012), only certain core indicators related to innovation output are extracted and included in the model. These include linkages and entrepreneurship, intellectual assets, innovators, and economic effects. The model excludes so-called enablers such as human resources, research systems, finance and support and firm investments as these variables do not transform into innovation and output.

Regarding the **organisation of work**, this paper draws on the model of Dohmen & Yelubayeva (2018) who investigate the impact of the organisation of work on economic output. As these indicators are derived from databases such as, for example, the OECD database, this paper refers to the official category names to ensure better comparability and uniformity: discretionary, lean, Taylorism and simple working environment. The empirical approach and methodology follows Lorenz and Valeyre (2005). The indicators of work organization are derived on the individual level from the European Working Conditions Survey (EWCS) waves 2005, 2010 and 2015. Using 15 binary variables derived from the 2005, 2010 and 2015 waves of the EWCS data, a principal component analysis was conducted to identify types of work

organisation.

Finally, the model includes **GDP per capita** as a proxy for technological progress. This approach follows Benhabib and Spiegel (1994) and Engelbrecht (2003) who use GDP per capita as an approximation a country's technology gap. Including GDP per capita in the model helps controlling for differences in the initial level of development which would lead to a bias in the results.

Following the human capital theory, the augmented growth regression model also includes various auxiliary which are described in more detail below.

According to Greenwald and Stiglitz (2016), learning requires specific resources such as access to capital which is included in the model in the form of **R&D expenditures**. The data are derived from the Eurostat database where countries' total intramural R&D expenditure (GERD) are available as a percentage of gross domestic product (GDP). However, note that total R&D spending also includes public spending such as, for example, expenditures on defence and medical research, which is not directly linked to increases in economic output.

Furthermore, the model includes the **share of tertiary educated adults** in a country's overall population. The data are derived from the Eurostat database representing the percentage share of a country's population aged 25-64 who successfully completed tertiary education (ISCED level 5-8). In accounting for educational attainment, the model developed in this paper follows the approach of hybrid (dual) modelling which includes variables on educational achievement levels and as well as flow variables (Engelbrecht, 2003).

The **share of graduates in science, technology, engineering and mathematics (STEM)** is included from the Eurostat database for countries, with the purpose to study the impact and control of the current flow of higher education achievement.

Another auxiliary variable included in the model refers to **PISA numerical test scores** in order to examine the effect of the skills levels of 15-year-old students on macroeconomic outcomes. In the analysis, skills levels are assumed to be constant and refer to the data of the previous waves of the PISA survey. Hence, in theory, these individuals are considered to be involved in the production process as part of the working population in the regression. More precisely, the data of PISA 2000 is matched with the data of PISA 2005, while the following waves are matched respectively (2003 data is matched to 2010 data; 2005 data is matched with 2015 data).

#### Descriptive statistics

Table 2 provides an overview of the descriptive statistics regarding the current stage of development of European countries in terms of their innovation index and growth of real GDP per capita. With respect to the innovation index, Western European countries show high scores, while Southern and Eastern European countries generally show the lowest scores. Regarding the change in the growth of real GDP per capita, no such geographical pattern can be identified as the countries show considerable variation in their scores. Ireland presents an outlier and is to be removed from the analysis. Countries with high changes in the growth of GDP per capita include CZ, BG, LU and SK. Countries that experienced negative changes in the years 2005, 2010 and 2015 include FI, IT and PT.



