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"R&D expenditures in the high-tech sector and economic growth across 30 OECD countries, a panel data analysis"

Lengos Gerasimos

Supervisor: Boikos Spyridon

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ABSTRACT

The present thesis examines the impact of research and development spending regarding the high-tech sector on short- and long-term economic growth. Specifically, this research provides new evidence utilizing a semiparametric empirical growth model (system GMM estimator) using panel data regarding 30 OECD countries from 1970 to 2019. It also constitutes an attempt to further enhance the findings presented in Falk (2007). Initially, this is sought by re-estimating the model utilized by Falk (2007) following the same methodology for the period from 1970 to 2004. Then, we estimate the growth equation utilizing an expanded panel dataset regarding the period from 1970 to 2019. The third subsection of the estimations concerns the addition of an alternative measure of innovation introduced by LeBel (2008). This study constitutes a continuation of the branch of research which investigates whether the composition of R&D activities (shifting from low- to high-tech areas) has an additional impact on economic growth. The estimations are carried out utilizing a two-step system GMM estimator which contributes to the minimization of endogeneity. The results indicate that the share of business R&D expenditures oriented to high-tech areas has indeed a positive effect on GDP per working-age population, GDP per hour worked, and GDP per employed person regarding the short-term horizon in both datasets (1970 to 2004 and 1970 to 2019). Regarding the long-term horizon, the R&D composition's impact is not consistent. Economic growth is positively and intertemporally affected by the population's education level, the ratio of business R&D to GDP, and the level of investment to GDP ratio. Finally, Innovindex proposed by LeBel (2008) is found to be statistically non-significant as an alternative measure of innovation (estimates from 1995 to 2019).

Keywords

Economic growth, Research and Development expenditures, system GMM, Panel data analysis

1. INTRODUCTION

1.1 General Information

The links between research and development activities and economic growth in OECD countries constitute an important research field in macroeconomics, especially after the disparities that were observed in the 1990s and the increase of business-sector-driven R&D compared to the 1980s. In general, R&D activity is suggested to be included in any quantitative analysis of growth (see Bassanini et al. (2001)) as it is considered to be an alternative form of investment. As Bassanini and Scarpetta (2002) claim, there is wide accordance in the relevant literature that R&D spending has a positive long-term effect on economic growth rates.

Furthermore, private sector R&D activities are of particular interest when growth analysis is performed since they are more targeted towards improving competitiveness through cost minimization, quality improvements, and opening new markets. It is also generally accepted that high-tech firms are associated with high value-added as well as spillover effects when R&D activities are performed (see Nadiri & Wolff (1993)). A broad definition of the high-tech sector could be the summation of industries with a high percentage of employees in STEM (Science, Technology, Engineering, Mathematics) occupations. As Acemoglu (2002) points out, there is a substantial change in the composition of R&D investment in the second half of the 20th century that has only been amplified in the 21st. There are also important indications that R&D activities in the high-tech sectors have an additional effect on economic growth rates and total factor productivity (see Nadiri (1993) and KH Tsai & JC Wang (2004)).

Falk (2007) uses the findings and indications mentioned above as motivation to shed more light on the impact of R&D spending composition on economic growth rates. This paper constitutes a starting point for further investigation into the relationship between R&D expenditures in the high-tech sector and economic growth. It is the first to address if the share of the high-tech R&D spending subset invokes additional economic growth. The estimations are performed on a panel dataset consisting of 30 OECD countries regarding the period from 1970-2004. The author utilizes a system GMM estimator which minimizes possible endogeneity problems. The findings indicate that the composition of R&D spending presents a remarkable long-term positive impact on GDP per capita and per hour worked even when controlling for the ratio of business R&D expenditures to GDP.

1.2 Motivation and framework

As data availability is constantly increasing, the investigation of different aspects of R&D investment and its impact on economic growth becomes more and more intriguing. Taking that into account we define the framework of this thesis as further research in order to better identify the relationship between these two macroeconomic variables. In this context, Falk (2007) operates as the main axis of our study. The main purpose can be defined as the verification of the relationship between R&D expenditures in the high-tech sector and economic growth following the same methodology as Falk (2007) and extending the data sample adding the period from 2005 to 2019. We also repeat the estimations with the addition of another control variable to the already existing ones (investment to GDP ratio, business R&D to GDP ratio, average years of education). The additional control variable used in this thesis is the ratio derived by LeBel, P. (2008) which constitutes an alternative measure of innovation. As Falk (2007) proceeds, we perform robustness checks alternating dependent variables (GDP per working-age population, GDP per hour worked, GDP per employed person) and data specifications using 10-year averages as opposed to the primary 5-year averages.

1.3 Organization of sections

The structure of the present thesis is as follows. Section 2 comprises the literature review on which the thesis is based. In Section 3 we collocate the specifications and particularities of the data used for the estimations including summary statistics. Section 4 is a detailed description of the methodology. Section 5 is devoted to the presentation of the results derived from the empirical analysis. Last but not least, section 6 provides a summary of the significant results.

2. LITERATURE REVIEW

The rapid increase in publications related to the dynamics between R&D expenditure and economic growth coincided with the expanding availability of datasets observed in the 90s. In this section, we are referring only to those papers that are essential for a better understanding of the foundation on which this research is based.

For that matter, it is necessary to further analyze Falk, M. (2007). This specific paper is of particular importance because it deals with R&D spending composition and the role that it plays as far as economic growth is concerned. The results of the paper show that there is indeed an additional positive effect on economic growth when the composition of R&D expenditures shift from the low-tech to the high-tech sector both in the short and long term. The research is carried out utilizing the data from 30 OECD countries for the period from 1970 to 2004 transformed to 5- and 10-year averages applying a system GMM estimator. Subsequently, we refer chronologically to the rest of the papers.

Coe, Helpman, and Hoffmaister (1997) examine the benefits of 77 less developed countries (from Africa, Asia, Latin America, and the Middle East) from R&D that is performed in 22 industrial countries despite the fact that there is no extensive investment in R&D by themselves (data sources: UNESCO, World Bank). Their results indicate that total factor productivity in developing countries is positively and significantly related to R&D in their industrial country trade partners and to their imports of machinery and equipment from the industrial countries.

Zachariadis (2003) investigates a system of three equations implied by a model of R&D-induced growth in steady-state for U.S. manufacturing industry data from 1963 to 1988 utilizing the Schumpeterian framework. The results show that R&D intensity positively affects the rate of patenting, the rate of patenting positively affects technological progress, and, finally, technological progress has a one-to-one relation with the growth rate of output per worker. Furthermore, the intensity of aggregate manufacturing R&D is shown to have a stronger effect on the rate of patenting than own-industry R&D which is an indication of technological spillovers across manufacturing industries.

As far as the EU is concerned, Bilbao-Osorio and Rodriguez-Pose (2004) address different aspects of the relation between innovation and economic growth in 9 European countries consisting of 103 regions. Overall, R&D expenditure leads to higher innovation growth rates that affect economic growth in peripheral regions while for non-peripheral regions no significant relationship between both factors is found. In relation to OECD countries, Guellec and Van Pottelsberghe de la Potterie (2004) attempt to comprehend the long-term impact of various sources of knowledge on multifactor productivity growth of 16 OECD countries from 1980 to 1998. The results conclude that the long-term elasticities of multi-factor productivity concerning foreign R&D and public R&D are about 0.45 and 0.17 respectively. Government funding seems to be fairly successful in enhancing business R&D with a higher social return. Moreover, R&D carried out by the higher education sector seems to be more impactful on growth than that by public laboratories.

Ulku (2004b) investigates the assertion that innovation is created in the R&D sectors, and it enables sustainable economic growth, provided that there are constant returns to innovation in terms of R&D. The analysis employs patent and R&D data for 20 OECD and 10 Non-OECD countries for the period 1981–97 utilizing GMM estimators, fixed effects and an OLS benchmark model. The results show that there is a strong positive relationship between innovation (patent stock) and per capita GDP in both OECD and non-OECD countries, while only the OECD countries with larger markets are able to increase their innovation by investing in R&D.

As far as the high-tech sector is concerned, Tsai and Wang (2004) study the impact of R&D on productivity within the private sector (136 firms) taking into account high-tech and traditional manufacturing firms as well as the spillover effects from the high-tech sector to the traditional manufacturing sector in Taiwan for the period of 1994-2000. Regarding the two sectors, the R&D elasticity for high-tech firms is around 0,3, but only 0,07 for other firms. In addition, the average rate of return on investment in high-tech firms is around 35 per cent whereas for other firms is around 9 per cent. Also, the R&D spillover effect from the high-tech sector into the traditional manufacturing industries is around 0,01 and the estimated rates of return on R&D investment across each sector are around 7 to 10 per cent. Moreover, Falk (2007) estimates the impact of the change in the high-tech export share on economic growth in 22 OECD countries for the period 1980-2004. When R&D and high-tech exports are included in the model, the coefficient of high-tech exports drops significantly which shows that overall, business R&D is more important than high-tech exports in explaining economic growth.

Blind and Jungmittag (2007) examine how the stock of patents and technical standards affect economic growth in four European countries (UK, France, Germany, Italy) regarding 12 sectors of each one from 1990 to 2001. The results show that there are significant impacts of the stock of standards in the sectors, characterized by low and medium R&D and technology intensity, whereas the stock of patents gains in importance with the increasing R&D intensity of sectors and the use of high technology.

Sinha (2008) investigates the relationship between patents and economic growth in Japan and South Korea for the period of 1963-2005. The results conclude that for Japan real GDP and the number of patents have a long-run relationship. There is also a bidirectional causality between the growth rates of real GDP and the number of patents. However, this is not the case for South Korea. Regarding the panel data estimation, real GDP and the number of patents are cointegrated and the growth of real GDP Granger causes the growth of the number of patents but there is no evidence of the reverse causality.

Goel et al. (2008) approach the R&D-growth nexus at a disaggregated level by considering the roles of federal, non-federal, and defense R&D outlays utilizing new bounds-testing and ARDL to estimate the long-run relation between R&D outlays and growth in a fairly standard model based on U.S. data for the period 1953–2000. The results indicate a strong association of growth rate with defense R&D which is a part of the high-tech sector R&D. This phenomenon is not observed as far as non-defense (federal) R&D is concerned.

In a rather important for the present thesis paper, LeBel (2008) tests the extent to which institutional policy choices enhance or delay the diffusion of innovation in order to explain relative differences in growth using a panel regression model on a sample of 103 countries for the 1980–2005 period. In order to accomplish that, the author introduces an alternative measure of innovation. This specific index (INNOVINDEX) constitutes a part of our empirical analysis as its addition enhances the robustness of our results. LeBel (2008) indicates that when the effect of innovation on economic growth is examined, it outweighs all other variables by a rough factor of 3–1. Moreover, while predicted savings rates and trade dependency affect growth positively, once risk and innovation are taken into account, their role is reduced.