Country	Innovation Index 2015	*Lead/Gap to EU-28 (current composition)	Trendline (2005-2015)	Real GDP growth rate 2015	*Lead/Gap to EU-28 (current composition)	Trendline (2005-2015)
EU-28	0.47	N/A		3.31	N/A	
AT	0.61	0.27		1.00	0.09	
BE	0.61	0.25		1.50	0.07	
BG	0.23	-0.42		3.60	-0.01	
CY	0.49	0.05		1.70	0.06	
CZ	0.43	-0.06		4.50	-0.04	
DE	0.68	0.38		1.60	0.06	
DK	0.72	0.45		1.40	0.07	
EE	0.41	-0.10		0.30	0.11	
EL	0.36	-0.19		1.10	0.08	
ES	0.34	-0.23		1.70	0.06	
FI	0.64	0.31		-0.20	-0.13	
FR	0.56	0.17		3.10	0.01	
HU	0.34	-0.22		26.30	-0.87	
IE	0.64	0.32		0.80	0.09	
IT	0.49	0.04		2.70	0.02	
LT	0.18	-0.52		1.80	0.06	
LU	0.68	0.38		4.00	-0.03	
LV	0.20	-0.48		7.30	-0.15	
MT	0.54	0.13		2.00	0.05	
NL	0.64	0.32		1.60	0.06	
NO	0.36	-0.18		3.80	-0.02	
PL	0.25	-0.39		1.60	0.06	
PT	0.40	-0.11		3.90	-0.02	
RO	0.16	-0.54		3.80	-0.02	
SE	0.67	0.37		2.30	0.04	
SI	0.48	0.02		3.20	0.00	
SK	0.34	-0.23		4.10	-0.03	
UK	0.57	0.19		2.20	0.04	

Table 2 Data overview of Innovation index and Real GDP per capita growth

\*Lead and Gap of countries are given in comparison with EU-28 (current composition countries) and are identified with normalization scores (0;1).

## 2.3 Results

Results from descriptive and pre-regression analyses

The method of choice in analysing human capital formation and types of organisation of work is to conduct a principal component analysis as it is more robust to different distributions of data. The approach is based on the idea that indicators referring to the same dimension are likely to be strongly correlated. This insight is used to reduce the complexity of large datasets into few composite variables that each reflect a specific dimension of variance in the data. Using so-called “rotations”, the loadings of the various indicators on the retained factors are adjusted to maximize the differences between them. More precisely, the method of “varimax normalized” rotations is applied as have been done in a number of empirical works (for example Arundel et al. 2007; Dohmen and Yelubayeva 2017; Holm and Lorenz 2015; Lorenz et al. 2005).

According to the principal component analysis, the factors related to the formation of human capital have the following loadings: the average number of hours spent on adult education per employee has a higher load, whereas the participation of employees in adult education has the weakest load. As all correlation coefficients are less than 0.9, there are no extreme correlations within factor scores, which indicates the absence of multicollinearity problems, (see Appendix 4). For multi-item measures, Cronbach’s alpha is calculated to establish their internal consistency. For human capital formation, Cronbach’s alpha takes the value of 0.48 (see Appendix 3), which is below the acceptable target value of 0.7 according to Acock (2016). However, Lance et al. (2006) argue that for newly developed constructs lower correlation coefficients ranging between 0.3 and 0.7 are, in fact, acceptable.

Looking at the scoring coefficients, we can differentiate the types of working environments. Initially, reliability coefficients and inter-item correlations are calculated to assess the uni-dimensionality and internal consistency of the data. Overall, there are low bivariate correlations between the independent variables (see Appendix 4). This indicates the absence of multicollinearity problems, which makes principal component analysis (PCL) a viable method of analysing the data. The reliability of measurement is assessed by Cronbach’s alpha which determines whether the 17 manifest variables are suited to construct four latent variables. The result shows good reliability and validity, and the constructed latent variables show high levels representation of variables included. The four latent variables, i.e. categories of working environments, constructed from the 17 EWCS variables are described below.

The first factor score may be referred to as a working environment of **discretionary learning**. It is characterised by high levels of discretion at work that provide scope for exploring new knowledge. Generally, adhocracies tend to show a superior capacity for radical innovation. Furthermore, this type of organization of work sees an overrepresentation of variables measuring task complexity (0,38), non-monotonous tasks (0,22), learning (0,28) and problem solving (0,15). The complexity of tasks in this working environment can be also seen from the variable – tasks require different skills – which shows high load in this working type (0,38). Variables reflecting monotony, repetitiveness and work rate constrains are underrepresented. Moreover, the discretionary learning category involves less dependency on control from the boss (-0,05), meeting precise quality standards (-0,01) and dependency on machine (-0,13). There is also a positive presence of the ability to choose one’s own method of work (0,06) and speed of work (0,41).

The second category involves **lean production**, also referred to as the J-form organisation. In theory, this type of work organisation is relatively bureaucratic and relies on formal team structures and rules of job rotation to embed knowledge within collective organization, thus contributing more towards

incremental innovation. According to the PCL results, however, these features are not clearly reflected in the factor loadings. Nonetheless, compared to the first type, the presence of complex tasks (0,16) and learning new things (0,21) are relatively low and tight quantitative production norms (0,51) and the inability to choose one's own rate of work (-0,14) are used to control employee efforts. Furthermore, the results show strong employees' problem solving (0,29) and the division of tasks being decided by employees (0,43).

The third type, the hierarchically structured **Taylorist form**, involves a working situation that is somewhat the opposite of the discretionary learning type. It is characterized by low levels of complexity (-0,44), minimal learning dynamics (0,09) and monotonous tasks (-0,22), while variables measuring precise quality standards (0,30) and assessing quality of work (0,44) are overrepresented.

Finally, the fourth group may be referred to as **traditional** organisation of work. This type is based on a simple management structure, where methods are presumably informal and non-codified. The PCL results show an overrepresentation of variables that measure constraints of work including colleagues (0,22), numerical targets (0,36), dependence on machines (0,50) and control from the boss (0,19). Furthermore, there is little learning (-0,01) and problem solving (0,09), minimal presence of complex tasks (-0,03) and less tasks requiring different skills (0,04).

#### Results from regression analyses

To determine whether to choose a fixed effects or a random effects regression model, the Hausman test is applied which tests the null hypothesis of a random effects model as the preferred model specification (for further details see Green 2008). The results show the p value to be not statistically significant which makes the random effects model the better fit. Furthermore, the Breusch-Pagan Lagrange multiplier (LM) test is applied to determine whether a random effects or a simple OLS regression model is to be preferred. The null hypothesis of the LM test is that variances across units of observation, i.e. countries, equals zero which implies no significant difference across units, i.e. no panel effects. The results show the p value to be statistically significant which indicates differences across countries, making random effects regression the method of choice. Finally, the data are tested for panel-level heteroskedasticity and autocorrelation. The results show that the model is homoscedastic and there are no autocorrelation issues. Consequently, the models is expected to yield consistent estimators.

The results are presented in **Fehler! Verweisquelle konnte nicht gefunden werden..** All models show high significance. Besides the base model (Model 1), five alternative models were tested to analyse the sensitivity of results. To this effect, the same set of countries was tested, while each model added another control variable to the basic set of independent variables. According to the value of R-squared, Model 1 explains 66% of the variation in the data. Human capital formation has a positive and statistically significant impact on the dependant variable, while the effect of GDP per capita is negative and statistically significant. Model 2 includes the innovation index as additional control variable. While at 69%, the explanatory power of this model is higher compared to the base model,69%the only independent variables that are statistically significant are human capital formation (positive) and GDP per capita (negative). Model 3 includes the independent variable of R&D expenditure. Compared to Models 1 and 2, its explanatory power further increases to 70%, while the effects of HCF and GDP per capita remain statistically significant. In Model 4, PIAAC data are included as an additional control variable. The model's explanatory power shows a decrease to 69%. While the effect of HCF remains positive and statistically significant, none of the remaining variables have a significant impact on the growth of real GDP per capita. Since the PIAAC survey was only conducted once and it, therefore, included

in the model as a constant over time, it is not included in any other specifications of the model. Model 5 includes all types of working environments; however, with the exception of HCF and GDP per capita, none of independent variables are statistically significant. Finally, Model 6 includes interaction terms of the different types of working environments and HCF. The results suggest that the effect of HCF (defined as adult education exclusively) remains positive and statistically significant, while the interaction terms are not statistically significant. The explanatory power of the model is 69%.