Ortiz-Villajos (2009) carries out a quantitative analysis on the relationship between patents and per capita income of 23 countries from 1826 to 1985. This paper emphasizes the existence of a high, significant correlation between the ratio of patents per inhabitant and per capita income over the period studied. The results also allow for an interpretation to be made according to which the technology used in production would have explained 30% of countries' per capita production. Overall, the fact that patents are more correlated with private investment and not with the public sort indicates that the private sector has the initiative of technological effort of the economy over the years examined.

Samimi and Alerasoul (2009) estimate the impact of R&D on the economic growth of 30 developing countries for the period 2000-2006. The results indicate the R&D elasticity is negative and insignificant. This fact indicates that in developing countries with low R&D expenditure the effect of this variable on economic growth was not significant. Sameti et al. (2010) analyze the impact of a determinant factor on the R&D investment with emphasis on openness in 30 OECD countries from 1996 to 2008 utilizing a panel data model of R&D. The results show that openness trade, GDP growth, and government R&D expenditures have a positive effect on R&D intensity while the main explanation for R&D is openness trade. In general, if the private rate of return is below the social rate of return, then expenditure on R&D could be lower than socially optimal. Another conclusion is that expenditure, especially by smaller firms, may be lower than optimal if firms experience significant external financial constraints.

Wang (2010) is an important effort to investigate the determinants of R&D investment with an emphasis on the roles of patent rights protection, international technology transfer through trade and FDI, economic growth, human capital accumulation, and the number of scientific researchers in 26 OECD countries from 1996 to 2006. The results indicate that the tertiary education level and the proportion of scientific researchers have a significantly positive effect on the intensity of R&D investments. Secondly, R&D investment intensity is not found to be affected by patent rights protection. Another fact worth noting is that fluctuations of the current and expected income growth rates do not present a statistically significant impact on R&D intensity variations.

Hasan and Tucci (2010) extend the line of research attempting to link innovation to economic growth based on a sample of 58 countries for the period 1980–2003. The results show that both the quantity and quality of inventive activity are associated with economic growth. Specifically, the ratio of R&D Expenditures to GDP as well as Total Patents Granted to Total R&D Expenditures have a positive and statistically significant relation with growth in per capita GDP. In general, countries that have higher levels of patenting activity tend to be the countries with higher growth rates. Moreover, it seems that an increase in the level of patenting activity tends to increase the growth rate.

Nunes et al. (2012) examine the relationship between R&D intensity and growth in 133 high-tech and 330 non-high-tech small and medium-sized enterprises (SMEs) in Portugal from 1999 to 2006, applying the two-step estimation method proposed by Heckman (1979). This study concludes that for non-high-tech SMEs there is a negative and statistically significant relationship between R&D intensity and growth. Regarding high-tech SMEs, there is a U-shaped, quadratic relationship between R&D intensity and growth and it seems that R&D intensity is a negative factor of growth in high-tech SMEs for low levels of R&D investment, but it positively affects growth for high levels of R&D investment.

On a similar path, Horvath (2011) investigates the effect of R&D on long-term economic growth in 72 countries using the Bayesian model averaging (BMA). The data used are real GDP from 1960 to 1992 and Nobel Prizes from 1945 to 1975 as an estimated lag of 20 years is taken into account by hypothesis. The results indicate that the R&D index, although with a rather lower posterior inclusion probability of 0.25, exerts a positive effect on long-term growth. Moreover, the most plausible explanation for lower PIP is related to the fact that the Nobel Prize is not a full picture of R&D in many countries.

Josheski and Koteski (2011) examine the dynamic link between patent growth and GDP growth in G7 economies over the period from 1963 to 1993 divided into quarterly data. The results conclude that there is a long-run cointegration between quarterly growth of output and quarterly growth of patents. Moreover, the Granger test shows that there is unidirectional causality from the growth of patents to the growth of output.

Kim (2011) studies the contributing impact of R&D stock for economic growth in Korea over the period of 1976-2009 utilizing the R&D-based Cobb-Douglas production function. The results show that R&D stocks in public and private sectors contribute to economic growth at around 16.03% and 18.78% respectively. The remaining 65% is contributed by the traditional production factors, namely labor, and capital. Overall, the results suggest that R&D activity (regardless of R&D sources) is necessary to maintain economic growth.

Saini and Jain (2011) investigate the impact of patent depositions on economic growth leading to sustainable economic development concerning 9 Asian countries for the period of 2000-2009. The results concluded that out of the sample of 9 countries, in 5 countries, namely, India, China, Indonesia, Philippines, and Malaysia there is no effect of the number of patent applications filed on GDP growth rate. On the contrary, regarding the other 4 countries, namely, Singapore, Thailand, Japan, and Vietnam there is a positive impact of the number of patent applications on the GDP growth rate.

Guloglu and Tekin (2012) examine the causal relations among R&D expenditures, innovation, and economic growth in 13 high-income OECD countries over the period 1991-2007. The findings are supportive of the idea that innovations are pro-cyclical. Overall, there are positive and significant relations between R&D and innovation, R&D and economic growth, and economic growth and innovation. Last but not least, the bivariate test results indicate that there is a reverse causality between R&D and technological change which suggests that successful investment in the R&D sector eventually causes further investment in R&D activities.

Guo and Wang (2012) approach the relationship between patent output in the high-tech industry and economic growth in China from 1995 to 2010. Five industries are taken into account as high-tech. These are pharmaceuticals, computers and office equipment, aircraft and spacecraft, electronics and telecommunication, medical equipment, and meters. The results show that there is a bidirectional Granger causality running between patent output and economic growth in the long term, and there is a Granger causality running from patent output to economic growth in the short term. Furthermore, it seems that patent output plays a more efficient role in Aircraft/Spacecraft (AS) and Medical equipment (MEM) sectors than in the rest of them.

Wang et al. (2013) follow a quantile regression approach to explore the marginal effect of R&D expenditures in the high-tech sector across different quantiles of the conditional GDP distribution for 23 OECD countries and

Taiwan from 1991 to 2006. The results show that the positive effect of high-tech R&D spending on income is especially evident when considering the extreme upper quantile while for low- and middle-income countries the effect is almost non-existent. Overall, only the high-tech R&D spending in the highest per capita income country can give a big boost to the economy and other types of R&D expenditures seem to play no role in a country's economic development.

Inekwe (2014) examines the role of R&D expenditure on the economic growth of 66 developing countries during 2000-2009. The results show that R&D spending has a positive effect on economic growth in developing countries, especially in upper-middle-income economies while it has no significant impact on growth in lower-middle-income economies at conventional levels. An examination of short- and long-run effects reveals different impacts on each horizon where R&D spending hampers growth in the short run while an expansionary effect exists in the long run. In addition, R&D spending in upper-middle-income economies has a beneficial impact in the short run, but in the long run, this impact is insignificant.

Akcali and Sismanoglu (2015) make a significant effort to compare the relationship between R&D expenditures and economic growth in 19 developed and developing countries from 1990 to 2013. The results show that regarding developed countries like the UK, France, and the Netherlands there is a one-to-one impact of R&D expenditures on economic growth. In countries such as Portugal, Iceland, and Austria the impact appears the lowest, which is around 0,3% and 0,4%. Overall, the impact does not seem to be parallel with R&D expenditures as a percentage of GDP.

Alternatively, Liu (2015) explores how IPRs, research and development (R&D) and foreign direct investment (FDI), and other possible variables affect the economic growth in 92 countries from 1970 to 2007. This paper utilizes the generalised method of moments (system GMM) methodology to solve the potential endogeneity problem. The results of different groups of countries classified by their levels of economic development conclude that besides the domestic investment, openness to trade and human capital, R&D is the most important factor of economic growth in the higher-income countries, while FDI is the corresponding factor of growth in both higher and middle-income countries. Last but not least, IPRs protection is found to positively and significantly affect economic growth in both higher-income and lower-income countries but that does not hold for middle-income countries.

Gumus and Celikay (2015) investigate the relationship between R&D expenditures and economic growth in 52 countries from 1996 to 2010 and employ a dynamic panel data model as well as error correction model, mean group estimator, and pooled mean group estimator. The results indicate that R&D expenditures have a strong and positive effect on GDP in both the short and long run for developed countries while for developing countries, the effects are strong in the long run but weak in the short run.

In a different approach, Gil et al. (2016) use an endogenous growth model of directed technical change with vertical and horizontal R&D in order to study a transitional-dynamics mechanism that is consistent with the changes in the share of the high- versus the low-tech sectors in 14 European countries from 1995 to 2007. The model estimates that the fluctuations of the share of the high-tech sector do not significantly affect the economic growth rate. The results suggest that raising the share of the high-tech sector may be largely ineffective in stimulating economic growth when the change in the industry structure depends on the proportion of highly skilled workers.

Ildırar et al. (2016) is a research of the effect of different types of R&D expenditures on economic growth for 29 OECD countries from 2003 to 2014 by utilizing from GMM framework similar to the present thesis. The results indicate that long-term economic development could be achieved through gaining productivity as well as that R&D expenditures have a significant impact on economic growth in selected OECD countries. It is also observed that the differences between the welfare of the countries are determined according to the knowledge and innovation capacity. Science and technology affect the countries' economic transformation and sustainable growth so countries to achieve sustainable economic growth transfer large amounts of resources to R&D activities and innovation.

In another fashion, Tunali (2016) which is an investigation of the effect of R&D spending on economic growth in 18 OECD countries over the period 1981-2012, shows that total R&D spending and business R&D spending do not have a statistically significant effect on economic growth while government R&D spending has a statistically significant impact which is negative in the short run and positive in the long run. These findings indicate that government R&D spending is efficient and governments of the OECD countries should continue to support R&D activities in government institutions.

Tüỉredi (2016) studies the causality relationship of economic growth with R&D expenditures and patent applications for the 23 OECD member countries for the period of 1996-2011. The findings are that 1% increases in the share of total R&D expenditures in the GDP and patent applications increase GDP per capita (economic growth) 0.40% and 0.07% respectively. The results also indicate that there is a positive two-way causality relationship between economic growth and R&D expenditures and a positive one-way causality relationship from patent applications to growth in the countries under examination.

In a similar fashion, Maradana et al. (2017) examine the long-run relationship between innovation and per capita economic growth in the 19 European countries over the period 1989–2014 employing six different indicators of innovation: patents-residents, patents-nonresidents, R&D spending, number of researchers occupied in R&D activities, high-technology exports, and scientific and technical journal articles. The findings reveal that because of the existence of reverse causality or bidirectional causality for some cases, policies that increase per capita economic growth (through investment) are likely to bring more innovation in the economy.