In conclusion, HCF is found to be a significant predictor of the growth of GDP per capita. Overall, the six models that include different control variable have a high explanatory power. Furthermore, the impact of HCF on the growth of GDP per capita is consistent across different model specifications. GDP per capita is found to negatively and significantly impact the dependent variable: a percentage increase in GDP per capita marginally decreases of the growth of real GDP per capita.

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)
VARIABLES	Real GDP per capita growth	Real GDP per capita growth	Real GDP per capita growth	Real GDP per capita growth	Real GDP per capita growth	Real GDP per capita growth
ln_GDP per capita	-2.538***	-2.798***	-2.672***	-2.078***	-2.473**	-2.317**
Graduates in STEM	-0.0524	-0.0564	-0.0862	-0.0307	-0.0628	-0.0564
Share of adults with tertiary education	-0.0428	-0.0379	-0.0424	-0.0431	-0.0553	-0.0546
HCF	0.952***	0.925***	0.845**	0.454	0.777*	0.815*
WO1					0.294	0.332
HCF#WO1					-0.174	-0.147
ln_PISA	1.241	0.521	-0.995	-5.474	-3.252	-5.412
Innovation Index		1.539	-1.270	-0.131	-1.768	-1.617
R&D expenditure as % GDP			0.775	0.358	0.373	0.252
WO2					-0.117	-0.154
HCF#WO2						-0.159
WO3					-0.0875	-0.0483
HCF#c.WO3						0.0507
WO4					0.233	0.207
HCF#WO4						0.131
ln_PIAAC				9.995		
Constant	3.844	8.261	17.79	-12.45	32.43	45.44
Observations	55	55	55	40	55	55
Number of countries	24	24	24	16	24	24
R - square	0,66	0,69	0,70	0,69	0,71	0,69

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3 Panel data models for Real GDP per capita growth

Furthermore, the data were tested for the reverse relationship of human capital and economic development, i.e. whether human capital development is driven by economic growth. To this effect, HCF was considered the dependent variable, while the independent variables included the growth in real GDP per capita as well as all other control variables as in the previous regression analysis. Furthermore, the preferred type of panel data analysis was again determined through Hausman and Breusch-Pagan

Lagrange multiplier (LM) tests, which indicated random effects panel data analysis to be the most suitable approach.

The base model (Model 1) shows that the growth of real GDP per capita, the share of adults with tertiary education and the PISA numeracy test scores to have positive and significant effects on the formation of human capital, while GDP per capita and the innovation index are statistically insignificant. Models 2 and 3 included PIAAC test scores and R&D expenditure respectively as additional control variables. In both models, only the impact of the share of adults with tertiary education remained positive and statically significant. Model 4 includes the different types of working environments and indicates positive and statistically significant effects of GDP per capita and R&D expenditure. Furthermore, a traditional working environment characterized by lower problem solving and autonomy negatively impacts the formation of human capital. The explanatory power of Model 4 is very high at 78%.

VARIABLES	(Model 1)	(Model 2)	(Model 3)	(Model 4)
	HCF	HCF	HCF	HCF
Real GDP per capita change	0.0627*	0.0665	0.0405	0.0616
ln_ GDP per capita	0.514	0.644	0.356	0.903**
Graduates in STEM	0.0271	0.00777	-0.0283	-0.0275
Share of adults with tertiary education	0.0500***	0.0507**	0.0563**	0.0393
ln_ PISA	8.798***	5.923	6.337	6.238
Innovation Index	1.148	0.0372	-1.365	-1.275
ln_PIAAC		5.171	2.107	2.173
R&D expenditure as of GDP			0.558	0.600*
WO1				0.0867
WO2				-0.105
WO3				-0.105
WO4				-0.302*
Constant	-58.57***	-69.24**	-53.74*	-54.72*
Observations	55	40	40	40
Number of countries	24	16	16	16
R-square	0,72	0,66	0,66	0,78
*** p<0.01, ** p<0.05, * p<0.1				