Hong (2017) looks into the Granger-causality between R&D investment and economic growth for Korea's ICT (Information and communication technologies) industry for the period from 1988 to 2013. In general, an increase in public ICT R&D investment leads to greater private investment and it has the dynamic to create secondary positive effects. Furthermore, when private R&D investment increases, it affects positively the growth of the public sector and contributes to national wealth, which subsequently causes higher governmental R&D investment. This mechanism constitutes a cycle of causality where public R&D investment incites R&D activities by the private sector which then lead to the enhancement of growth. Then, the state accumulates more resources which contribute to the amplification of ICT R&D investment.

Vetsikas et.al (2017) also studies the relationship between innovation outcomes (patent applications, industrial design applications, and trademark applications) and economic growth in 19 European countries for the period 1980-2015 using the Johansen cointegration technique and employing Granger causality analysis to check for causal relationships. Overall, there is a powerful causal relationship running from economic growth to three different types of innovation for a significant number of time lags. Findings also indicate that there is a unidirectional causal relationship from R&D expenditure to economic growth in developed countries but not in the case of Southern European countries.

Yazgan and Yalçinkaya (2018) seem to be in accordance with the aforementioned findings. They examine the effects of the R&D investment variables of various qualifications on economic growth for the period of 1996-2015 in OECD countries which are grouped as OECD-20 and OECD-9 based on their income levels. The results indicate that the effects of all qualitatively different R&D investments on economic growth are positive and statistically significant. Specifically, there is a positive and statistically significant effect of R&D investments of the private sector, universities, and total R&D investments on economic growth in the OECD-9 group, while the

R&D investments of the public sector and staff number work in the R&D field are statistically insignificant. Furthermore, there is an important causal connection regarding the R&D investment proxies of different quality and the economic growth in the OECD-20 group.

Liu and Xia (2018) investigate the relationship between an indicator system of R&D investment, technological innovation, and economic growth as research variables regarding China from 1995 to 2016. There are strong indications that although there is a stable interrelationship among R&D investment, technological innovation, and economic growth, the innovation system is not very effective due to the lack of a transmission mechanism. Last but not least technological innovation has a restraining effect on R&D investment in the short term.

Freimane and Bāliņa (2016) look into the empirical relationship between R&D expenditures and economic growth in the EU member states for the period of 2000–2013. The results show a positive, statistically significant relationship between R&D and GDP per person employed. In the short-run, a 10 % increase in R&D intensity should generate an increase of about 0.2 % on growth while regarding long-run coefficients, a 10 % permanent increase in R&D should generate about 0.9 % increase in the growth of GDP per capita. The examination of homogenous groups of countries shows that there are no statistically significant differences in the short-run R&D elasticities for medium and high R&D to GDP ratio groups. However, for low R&D expenditures (less than 1 % per GDP) R&D activities are more important (partial elasticity is 0.06% higher) for GDP growth. Overall, short-run effects are lower than long-run ones.

3. DATA

The present empirical research utilizes data from 30 OECD countries for the period from 1970 to 2019. Specifically, these countries are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the USA. The estimations are divided into three main sectors that are utilizing different portions of the whole dataset. Moreover, for the purpose of the third sector of the estimations, one extra variable is added (INNOVINDEX). The variables are presented in Table 1 below.

Table 1: Variables' names and sources

Variable Name / Label:	Source:
GDP per capita / GDPCAP	https://stats.oecd.org
GDP per hour worked / GDPHW	https://stats.oecd.org
GDP per employed person / GDPEP	https://stats.oecd.org
Investment Ratio (%) / INV	https://datacatalog.worldbank.org
Average years of education / EDU	http://www.barrolee.com
Business sector R&D expenditures (BERD) % GDP / BERDXGDP	https://stats.oecd.org
Share of BERD in the high-tech sector in total manufacturing BERD (%) / BERDHT	https://stats.oecd.org
Innovindex / INNOV	https://datacatalog.worldbank.org and https://www.scimagojr.com

Firstly, there is worth noting general information about the variables used in the estimations. The first three variables in the table above constitute the three alternative dependent variables and they are taken directly from the OECD Economic Outlook database, expressed in US dollars in constant prices (2015 purchasing power parities). The investment ratio (independent variable) is calculated as the division between gross fixed capital formation and GDP expressed in US dollars in constant prices (2015 purchasing power parities). The data for the calculation of the investment ratio is taken from the World Bank's World Development Indicators database. Average years of education in the working-age population (from 25 to 64 years of age) have been collected from Barro and Lee's (2018) educational attainment dataset. The last variable functions as a human capital proxy for our model. The sixth variable of Table 1 is another independent one and equals the percentage of business enterprise R&D expenditures to GDP. The variable is directly collected from the OECD Economic Outlook database and no manual calculations are done.

The last two variables of Table 1 need a more detailed explanation of their respective way of construction.

Innovindex:

This alternative measure of innovation is added in our model in the third part of the estimations. It is calculated for the period from 1995 to 2019. As Lebel (2008) points out, R&D expenditures are an often useful measure of innovation but sometimes the data are infrequent and sparse. With the addition of this variable we do not only examine the utility of this measure but the robustness of our results as well. The calculation of this index is defined as

$$INNOVINDEX = \frac{per\ capita\ scientific\ citations + per\ capita\ net\ royalty\ ratio}{2} \qquad (1)$$

, where $per\ capita\ net\ royalty\ ratio = \frac{per\ capita\ royalty\ fees}{per\ capita\ royalty\ fee\ payments}$. (2)

The variable of per capita scientific citations constitutes the accumulation of articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. In the attempt to expand this dataset as far as possible we use data from two different sources. So, the first portion of our data from 2000 to 2019 (maximum availability) is taken from the World Development Indicators database. The second portion from 1995 to 1999 is collected from Scimago Institutional Rankings according to the number of publications omitting the field of Arts and Humanities. Now, for the calculation of the per capita net royalty ratio we use receipts (revenue) and payments (expenses) for the use of intellectual property collected directly from the World Development Indicators database. We then divide each of these variables with the respective population of each country and the calculation of the index is completed as shown in equations (1) and (2).

Share of BERD in the high-tech sector in total manufacturing BERD (%):
The data for the calculation of this variable is collected from three separate databases of OECD's official website. These are namely ANBERD ISIC rev. 2, rev. 3 and rev. 4. Each version differentiates the categories that constitute the R&D expenditure of the high-tech sector. The taxonomy of each version is presented in Table 2 below.

Table 2: ANBERD databases and their respective taxonomy

Database	Category (name / code)
Isic rev. 2	Aerospace / 3845 Computers, office machinery / 3825 Electronics and communications / 3832 Pharmaceuticals / 3522
Isic rev. 3	Aircraft and spacecraft / C353 Pharmaceuticals / C2423 Office, accounting and computing machinery / C30 Radio, TV and communication equipment / C32 Medical, precision and optical instruments / C33
Isic rev. 4	Air and spacecraft and related machinery / 303 Pharmaceuticals / 21 Computer, electronic and optical products / 26 Scientific R&D / 72 Software publishing / 582

For the construction of this variable, we utilize the data available from all three databases. In the case in some years the values of two or more surveys coincide, we utilize the value of the most recent one. For example, if the high-tech R&D expenditures of Austria for the year 1995 are available to every database, we utilize the value collected from ISIC rev. 4.

Following the methodology of Falk (2007) all the variables are then transformed into five-year and ten-year averages as presented here:

- Five-year periods: 1970-1974, 1975-1979, 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009 and 2010-2019.
- Ten-year periods: 1970-1979, 1980-1989, 1990-1999, 2000-2009, 2010-2019.

This data transformation minimizes the number of missing values in our dataset. Last but not least, the variables are subjected to the last transformation, that is their natural logarithms in order to minimize the range and improve linearity between our dependent and independent ones. It is also worth noting that the transformation to 10-year averages allows us to produce long-term coefficients.

We now proceed to the explanation of the dataset for each part of the estimations. The summary statistics of all datasets are presented at their original values in order to form a more complete perspective of our data.

3.1 Data from 1970 to 2004 [Falk (2007) estimations]

All the variables used for these estimations are calculated and collected as mentioned above except BERDHT. For the construction of this specific variable, only ISIC rev.2 and rev.3 are utilized replacing the values of rev.2 with those of rev.3. Table 3 below presents the summary statistics of this dataset.

Table 3: Summary statistics (1970-2004 sample), 5 year averages					
	Mean	s.d.	Min	Max	Observations
GDP per capita, working-age population	29590.4	12374.21	3076731	92936.96	N = 155
Share of BERD in the high-tech sector in total manufacturing BERD (%)	.3673605	.1533581	0	.6872937	N = 147
Business sector R&D expenditures (BERD) % GDP	.0091907	.0063065	.0003317	.027114	N = 131
Average years of education	9.361238	2.267727	2.2325	13.33	N = 210
Investment Ratio (%)	.2175467	.0445072	.1377953	.3931467	N = 171
GDP per hour worked	37.61555	15.14231	3.3783	92.29012	N = 182
GDP per employed person	65032.38	21717.15	9819.349	146288.5	N = 187

Comparing this table with Table 2 of Falk (2007) we can locate certain differences that can be explained by the fact that different editions of each database are utilized. Specifically, our data are modified with 2015 purchasing power parities whereas Falk (2007) utilizes data modified with 1995 purchasing power parities.

3.2 Data from 1970 to 2019 (expansion of the initial estimations)

Similarly to the previous part, BERDHT is constructed replacing the values of rev.2 or rev.3 with those of rev.4 in order to expand the sample for the interval of 2005 to 2019. Table 4 below presents the summary statistics of this dataset.

Table 4: Summary statistics (1970-2019 sample), 5 year averages					
	Mean	s.d.	Min	Max	Observations
GDP per capita, working-age population	34474.93	15271.27	3076.731	105617.8	N = 243
Share of BERD in the high-tech sector in total manufacturing BERD (%)	.3627063	.1510961	0	.6872937	N = 231
Business sector R&D expenditures (BERD) % GDP	.0104684	.0069567	.0003317	.0338883	N = 221
Average years of education	10.2317	2.438751	2.2325	14.03	N = 300
Investment Ratio (%)	.2188386	.0424629	.1095793	.3931467	N = 261
GDP per hour worked	43.09258	17.70284	3.3783	96.22867	N = 272
GDP per employed person	72689.92	24760.89	9819.349	169747.5	N = 277

The expansion of the dataset from 2005 to 2019 has a clear magnifying effect on all variables.

3.3 Data from 1995 to 2019 (addition of Innovindex)

This dataset utilizes ANBERD ISIC rev.4 for the construction of BERDHT. There is also the addition of the INNOV variable which is calculated as analysed above. Table 5 below presents the summary statistics of this dataset.

Table 5: Summary statistics (1995-2019 sample with the addition of Innovindex), 5 year averages

	Mean	s.d.	Min	Max	Observations
GDP per capita, working-age population	40113.8	15754.79	13563.04	105617.8	N = 144
Share of BERD in the high-tech sector in total manufacturing BERD (%)	.361046	.160572	0	.6872937	N = 141
Business sector R&D expenditures (BERD) % GDP	.0114426	.0072499	.0006691	.0338883	N = 149
Average years of education	11.69933	1.657582	5.37	14.03	N = 150
Investment Ratio (%)	.2206551	.0390348	.1095793	.3778729	N = 149
GDP per hour worked	50.56469	17.69398	16.75409	96.22867	N = 150
GDP per employed person	83754.14	23933.27	34697.79	169747.5	N = 150
Innovindex	.3905062	.3939826	.0000524	1.756683	N = 142

The subtraction of the interval from 1970 to 1994 has an additional magnifying effect on the measures. That is normal as all macroeconomic figures are progressively increasing through time. Especially those which are connected with the wider fields of technology and innovation.

4. METHODOLOGY

A fact worth noting is that there are two main categories of empirical research publications regarding the impact of R&D expenditures. The first one examines the effect of R&D expenditures on total factor productivity whereas the second one on economic growth (GDP) mainly by utilizing the model introduced by Mankiw et al. (1992). The expansion of this model is presented in Nonneman and Vanhoudt (1996) by the addition of the R&D to GDP ratio which is particularized by many posterior papers as the ratio of business sector R&D expenditures to GDP. Falk (2007) follows a similar approach to construct the main model which describes the steady-state level of GDP per capita as:

$$ln(GDPCAP_{it}) = \alpha\, ln(GDPCAP_{it-1}) +$$
$$\beta_1\, ln(INV_{it}) + \beta_2\, ln(EDU_{it}) + \beta_3\, ln(BERDXGDP_{it}) + \beta_4\, ln(BERDHT_{it}) +$$
$$\eta_i + \lambda_t + \varepsilon_{it} \quad (3),$$

where $i \in [1,2,\dots,30]$ represents each country's numerical id and $t \in [1,2,\dots,10]$ represents each period's numerical id depending on which sample is used in every estimation; λ_t is a period-stating dummy variable which controls for business cycle effects; η_i is a country-stating dummy variable; and ε_{it} is the error term. GDPCAP can be replaced by GDPEP or GDPHW as presented in Table 1. BERDHT is the main variable of interest as the purpose of the estimations is to showcase if the structure of R&D expenditures is essential to economic growth. BERDXGDP operates as a control variable for innovation and EDU as an alternative quantification of human capital. The fourth basic independent variable is INV which is a proxy for investment activity. Last but not least, in the third part of the estimations, INNOV is included as an additional innovation proxy. That allows us to examine the robustness of the previous sections as well as the adequacy of INNOV as an alternative measure of innovating activity.

With that being mentioned, equation (3) can be presented as:

$$ln(y_{it}) = \alpha\, ln(y_{it-1}) + \beta\, ln(x_{it}) + \eta_i + \lambda_t + \varepsilon_{it} \quad (4),$$

where y_{it} is the corresponding aforementioned dependent variable and x_{it} includes the totality of the explanatory variables.

The estimations are carried out with Stata/MP 16.0.

4.1 General remarks on the method applied

To estimate the model, a system GMM estimator is utilized as developed by Arellano and Bover (1995). The GMM estimator is widely accepted as a dynamic panel data estimator which controls for the endogeneity of the lagged dependent variable, meaning the correlation between the explanatory variable and the error term. Furthermore, the estimator presents the following advantages:

- It is not affected by the omitted variable bias.
- It controls for measurement errors in the dataset and
- unobserved panel heterogeneity

Another important aspect of the methodology is the GMM specifics which in a nutshell are:

- The number of groups or cross-sections (N) must be greater than the number of time periods (T).
- The instrumental variables (Z) must be exogenous, meaning that E(Z'u)=0.
- The number of instruments (Z) must not be greater than or equal to the number of groups (N).

All the aforementioned specifics hold in the case of the present empirical research.

As Falk (2007) mentions, the implementation of Blundell and Bond (1998) is also taken under consideration. In comparison to first-differenced GMM, system GMM is associated with a higher level of efficiency and consistency as shown by Blundell and Bond (1998). Specifically, system GMM constitutes a viable solution to the problem of weak instruments which appears when the relative variance of (η_i) increases and (a) approaches the value of (1). Moreover, we specifically implement a two-step system GMM whereas in Falk (2007) a one-step system GMM is utilized. According to Hwang and Sun (2015), the two-step GMM estimator has two major advantages over the one-step estimator. Those are a smaller asymptotic variance and asymptotically more powerful statistical tests. This variation of the methodology is expected to derive more credible results.

To continue with the explanation of the estimation process it is essential to emphasize that first-differenced GMM transforms equation (4) by taking first differences. This leads to the eradication of the country-specific effects quantified by (η_i). That is:

$$ln(y_{it}) - ln(y_{it-1}) = \alpha\,(ln(y_{it-1}) - ln(y_{it-2})) + \beta\,(ln(x_{it}) - ln(x_{it-1})) + \lambda_t + (\varepsilon_{it} - \varepsilon_{it-1}) \qquad (5).$$

In order to use equation (5) as a valid vehicle for the estimations, it is necessary to assume that the residuals of equation (4) are serially non-correlated. This assumption allows the use of the two-period lagged variables as instruments in equation (5). In addition, a proper application of first-differenced GMM presupposes a solution to the potential endogeneity problem. To deal with that we assume that the independent variables (x_{it}) are not strictly exogenous but rather predetermined which means that they are correlated with past errors but not with present or future ones. The two necessary assumptions can be depicted as follows:

- $E(y_{it-s}, \Delta\varepsilon_{it})=0$ *t=3,…,T and s≥2*

- $E(\Delta x_{it-s}, \Delta\varepsilon it)=0$ *t=3,…,T and s≥2*

After explaining the first-differenced GMM nuance, we now move on to the presentation of the system GMM approach. System GMM corrects endogeneity by introducing more instruments to dramatically improve efficiency as it transforms the instruments to make them uncorrelated (exogenous) with the fixed effects. That is achieved by building a system of two equations: the original equation and the transformed one. The first one expressed in levels utilizes first differences as instruments whereas the second one expressed in first differences uses instrumental variables at levels. This method also utilizes orthogonal deviations. Instead of subtracting the previous observation from the contemporaneous one, it subtracts the average of all future available observations of a variable. This approach minimizes data loss by allowing the computation for all observations except the last for each variable. This brief explanation of Blundell and Bond (1998) leads as to the apposition of the suggested moment conditions that supplement the previous two:

- $E(\varepsilon_{it}, \Delta y_{it-s})=0$ $t=3,\ldots,T$ and $s\geq 1$
- $E(\varepsilon_{it}, \Delta x_{it-s})=0$ $t=3,\ldots,T$ and $s\geq 1$

Once we have defined the moment conditions, the ideal scenario is to obtain as much information as possible from them. According to Hall (2005), that is possible only when using the optimal weighting matrix that minimizes the asymptotic variance of the GMM estimator. At this stage, we encounter a problem of circularity where we first need to estimate the optimal weighting matrix in order to estimate θ_0 while we already need the parameter vector for the calculation of the matrix. This is where the two-step estimator comes in which is described by the following steps:

- Derivation of a consistent but preliminary estimate of the parameter vector θ_0 by choosing a sub-optimal weighting matrix.
- Estimation of the optimal weighting matrix using the estimate of θ_0.
- Estimation of the consistent and efficient θ_0 utilizing the optimal weighting matrix.

4.2 Model specifications

Based on the two-step estimator described above we now move on to the apposition of the different versions of the model which are used for the examination of the results' robustness. As mentioned in Section 3, there are three different dependent variables utilized for the estimations. Following the methodology of Falk (2007), we also apply three different specifications of the original regression equation (4) as presented here:

i. $ln(GDP \ldots_{it}) = \alpha\, ln(GDP \ldots_{it-1}) + \beta_1\, ln(INV_{it}) + \beta_2\, ln(BERDHT_{it}) + \lambda_t + \varepsilon_{it}$

ii. $ln(GDP \ldots_{it}) = \alpha\, ln(GDP \ldots_{it-1}) +$
$\beta_1\, ln(INV_{it}) + \beta_2\, ln(EDU_{it}) + \beta_3\, ln(BERDXGDP_{it}) + \lambda_t + \varepsilon_{it}$

iii. $ln(GDP \ldots_{it}) = \alpha\, ln(GDP \ldots_{it-1}) +$
$\beta_1\, ln(INV_{it}) + \beta_2\, ln(EDU_{it}) + \beta_3\, ln(BERDXGDP_{it}) + \beta_4\, ln(BERDHT_{it}) +$
$\lambda_t + \varepsilon_{it}$

Each of these specifications is executed separately with each one of the three dependent variables (GDPCAP, GDPEP, GDPHW). That means that we have nine regression equations for each part of the estimations that varies depending on the sample that we use applying the two-step system GMM for the five-year averages and a fixed-effects model for the ten-year averages. The three parts of the estimation process are:

- Part 1: Data from 1970 to 2004 [Falk (2007) estimations]. This part examines the validity of the results presented in Falk (2007).

- Part 2: Data from 1970 to 2019 (expansion of the initial estimations). This part looks into the theoretical proposition that these results hold and have even been enlarged with the expansion of the sample as the composition of the R&D expenditures has shifted more towards the high-tech sector from 2005 to 2019.

- Part 3: Data from 1995 to 2019 (addition of Innovindex). Here INNOV is added in each one of the three model specifications without replacing a pre-existing variable. The purpose is to examine if it is statistically significant in any of these specifications and if its addition affects the coefficients of the other explanatory variables.

Another aspect to be mentioned is that outliers are removed following Falk (2007) where the data points with standardized residuals outside the range from (-2) to (2) are excluded from the dataset.

According to Arellano and Bond (1991), the GMM estimator produces short-run coefficients. Thus, it is necessary to calculate long-run coefficients only for the statistically significant explanatory variables in order to examine the long-term effects on economic growth.

4.3 Diagnostic tests and credibility pointers

The main basis for examining the accuracy and reliability of our results except from Falk (2007) is the propositions of Roodman (2009). First and foremost we give weight to the number of instruments as their excessive proliferation can weaken the Hansen test's ability to detect their invalidity. An extreme number of instruments can be identified when a perfect Hansen statistic of (1) is reported.

Moreover, the robustness of the model is enhanced by minimizing the number of lagged variables and by collapsing the instruments. As mentioned by Roodman (2009), in the case of a two-step system GMM regarding the Hansen test, we look for a p-value greater than 0.1 and lower than 0.25. The specification choices concerning the *xtabond2* command in Stata are nodiffsargan, robust errors, orthogonal deviations, twostep, small.