Table 4 Panel data models for HCF

### 3 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

As outlined in the previous chapter, the literature on the relation of human capital and economic growth provides an extensive discussion of the difficulties in the empirical approach to this topic – the issues of measurement of human capital and statistical specification. Moreover, longitudinal studies are faced with limitations in the availability of data on the quality of education and aggregate measures of human capital, which severely limits the scope of econometric solutions to the endogeneity problem.

The findings of the empirical analysis show the interrelation of economic growth and adult education to be of a highly complex nature. There are a number of factors that may have contributed to the complexity and ambiguity in their correlations. These include different shortcomings of the research methodology as well as the specific properties of adult education such as the complexity of the nature of education and the organization of work, their non-measurability and non-commensurability and the multidimensional impact of the different constituents of the structure and diversity of their impacts depending on the specific conditions of their (adult education) usage. In the following, the limitations of the findings in this paper are explored in more detail with respect to errors in the measurement of human capital and the specification of economic growth as well as pitfalls of the regression model developed in this paper.

#### 3.1 Errors in the measurement of human capital

There are main issues related to the measurement of human capital: problems concerning the methodology of measuring human capital and its statistical collection, and problems related to the aggregation of data from the individual to the macroeconomic level.

The approach to estimating human capital in this paper is faced with various shortcomings. Above all, these involve errors of measuring data that proxy human capital. Furthermore, the research literature largely suffers from limitations in empirical findings that are due to the narrow concept of human capital that is focused on formal education only. Another type of measurement error occurs in the context of accumulating and aggregating data on adult education. Moreover, the collection of data on adult education is flawed with respect to consistency in methodologies over time. As highlighted in the Bologna report on higher education as well as in the different surveys on adult education, there is considerable variation in the quality of education across different countries which leads to differences in the stock of human capital.

To summarise, the empirical approach of this paper, i.e. using factor analysis to model human capital, is widely accepted across academic and policy papers (CEDEFOP 2012). Nonetheless, there remains room for improvement regarding the theoretical foundation of the operationalisation of adult education.

#### 3.2 Errors in the measurement and specification of economic growth

With respect to collecting data on economic growth as proxied by the growth in real GDP per capita, problems are due to changes in the composition of GDP. Hence, collecting data on GDP over time is to be treated with caution for countries (see Eurostat Metadata analysis, nd.). Furthermore, the measure of economic output itself presents a complicated issue in the context of international trade and governmental policies.

The literature spans a variety of GDP measures to proxy economic growth: some authors use GDP per capita, while others use the growth of GDP per capita and yet others use the change in the growth of GDP per capita. This poses a further challenge with respect to properly defining economic growth variable and



comparing results across studies that use different measures.

### 3.3 Limitations of the regression model

The limitations of the regression model developed in this paper mainly relate to the following main aspects: low sample of cases and possible endogeneity.

Less observations due to limited countries participated in the survey, because we took only European countries to those data available in three survey periods. In our analysis, we initially tested for the presence of any outliers, and limited our dataset. Furthermore, in keeping the model concise, problems of oversimplifications may arise that could lead to an omitted variable bias.

Another problem caused by the choice of variables is the issue of endogeneity. Many explanatory variables not only impact economic growth, but are also, in turn, influenced by economic growth. This applies to variables measuring human capital variables in general and to variables measuring adult education in particular. The issue of endogeneity also applies to the explanatory variables: for example, a higher initial level of education may lead to higher rates of participation in adult education, while STEM graduates often enter high technology sectors where they have comparably better opportunities of learning.