The examination for serial correlation is implemented by Arellano and Bond tests for AR(1) and AR(2). We also apply the Wald statistic in specifications (ii) and (iii) in order to examine the joint significance of the explanatory variables: EDU, BERDXGDP, BERDHT, and INNOV (only for part 3 of the estimations).

The tests are implemented as presented below:

Table 6: Wald-test versions

Model Specifications:	Variables:
(ii)	EDU, BERDXGDP and INNOV (added in part 3)
(iii)	BERDHT, EDU, BERDXGDP and INNOV (added in part 3)
	BERDHT, BERDXGDP and INNOV (added in part 3)

5. EMPIRICAL RESULTS

This section provides the detailed presentation of our results following an analogical structure to that of Section 3. The results of the two first datasets are divided into two subsections which concern the 5-year and 10-year averages respectively. The last part of the estimations utilizes only 5-year averages of the dataset as it is dedicated to the addition of Innovindex. It is essential to mention that the tables which concern the robustness to the use of the alternative dependent variables (ln GDPHW, ln GDPEP) are presented in the Appendix.

For the evaluation of our results, we follow the methodology presented in Section 4.

5.1 Data from 1970 to 2004 [Falk (2007) estimations]

This part of the presentation is dedicated to the re-evaluation of the results presented in Falk (2007).

5.1.1 Data averaged over 5-year periods

Table 7 below presents the results of the two-step system GMM estimator utilizing five-year averaged data from 1970 to 2004. The Table includes the results for the three different specifications of the growth equation.

Table 7: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2004, dependent variable: ln GDP per capita in PPP)

Specification		(i)			(ii)			(iii)	
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per capita, working-age population (GDPCAP)	0,895	15,04	b	0,868	17,81	b	0,930	14,49	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,054	2,08	b				0,053	3,22	b
ln Business sector R&D expenditures (BERD) % GDP				0,006	0,29		-0,020	-1,05	
ln Average years of education (EDU)				0,110	2,13	b	0,086	1,60	
ln Investment Ratio (%) (INV)	0,204	3,10	b	0,172	1,36		0,165	2,16	b
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	-0,036	-2,16	b	-0,024	-0,86		-0,008	-0,39	
Period dummy 1985-1989	-0,004	-0,23		0,006	0,25		0,019	0,93	
Period dummy 1990-1994	-0,023	-1,59		-0,006	-0,31		-0,012	-0,54	
Period dummy 1995-1999	0,002	0,18		-0,006	-0,73		0,007	0,65	
Period dummy 2000-2004	omitted			omitted			omitted		
Constant	1,576	2,36	b	1,515	3,07	b	0,842	1,41	
Hansen test of overidentifying restrictions (p-value)		0,220			0,114			0,175	
AB test for AR(1) (p-value)		0,008			0,074			0,026	
AB test for AR(2) (p-value)		0,446			0,945			0,696	
No. of observations		77			77			77	
Wald-test: EDU = BERDXGDP = 0					F(2, 25) = 3,74 Prob > F = 0,0379				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 25) = 5,32 Prob > F = 0,0056	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 25) = 7,53 Prob > F = 0,0028	
Lags in the first-differenced equation		t-0/t-2			t-1/t-2			t-1/t-1	
Lags in the level equation		t-1/t-1			t-0/t-1			t-1/t-1	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, and 2000–2004. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: lagged ln GDPCAP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU.

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

First and foremost, it is essential to examine the validity of our instruments. The Hansen test is within the interval of 0.100 and 0.250 regarding all three of the specifications. Thus the instruments used are valid. The second step is the check of second-order autocorrelation. At all three specifications, we fail to reject the null hypothesis of no second-order autocorrelation of the AR(2) test at the 10% significance level. So there is no second-order autocorrelation and the results are valid. Moreover, the number of instruments of each specification is 14, 15, and 12 respectively in comparison to the 28 groups, so the model is correctly specified. Last but not least, the lagged value of the dependent variable is statistically significant at the 5% level at all three specifications taking values of 0.895, 0.868, and 0.930 respectively.

Regarding the results of specification (i) we observe that a percentage change in the share of high-tech BERD is associated with a 0.054% increase in GDP per capita in the short-run, on average ceteris paribus. The result agrees with Falk (2007). As long as specification (ii) is concerned, we find out that the average years of education have a positive effect of 0.110% on economic growth at the 5% significance level which indicates the positive contribution of a high-quality human capital. The last specification shows that the significance of the composition of BERD remains as it is associated with a 0.053% increase in economic growth at the 5% level. The proxy for human capital is no longer significant and is replaced by the investment ratio which when increased by one percentage has, ceteris paribus, a 0.165% positive effect on economic growth. To sum up, the results indicate that the share of high-tech BERD and the ratio of gross fixed capital formation to GDP are the main contributors to economic growth in the short run.

Another important aspect of these results is the joint significance of the explanatory variables. The Wald tests show a jointly significant effect of the share of high-tech BERD, the ratio of BERD to GDP, and the average years of education on economic growth. Interestingly, while BERDXGDP is not statistically significant, there is an indication that it contributes to the acceleration of economic growth when considered with the other explanatory variables.

At this point, the long-run coefficients are presented.

Table 8: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2004, dependent variable: ln GDP per capita in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,7557172	0,95	
ln Average years of education (EDU)	1,230	1,40	
ln Investment Ratio (%) (INV)	2,367803	0,83	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.

As it is presented in Table 8, none of the variables is statistically significant in the long run. That is a major difference as compared with the results of Falk (2007). In total, there are no indications of a long-run effect of any explanatory variable on economic growth.

5.1.2 Data averaged over 10-year periods (long-term coefficients)

The purpose of these estimations is to check the robustness of the results. Table 9 presents a statistically significant coefficient regarding only the first specification. Specifically, the share of high-tech BERD has a negative effect of 0.085% on economic growth. That result does not agree with the results of the OLS estimator presented in Table 19 of the Appendix. There the same variable is not statistically significant while there are indications that the ratio of BERD to GDP and the human capital proxy have significant positive effects on economic growth both in the short and the long run. The investment ratio instead seems to affect economic growth negatively.

Table 9: Estimation results for the fixed-effects estimator (10-year averages over 1970-2009)									
Dependent variable	ln GDP per capita, working-age population			ln GDP per hour worked			ln GDP per employed person		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	-0,085	-2,20	b	-0,093	-1,43		-0,054	-0,90	
ln Business sector R&D expenditures (BERD) % GDP	-0,029	-1,14		0,046	1,06		0,053	1,23	
ln Average years of education (EDU)	-0,178	-1,63		0,231	1,30		0,081	0,49	
ln Investment Ratio (%) (INV)	0,003	0,03		-0,194	-1,11		-0,217	-1,38	
Period dummy 1980-1989	-0,453	-14,49	b	-0,028	-0,76		-0,021	-0,62	
Period dummy 1990-1999	-0,226	-11,12	b	omitted			omitted		
Period dummy 2000-2009	omitted			omitted			omitted		
Constant	10,754	34,26	b	-27,008	-3,64	b	-18,886	-3,30	b
R-sq (within)		0,9796			0,9582			0,9509	
No. of observations		48			43			43	

The model uses data averaged over periods 1970–1979, 1980-1989, 1990-1999, 2000-2009.
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

5.1.3 Robustness check (alternative dependent variables)

In this part, we comment on the results of the estimations utilizing the alternative dependent variables. First of all, regarding the validity of these results, we can safely conclude that the tests performed show that the instruments are valid and there are no signs of second-order autocorrelation. Also, the number of instruments at all three specifications is lower than half of the number of groups (countries). Last but not least, the lagged variable is statistically significant in all of the model’s variations contributing 0.800% or more to economic growth with a percentage change of it.

Table 15 presents the results of the two-step estimator with the log of GDPHW as the dependent variable. Again, the composition of business R&D expenditures has, ceteris paribus, a significant and positive effect of 0.042% (specif. i) and 0.032% (specif. ii) on economic growth in the short run. We also find a statistically significant investment ratio coefficient of 0.219 in the first model specification. There is also an indication in specification (ii) that the ratio of BERD positively affects economic growth at the 10% significance level. Additionally, there is a strong joint significance of BERDHT and BERDXGDP regarding the third specification.

As long as GDP per employed person is concerned, those results are presented in Table 17 of the Appendix. The results are similar to those of Table 15 with the main difference being that regarding specification (i), BERDHT and INV are statistically significant at the 10% level.

The fixed-effects estimations presented in Tables 16 and 18 do not indicate a long-term effect on economic growth. That is in line with the previous results but not with Falk (2007).

Overall, there are confirmatory findings of the positive relationship between the composition of business R&D and economic growth in the short run. There are also important indications that both the ratio of gross fixed capital formation to GDP and the average years of education positively affect economic growth. In comparison to Falk (2007), the ratio of business R&D to GDP does not seem statistically significant although it is found jointly significant for the explanation of economic growth's variations.

5.2 Data from 1970 to 2019 (expansion of the initial estimations)

After the partial confirmation of the findings presented in Falk (2007), we now proceed to the apposition of the results utilizing the expanded dataset from 1970 to 2019.

5.2.1 Data averaged over 5-year periods

Similarly to the previous part, Table 10 presents the results of the two-step system GMM estimator for the period 1970-2019 utilizing five-year averaged data for all three specifications of the model.

Table 10: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2019, dependent variable: ln GDP per capita in PPP)

Specification	(i)			(ii)			(iii)		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per capita, working-age population (GDPCAP)	0,849	15,03	b	0,789	9,54	b	0,834	11,63	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,034	2,04	a				0,040	2,49	b
ln Business sector R&D expenditures (BERD) % GDP				0,026	0,87		0,0001	0,00	
ln Average years of education (EDU)				0,125	2,44	b	0,127	3,02	b
ln Investment Ratio (%) (INV)	0,223	3,54	b	0,179	2,47	b	0,245	3,19	b
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	-0,023	-1,01		-0,010	-0,36		-0,002	-0,08	
Period dummy 1985-1989	0,005	0,23		0,018	0,66		0,023	0,87	
Period dummy 1990-1994	-0,025	-1,13		0,008	0,29		0,005	0,16	
Period dummy 1995-1999	-0,004	-0,27		0,002	0,13		0,007	0,42	
Period dummy 2000-2004	0,003	0,23		0,016	1,13		0,008	0,63	
Period dummy 2005-2009	omitted			omitted			omitted		
Period dummy 2010-2014	-0,033	-1,87	a	-0,037	-2,48	b	-0,037	-2,42	b
Period dummy 2015-2019	0,006	0,48		-0,003	-0,30		0,002	0,12	
Constant	2,041	3,35	b	2,378	2,51	b	1,926	2,52	b
Hansen test of overidentifying restrictions (p-value)		0,247			0,188			0,216	
AB test for AR(1) (p-value)		0,061			0,075			0,053	
AB test for AR(2) (p-value)		0,930			0,804			0,977	
No. of observations		152			152			152	
Wald-test: EDU = BERDXGDP = 0					F(2, 28) = 3,02 Prob > F = 0,0649				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 28) = 4,19 Prob > F = 0,0143	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 28) = 3,58 Prob > F = 0,0411	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: lagged ln GDPCAP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-0/t-1	t-1/t-2	t-1/t-3
Lags in the level equation	t-1/t-1	t-1/t-2	t-1/t-1

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Source: OECD, World Bank, own calculations.

Regarding the validity of our results, the Hansen test is within the interval of 0.100 and 0.250 at all three of the specifications. The instruments are characterized as valid as their number ranges between 15 and 19 which is acceptable considering the 29 groups. There is also no sign of second-order autocorrelation as we fail to reject the null hypothesis of the AR(2) test at the 10% significance level at all three specifications. Thus the model is characterized again as correctly specified. Another fact worth to be mentioned is that the lagged value of the dependent variable is statistically significant at the 5% level taking values above 0.750 at all three specifications.

Specification (i) provides us with evidence of a positive and statistically significant effect of BERDHT on economic growth at the 10% significance level. Furthermore, the percentage of investment to GDP remains important as it positively affects economic growth at the 5% significance level with a coefficient of 0.223. Specification (ii) has also similar results with the previous part. It enhances the indications that education and investment as a percentage of GDP are significant macroeconomic factors of growth. The third specification provides us with further evidence of a positive effect on economic growth which is caused by the coefficients of BERDHT, EDU, and INV. Specifically, those coefficients are 0.039, 0.126, and 0.245 respectively at the 5% level of significance.

As a confirmation of the results of part 5.1, BERDXGDP does not seem to affect economic growth in the short run. However, the Wald test shows again a joint significance of BERDHT, BERDXGDP, and EDU.

Table 11 below presents the long-run coefficients estimated by the fixed-effects model. Again, no statistically significant results are reported.

Table 11: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2019, dependent variable: ln GDP per capita in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,756	0,95	
ln Average years of education (EDU)	1,230	1,4	
ln Investment Ratio (%) (INV)	2,368	0,83	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

5.2.2 Data averaged over 10-year periods (long-term coefficients)

In contrast with the results of 5.2.1 subpart, these presented in Table 12 are in a sense supportive of the contribution of BERDXGDP to economic growth.

Table 12: Estimation results for the fixed-effects estimator (10-year averages over 1970-2019)

Dependent variable	ln GDP per capita, working-age population			ln GDP per hour worked			ln GDP per employed person		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,034	0,86		0,020	0,68		0,044	1,45	
ln Business sector R&D expenditures (BERD) % GDP	0,086	1,84	a	0,091	2,22	b	0,053	1,51	
ln Average years of education (EDU)	-0,074	-0,49		-0,037	-0,26		-0,090	-0,75	
ln Investment Ratio (%) (INV)	0,182	1,70	a	-0,221	-1,96	a	0,022	0,26	
Period dummy 1980-1989	-0,470	-8,02	b	-0,480	-8,53	b	-0,411	-8,57	b
Period dummy 1990-1999	-0,296	-6,60	b	-0,281	-6,81	b	-0,240	-6,89	b
Period dummy 2000-2009	-0,104	-3,26	b	-0,093	-3,25	b	-0,095	-3,69	b
Period dummy 2010-2019	omitted			omitted			omitted		
Constant	11,508	22,79	b	4,185	9,16	b	11,947	30,02	b
R-sq (within)		0,869			0,880			0,861	
No. of observations		77			86			87	

The model uses data averaged over periods 1970–1979, 1980-1989, 1990-1999, 2000-2009, 2010-2019.
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

The equations regarding the dependent variables of GDP per capita and per hour worked produced statistically significant results that indicate that the ratio of business R&D expenditures to GDP positively affects economic growth. The coefficients are respectively 0.086 and 0.091 at the 10% and 5% significance levels. In addition, the positive and significant at the 10% level coefficients of INV enhance the idea that the ratio of investment to GDP is an undeniable factor of economic growth. The results presented here are in line with those presented in Table 24 of the Appendix. The OLS estimator further enhances the importance of BERDXGDP and INV to economic growth. Strangely enough, EDU is not found statistically significant except for the results regarding the GDPCAP variable of the OLS estimator.

5.2.3 Comparison between 1970-2004 and 1970-2019 results

This subsection provides us with a comparison of the results regarding the 1970-2004 and the 1070-2019 sample.

As far as the 5-year averages are concerned, the results are presented in Table 7 (1970-2004 sample) and Table 10 (1970-2019 sample). The coefficients that are found to be statistically significant in both tables are the lagged value of ln GDPCAP, ln BERDHT, ln EDU, and ln INV. Regarding specification (i), the coefficient of BERDHT is 0.054 from 1970 to 2004 and 0.034 from 1970 to 2019 (significant at the 10% level). On the contrary, the investment ratio's coefficient is increased in the 1970-2019 sample from 0.204 to 0.223. Comparing the results of specification (ii), we observe that only EDU is statistically significant in both samples with an increased coefficient from 0.110 to 0.125. The investment ratio positively affects economic growth only in the second sample with a coefficient of 0.179. The estimates of specification (iii) follow a suchlike pattern. BERDHT decreases from 0.053 to 0.040 whereas INV presents an increase from 0.165 to 0.245. EDU cannot be compared since its statistical significance is accepted only for the second sample. Generally, a common pattern is observed where the coefficients of BERDHT decrease and the other variables' decrease with the sample's expansion.

The long-run estimations utilizing 10-year averages produce different results and fluctuations. From those estimations, only those with GDPCAP as a dependent variable can be compared as the results of Table 9 with the two alternative dependent variables are not statistically significant. Moving on to the comparison, we observe that BERDHT presents a negative coefficient of 0.085 concerning the subsample of 1970-2004 whereas it does not affect economic growth when the sample is expanded. The exact opposite holds for BERDXGDP which positively affects GDPCAP from 1970 to 2019 with a coefficient of 0.086. Also, the investment ratio presents a statistical significance at the 10% level only for the second sample with a coefficient of 0.182.

5.2.4 Robustness check (alternative dependent variables)

This part presents the results of the expanded dataset of five-year averages with GDP per hour worked and per employed person as dependent variables. The Hansen statistic remains within the acceptable boundaries. There is also a slight increase in the number of instruments on average. Furthermore, the estimator that utilizes GDP per hour worked as a dependent variable suffers from second-order autocorrelation which makes its results invalid. On the other hand, the estimator of the GDP per employed person as a dependent variable presents AR(2) tests that fail to reject the null hypothesis.

Table 20 presents the results of the two-step estimator with the log of GDPHW as the dependent variable. Although there are indications that BERDHT is statistically significant the results cannot be taken into consideration as the model suffers from serial correlation.

As long as Table 22 is concerned, the results presented are enhancing the previous findings. BERDHT is found statistically significant at the 10% level with a coefficient of 0.020 regarding specification (i) and 0.021 regarding specification (iii). Specification (ii) provides us with an indication of a positive and significant coefficient of BERDXGDP with a value of 0.022. Last but not least, similarly to the estimations of part 5.2.1, there is a joint significance of BERDHT, BERDXGDP, and EDU which further supports the idea that the ratio of BERD to GDP is indirectly essential to the explanation of economic growth.

The fixed-effects estimations presented in Table 21 present a statistically significant coefficient at the 10% level. It concerns the BERDHT variable and constitutes an indication of a long-term positive effect on economic growth. In contrast with that, Table 23 provides us with no further indications.

Once more, the results indicate that the composition of R&D expenditures is an important factor of economic growth's enhancement. Moreover, we find more evidence about the importance of human capital and investments for amplifying economic growth as well as the indirect effect of the percentage of business R&D expenditures on GDP.

5.3 Data from 1995 to 2019 (addition of Innovindex)

In this subsection, we present the results of the estimations regarding the period 1995-2019 with the addition of Innovindex. The targeting of the estimations is double. Firstly, we examine if the previous results are significantly affected. Secondly, we aim to investigate if the index introduced by LeBel, P. (2008) constitutes an effective measure of innovation.

5.3.1 Main results

The results of these estimations are presented in Table 13 below regarding GDP per capita as the proxy for economic growth.

Table 13: Estimation results for the two-step system GMM estimator (5-year averages over 1995-2019, dependent variable: ln GDP per capita in PPP)

Specification	(i)			(ii)			(iii)		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per capita, working-age population (GDPCAP)	0,812	7,93	b	0,834	10,12	b	0,852	8,43	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,031	2,60	b				0,029	2,65	b
ln Business sector R&D expenditures (BERD) % GDP				0,016	0,80		-0,007	-0,24	
ln Average years of education (EDU)				0,129	2,14	b	0,159	2,45	b
ln Investment Ratio (%) (INV)	0,266	2,82	b	0,150	2,09	b	0,277	2,58	b
ln Innovindex (INNOV)	0,018	1,00		0,005	0,90		0,006	0,89	
Period dummy 2000-2004	0,049	1,92	a	0,074	3,36	b	0,065	3,41	b
Period dummy 2005-2009	0,040	2,76	b	0,059	5,03	b	0,047	3,76	b
Period dummy 2010-2014	omitted			omitted			omitted		
Period dummy 2015-2019	0,045	4,49	b	0,046	4,60	b	0,044	4,28	b
Constant	2,474	2,07	b	1,756	2,07	b	1,619	1,64	
Hansen test of overidentifying restrictions (p-value)		0,196			0,192			0,172	
AB test for AR(1) (p-value)		0,208			0,128			0,272	
AB test for AR(2) (p-value)		0,639			0,827			0,671	
No. of observations		95			95			95	
Wald-test: EDU = BERDXGDP = INNOV=0					F(3, 28) = 2,16 Prob > F = 0,1156				
Wald-test: BERDHT = EDU = BERDXGDP =INNOV= 0								F(4, 28) = 5,35 Prob > F = 0,0025	
Wald-test: BERDHT == BERDXGDP =INNOV= 0								F(3, 28) = 2,70 Prob > F = 0,0646	
t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.									
The model uses data averaged over periods 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: lagged ln GDPCAP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU, lnINNOV.									
Lags in the first-differenced equation		t-1/t-1			t-0/t-1			t-1/t-1	
Lags in the level equation		t-1/t-1			t-0/t-0			t-0/t-0	

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Similarly to the previous parts we first examine the validity of our instruments. The Hansen test of 0.196 for specification (i) is indeed within the acceptable boundaries of 0.100 and 0.250. The same holds for the other specifications as well. In addition, the number of instruments for each specification is beneath half of the 29 groups (10, 13, and 12 respectively). Consequently, the instruments are considered valid. As far as the lagged value of the dependent variable is concerned, it is significant at the 5% level of significance. Taking all the aforementioned into consideration we conclude that the model is well specified.