### 3.4 Additional suggestions

The following suggestions for further research are given and it is recommended to do a more in-depth study of countries' economic structure on the regional level controlling, for example, for types of industries and occupations. Such a region-level analysis may lead to improved insights about the drivers of economic growth as regional output level is strongly linked to a country's economic structure. While comparing national economic structures would go beyond the scope of this paper, future research on the topic would benefit from considering these national characteristics when it comes to interpreting results for individual countries. In this respect, scholars need to pay attention to the institutional structure of the country in question and to the links between human capital, the institutional structure and the sources of economic growth. Moreover, using qualitative methods to assess the drivers of countries' economic growth and structural policies may yield further insights to complement the findings of this study.

Furthermore, future empirical research may include other determinants of human capital such as the quality of education, the experience of the workforce, and social capital in defining the benefits of adult education. These factors were omitted from this paper due to the individual nature of certain skills and knowledge as well as the rigidity of certain working environments.

Economic growth can only be sustainable and beneficial for a country if there is a social security system in place that protects the members of society (Stiglitz, 2016). In this respect, future research may also focus on the impact of adult education on social equity, and its overall impact on output as achievement of equity seemed to be balanced by growth rates (Harris, 1993).

Concerning the specific methods of analysis, further research may involve quasi-experimental regression models if data limitations overcome for example – instrumental variables (IV) estimation technique for panel data. Other techniques of estimation such as, for example, instrumental variables estimation and stochastic frontier analysis may also be applied to microdata. That way, future research may help determine whether or not the findings in this paper suffer from upward or downward biases caused by endogeneity.

## 4 CONCLUSION

Today, human capital is considered to be the most important element generating value for companies and economies, which has led to a growing number of academic and empirical works considering the interrelation of human capital and growth in GDP. The quality of human capital, i.e. the skills and competencies that individuals acquire through adult education, contribute to the improvement of economic growth potential. Increased output through education is sustainable and governments may reap the greatest economic benefits from it as in the previous study paper it is found that human capital has a positive impact to innovation as well.

The impact of education on economic growth is subject to ongoing research. While some studies estimate a positive relationship of education and economic growth (Barro 2003; Benhabib and Spiegel 1994; Hanushek and Woessmann 2012; Mankiw et al. 1992), others find the relationship to be negative (Benhabib and Spiegel 1994; Pritchett et al. n.d.). These contrasting results are partly due to the use of different data measures to proxy education which, in turn, lead to contradictory conclusions and policy recommendations (Atkinson and Brandolini 2001; Benos and Zotou 2014; de la Fuente and Doménech 2006).

The VoRREFi project aims to close this gap by providing a theoretical framework and empirical basis for an improved understanding of the wider macroeconomic benefits of adult education. This paper investigates the causal relationship between adult education and economic growth in European countries for the period between 2005 and 2015 by means of random effects regression model. The results show that human capital has a positive and statistically significant impact on economic growth, whereas higher education attainment and the share of graduates with STEM degrees are found to have no significant effect on economic growth. While the determinants of economic growth under given estimation procedure with the possible dataset to measure are found to be workplace learning, adult education measured from various variables into human capital while controlling for the other factors such as PISA scores, educational attainment levels, R&D, etc.

Furthermore, investigating the possibility of reversed causality, i.e. whether economic growth is a driver of the formation of human capital, showed that it is not. This means that increase of economic growth itself does not show statistically that it positively contributes to the positive increase of participation in adult education.

The results of the literature review conducted in this paper contribute to knowledge on the interrelation of human capital formation and economic growth, while pointing to further research needs regarding the benefits of adult education, especially with respect to vulnerable groups. Moreover, this paper contributes to the discussion of the macroeconomic growth benefits from further education, which is in line with the growing academic interest in topics such as work-based learning and organisational innovation.



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