Proceeding to the analysis of the results regarding specification (i), it is observed that a percentage change in the share of high-tech BERD is associated with a 0.031% increase in GDP per capita in the short-run, on average ceteris paribus. Specification (i) also provides us with further indications that the ratio of gross fixed capital formation to GDP has a positive effect on economic growth at the 5% significance level. That is supported by the results of specification (ii) as well. Moreover, the human capital proxy presents a positive coefficient of 0,129 which enhances the results of parts 5.1 and 5.2. Then, specification (iii) functions as a confirmation of the previous results as BERDHT, EDU and INV remain statistically significant at the 5% level.

As far as Innovindex is concerned, there are no statistically significant findings that could support its introduction as a representative measure of innovation as proposed by LeBel, P. (2008). Furthermore, the significance of the other explanatory variables is not affected to a minimum. This fact indicates that the share of high-tech business R&D in total manufacturing R&D expenditures constitutes a much more effective proxy for innovation. In addition, the inclusion of Innovindex leads to results that are quantitatively similar to those of the initial growth equation. This fact enhances the robustness of the findings presented in subsection 5.2. However, the joint significance of BERDHT, BERDXGDP, INNOV, and EDU is found statistically significant at the 5% level which could be a prompt for further investigation of this aspect.

Moving on, we present the long-run coefficients for this period. As apposed in Table 14, only the human capital proxy is found significant at the 5% significance level. Intuitively, a percentage change in the log of EDU increases the rate of economic growth by 1,078%. That is important considering that the addition of INNOV has indeed changed the results of the fixed-effects estimator.

Table 14: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1995-2019, dependent variable: ln GDP per capita in PPP)			
	Coeff.	z	Signif.
ln Average years of education (EDU)	1,078	2,11	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,196	1,29	
ln Investment Ratio (%) (INV)	1,875	1,05	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

5.3.2 Robustness check (alternative dependent variables)

Commenting on the results of the estimations utilizing the alternative dependent variables, it is essential to examine the validity of our estimations. The Hansen test of over-identifying restrictions is indeed between the boundaries of the appropriate range of 0.100 - 0.250. Furthermore, the model does not suffer from second-order serial correlation in any of the three specifications as presented in Tables 25 and 27. Also, the lagged values of GDP per hour worked and per employed person are statistically significant at the 5% level regarding all three specifications. These facts point out that the growth equation is once again well specified.

The results of the two-step estimator regarding the GDP per hour worked as a dependent variable are presented in Table 25 of the Appendix. BERDHT is found significant again at the 5% level of significance at the first specification. Moving on, specification (ii) provides additional proof that the ratio of BERD to GDP has indeed a positive and significant effect on economic growth. Specification (iii) erases that aspect and suggests that the share of high-tech business R&D overlays the effect of BERDXGDP. Moreover, a percentage change of the average years of education positively affects the rate of economic growth by 0.158%. Confirming the initial results of 5.3.1 subsection, Innovindex is not found statistically significant.

The results with GDP per employed person as the dependent variable are presented in Table 27 of the Appendix. The results further enhance the findings of Table 25 as analysed above. It has to be pointed out that a percentage change in BERDHT positively affects economic growth by 0.020% and 0.023% in specifications (i) and (iii) respectively. Though, it is important to note that BERDXGDP is not found significant in any of the specifications. The impact of this variable in specification (ii) is replaced to some extent by the effect of the human capital proxy. Last but not least, we do not find any indications of an Innovindex effect.

Proceeding to the long-run coefficient estimations, those are presented in Tables 26 and 28. Regarding Table 26, there are no significant results to be analysed. On the contrary, Table 28 provides us with significant results regarding the BERDHT and EDU explanatory variables. Specifically, BERDHT is found to have a long-run positive effect of 0.166 on economic growth (at 5% significance level). At the same time, the human capital proxy positively affects economic growth by 0.756 in the long term (at 10% significance level).

Summarily, the present subsection's set of results translates to strong indications that the addition of the extra measure of innovation does not cause fluctuations of the other coefficients. Thus, the results of subsection 5.2 can be characterized as robust. As a consequence of this, it is legitimate to claim that Innovindex does not respond as well as BERDHT when utilized as a proxy for innovation. There are also confirmatory results about the positive effects of BERDHT, EDU, and INV on economic growth regardless of the proxy used for it, which agree with subsections 5.1 and 5.2.

6. CONCLUSION

The current thesis constitutes an attempt to explore the importance of R&D activity's composition in relation to the acceleration of economic growth. According to the literature presented, it is generally expected that a relationship should exist between R&D expenditures and the growth of GDP. Falk (2007) introduces the concept that research and development targeted in the field of high technology has an additional effect on economic growth. This proposition is supported by the findings of the empirical analysis which is a cornerstone of all subsequent empirical studies regarding the R&D expenditures composition. Those researches are also in line with the rapid development of the high technology sector from 2000 onwards and the overall shifting from low to high-tech areas. The present dissertation is therefore intended to be included in this branch of research examining the robustness of the estimations presented in Falk (2007). The contribution consists in extending the research period by 15 years (2005-2019). Finally, the influence of Innovindex, an alternative indicator of innovation introduced by LeBel (2008), is examined in order to determine if it is a better measure of innovating activity than the private R&D spending in the high technology sector.

The two-step system GMM estimator allows a more reliable investigation of such influences between the variables as it minimizes endogeneity problems. It also produces a smaller asymptotic variance and diagnostic tests of more power and credibility. As Falk (2007) suggests, we also utilize three different specifications of the growth equation to examine the impact of each explanatory variable. Moreover, the use of three separate proxies of economic growth further enhances the robustness of our results.

Overall, there are findings that corroborate with those of Falk (2007) but there are also some contradictions that should be mentioned. In general, it is found that the share of high-tech R&D spending has indeed a positive effect on economic growth regardless of the dependent variable or the specifications of the model. These indications also hold when the dataset is expanded from 2005 to 2019. The main contradiction of the current thesis' results is that there is a significant short-run effect of BERDHT but only BERDXGDP, INV, and EDU seem to have a remarkable long-term effect on economic growth. In addition, the control variable of the ratio of business R&D expenditures to GDP does not show particular effects on the magnification of the economy in the short run. Last but not least, the addition of Innovindex does not undermine the effectiveness of the share of business R&D in the high-tech sector. This implies that the latter is indeed an appropriate measure of innovation and it should be included in similar empirical research.

More specifically, the results of subsection 5.1 reinforce the findings of Falk (2007) regarding the short-run. Our findings support a strong positive effect of the high-tech-oriented R&D spending on economic growth in a short-term horizon whereas the control variables of BERDXGDP, EDU, and INV seem to have long-term effects on the magnification of the economy.

The second part of this empirical research further enhances those results. Firstly, both the share of BERD and the investment ratio positively and significantly affect economic growth. There are also indications that the human capital proxy has also a positive effect in the short run. Regarding the long-term horizon, only the ratio of business R&D and the investment ratio present positive effects on the economic growth proxies.

Moving on to the last part of estimations, Innovindex is not found to be an appropriate measure of innovation regarding the 30 OECD countries under examination. The share of business R&D in the high-tech sector remains the most important driving force of growth in the short run and the overall results are found to be similar to those of the initial estimations. To wit, the results of subsection 5.2 are indeed robust to the inclusion of Innovindex. The long-run estimations indicate a positive effect of human capital on GDP per capita. There is also a slight effect of BERDHT on growth in the long term which indicates that this matter needs further investigation.

In summary, the results indicate that the composition of R&D expenditures is an important factor of economic growth's enhancement. Moreover, we find more evidence about the importance of human capital and investments for amplifying economic growth as well as the indirect effect of the percentage of business R&D expenditures on GDP. Generally, the share of high-tech-oriented R&D expenditures seems to have a significant positive effect on growth regarding only the short-term horizon. This effect is replaced by that of the variable BERDXGDP in the long run. The proxies for the volume of investment and human capital have a positive effect both in the short and long-term with the latter being more consistent concerning the long-term horizon.

An intuitive recapitulation of the above could be that the composition of R&D spending in OECD countries constitutes a starting factor of economic growth when it is high-tech-oriented. However, its positive impact is not found to be intertemporal as the long-run coefficients of BERDHT do not present statistical significance. As far as long-term economic growth is concerned, it is enhanced by well-known factors such as the population's educational level, the general investment to GDP ratio, and the magnitude of business R&D activities as a whole. Overall, it seems that the global shifting of R&D spending from the low-tech areas to the high-tech ones provides a positive short-term shock that does not hold in the long term. To conclude, the economies of OECD benefit intertemporally by the level of business-oriented R&D spending in relation to GDP and not by its composition. With that being mentioned, it is essential to point out that our results indicate the necessity of further investigation in order to enhance or to overlay the conclusions of the present empirical research.

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7. APPENDIX

Table 15: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2004, dependent variable: ln GDP per hour worked in PPP)

Specification	(i)			(ii)			(iii)		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per hour worked (GDPHW)	0,926	27,33	b	0,848	16,46	b	0,906	10,83	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,042	3,34	b				0,032	2,17	b
ln Business sector R&D expenditures (BERD) % GDP				0,035	1,83	a	0,012	0,45	
ln Average years of education (EDU)				-0,028	-0,58		-0,003	-0,06	
ln Investment Ratio (%) (INV)	0,219	2,97	b	0,032	0,31		0,095	0,70	
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	0,019	0,98		-0,020	-0,66		0,005	0,13	
Period dummy 1985-1989	0,011	0,55		-0,020	-0,73		-0,006	-0,26	
Period dummy 1990-1994	0,021	1,27		-0,002	-0,08		0,007	0,27	
Period dummy 1995-1999	0,009	0,68		-0,005	-0,35		0,002	0,13	
Period dummy 2000-2004	omitted			omitted			omitted		
Constant	0,751	8,48	b	0,948	3,76	b	0,691	2,05	b
Hansen test of overidentifying restrictions (p-value)		0,144			0,220			0,139	
AB test for AR(1) (p-value)		0,160			0,281			0,196	
AB test for AR(2) (p-value)		0,526			0,261			0,324	
No. of observations		96			96			96	
Wald-test: EDU = BERDXGDP = 0					F(2, 28) = 2,24 Prob > F = 0,1257				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 28) = 2,41 Prob > F = 0,0877	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 28) = 3,58 Prob > F = 0,0414	
Lags in the first-differenced equation		t-1/t-2			t-1/t-2			t-1/t-1	
Lags in the level equation		t-0/t-1			t-0/t-1			t-1/t-2	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, and 2000–2004. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPHW, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU.

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Table 16: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2004, dependent variable: ln GDP per hour worked in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,338	0,93	
ln Business sector R&D expenditures (BERD) % GDP	0,126	0,70	
ln Investment Ratio (%) (INV)	1,004	0,45	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Table 17: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2004, dependent variable: ln GDP per employed person in PPP)

Specification		(i)			(ii)			(iii)	
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per employed person (GDPEP)	0,959	14,20	b	0,809	15,42	b	0,908	12,54	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,032	2	a				0,034	2,27	b
ln Business sector R&D expenditures (BERD) % GDP				0,037	2,16	b	0,009	0,46	
ln Average years of education (EDU)				-0,041	-1,10		-0,008	-0,21	
ln Investment Ratio (%) (INV)	0,133	1,88	a	-0,016	-0,28		0,078	0,83	
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	-0,010	-0,60		-0,047	-2,44	b	-0,023	-1,01	
Period dummy 1985-1989	-0,008	-0,54		-0,029	-2,08	b	-0,018	-0,95	
Period dummy 1990-1994	-0,004	-0,29		-0,015	-1,06		-0,010	-0,57	
Period dummy 1995-1999	omitted			omitted			omitted		
Period dummy 2000-2004	-0,012	-1,30		0,007	0,59		-0,007	-0,63	
Constant	0,796	1,10		2,469	3,86	b	1,339	1,70	a
Hansen test of overidentifying restrictions (p-value)		0,105			0,113			0,139	
AB test for AR(1) (p-value)		0,087			0,020			0,079	
AB test for AR(2) (p-value)		0,943			0,871			0,963	
No. of observations (no. of countries)		100			100			100	
Wald-test: EDU = BERDXGDP = 0					F(2, 28) = 2,37 Prob > F = 0,1117				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 28) = 3,78 Prob > F = 0,0215	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 28) = 4,21 Prob > F = 0,0252	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, and 2000–2004. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPEP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-1/t-2	t-0/t-1	t-1/t-2
Lags in the level equation	t-1/t-1	t-0/t-1	t-1/t-2

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Table 18: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2004, dependent variable: ln GDP per employed person in PPP)			
	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,370	1,05	
ln Business sector R&D expenditures (BERD) % GDP	0,092	0,61	
ln Investment Ratio (%) (INV)	0,841	0,54	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.

Table 19: Estimation results for the OLS estimator (10-year averages over 1970-2009)

Dependent variable	ln GDP per capita, working-age population			ln GDP per hour worked			ln GDP per employed person		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,064	0,76		-0,037	-0,36		0,042	0,50	
ln Business sector R&D expenditures (BERD) % GDP	0,208	3,43	b	0,204	3,14	b	0,111	2,02	b
ln Average years of education (EDU)	0,418	2,07	b	0,111	0,53		0,146	0,81	
ln Investment Ratio (%) (INV)	-0,259	-1,15		-0,976	-3,98	b	-0,431	-2,17	b
Period dummy 1980-1989	-0,116	-1,50		omitted			omitted		
Period dummy 1990-1999	omitted			0,010	0,15		0,008	0,14	
Period dummy 2000-2009	0,061	0,79		omitted			omitted		
Constant	10,080	15,81	b	-24,360	-2,71	b	-11,816	-1,53	
Adjusted R-sq (within)	0,614			0,4607			0,3634		
No. of observations	48			43			43		
Wald-test: BERDHT == BERDXGDP = 0	F(2, 41) = 11,61 Prob > F = 0,0001			F(2, 41) = 12,61 Prob > F = 0,0001			F(2, 41) = 10,29 Prob > F = 0,0002		

The model uses data averaged over periods 1970–1979, 1980-1989, 1990-1999, 2000-2009.
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Table 20: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2019, dependent variable: ln GDP per hour worked in PPP)

Specification		(i)			(ii)			(iii)	
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per hour worked (GDPHW)	0,869	23,76	b	0,813	14,50	b	0,856	16,19	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,041	2,71	b				0,024	2,39	b
ln Business sector R&D expenditures (BERD) % GDP				0,036	1,95	a	0,0191	0,89	
ln Average years of education (EDU)				0,022	0,39		0,027	0,59	
ln Investment Ratio (%) (INV)	0,268	2,73	b	0,065	0,62		0,090	0,67	
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	0,009	0,34		-0,004	-0,11		0,021	0,57	
Period dummy 1985-1989	0,010	0,45		0,001	0,04		0,010	0,37	
Period dummy 1990-1994	0,027	1,12		0,020	0,66		0,033	1,06	
Period dummy 1995-1999	0,013	0,68		0,009	0,48		0,019	0,94	
Period dummy 2000-2004	0,010	0,59		0,016	1,18		0,026	1,53	
Period dummy 2005-2009	0,003	0,20		0,009	0,75		0,018	1,75	
Period dummy 2010-2014	0,006	0,65		omitted			0,009	0,75	
Period dummy 2015-2019	omitted			-0,006	-0,72		omitted		b
Constant	1,025	5,32	b	0,991		b	0,802	3,87	
Hansen test of overidentifying restrictions (p-value)		0,184			0,223			0,118	
AB test for AR(1) (p-value)		0,017			0,008			0,004	
AB test for AR(2) (p-value)		0,010			0,013			0,023	
No. of observations		177			177			177	
Wald-test: EDU = BERDXGDP = 0					F(2, 28) = 3,93 Prob > F = 0,0313				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 28) = 3,79 Prob > F = 0,0212	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 28) = 5,61 Prob > F = 0,0089	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPHW, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-1/t-1	t-0/t-1	t-1/t-1
Lags in the level equation	t-0/t-1	t-0/t-1	t-1/t-2

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Source: OECD, World Bank, own calculations.

Table 21: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2019, dependent variable: ln GDP per hour worked in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,170	1,77	a
ln Business sector R&D expenditures (BERD) % GDP	0,132	1,09	
ln Investment Ratio (%) (INV)	0,625	0,58	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Table 22: Estimation results for the two-step system GMM estimator (5-year averages over 1970-2019, dependent variable: ln GDP per employed person in PPP)

Specification	(i)			(ii)			(iii)		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per employed person (GDPEP)	0,935	16,59	b	0,851	18,13	b	0,898	13,21	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,020	1,84	a				0,021	2,03	a
ln Business sector R&D expenditures (BERD) % GDP				0,022	2,31	b	0,0078	0,50	
ln Average years of education (EDU)				-0,016	-0,44		-0,006	-0,19	
ln Investment Ratio (%) (INV)	0,100	1,30		-0,005	-0,09		0,058	0,67	
Period dummy 1975-1979	omitted			omitted			omitted		
Period dummy 1980-1984	0,028	0,92		-0,039	-2,03	a	-0,021	-0,93	
Period dummy 1985-1989	0,032	1,24		-0,025	-1,74	a	-0,014	-0,93	
Period dummy 1990-1994	0,032	1,31		-0,018	-1,37		-0,011	-0,76	
Period dummy 1995-1999	0,039	2,00	a	omitted			omitted		
Period dummy 2000-2004	0,035	1,97	a	0,000	0,00		-0,002	-0,26	
Period dummy 2005-2009	0,015	1,38		-0,013	-0,91		-0,017	-1,14	
Period dummy 2010-2014	0,002	0,24		-0,030	-2,07	b	-0,030	-1,80	a
Period dummy 2015-2019	omitted			-0,028	-2,04	a	-0,031	-1,77	a
Constant	0,950	1,49		1,888	3,53	b	1,389	1,86	a
Hansen test of overidentifying restrictions (p-value)		0,135			0,164			0,123	
AB test for AR(1) (p-value)		0,016			0,012			0,012	
AB test for AR(2) (p-value)		0,111			0,232			0,197	
No. of observations		178			178			178	
Wald-test: EDU = BERDXGDP = 0					F(2, 28) = 3,27 Prob > F = 0,0529				
Wald-test: BERDHT = EDU = BERDXGDP = 0								F(3, 28) = 1,84 Prob > F = 0,1636	
Wald-test: BERDHT == BERDXGDP = 0								F(2, 28) = 2,41 Prob > F = 0,1084	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPEP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, ln EDU.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-1/t-2	t-0/t-2	t-1/t-2
Lags in the level equation	t-1/t-2	t-1/t-2	t-1/t-2

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Source: OECD, World Bank, own calculations.

Table 23: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1970-2019, dependent variable: ln GDP per employed person in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,203	1,32	
ln Business sector R&D expenditures (BERD) % GDP	0,077	0,64	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Table 24: Estimation results for the OLS estimator (10-year averages over 1970-2019)

Dependent variable	ln GDP per capita, working-age population			ln GDP per hour worked			ln GDP per employed person		
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,006	0,11		0,022	0,47		0,049	1,11	
ln Business sector R&D expenditures (BERD) % GDP	0,233	4,85	b	0,235	6,00	b	0,152	4,48	b
ln Average years of education (EDU)	0,446	2,34	b	-0,008	-0,05		0,031	0,22	
ln Investment Ratio (%) (INV)	-0,352	-2,34	b	-0,901	-5,71	b	-0,408	-3,40	b
Period dummy 1980-1989	-0,078	-0,95		omitted			-0,143	-2,46	b
Period dummy 1990-1999	omitted			0,159	2,17	b	omitted		
Period dummy 2000-2009	0,103	1,38		0,316	3,93	b	0,111	1,94	a
Period dummy 2010-2019	0,101	1,31		0,342	4,13	b	0,126	2,20	b
Constant	9,890	17,38	b	3,346	6,80	b	11,265	28,21	b
Adjusted R-sq (within)	0,594			0,536			0,476		
No. of observations	77			86			87		
Wald-test: BERDHT == BERDXGDP = 0	F(2, 71) = 11,88 Prob > F = 0,0000			F(2, 78) = 15,38 Prob > F = 0,0000			F(2, 78) = 20,30 Prob > F = 0,0000		

The model uses data averaged over periods 1970–1979, 1980-1989, 1990-1999, 2000-2009, 2010-2019.

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.

Source: OECD, World Bank, own calculations.

Table 25: Estimation results for the two-step system GMM estimator (5-year averages over 1995-2019, dependent variable: ln GDP per hour worked in PPP)

Specification		(i)			(ii)			(iii)	
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per hour worked (GDPHW)	0,822	17,11	b	0,808	14,67	b	0,910	9,04	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,026	3,11	b				0,028	3,07	b
ln Business sector R&D expenditures (BERD) % GDP				0,036	2,99	b	0,028	0,06	
ln Average years of education (EDU)				0,088	1,23		0,158	2,89	b
ln Investment Ratio (%) (INV)	0,073	0,83		0,014	0,34		0,022	0,26	
ln Innovindex (INNOV)	0,012	1,06		0,004	0,44		-0,010	- 1,04	
Period dummy 2000-2004	0,016	1,17		0,033	2,06	b	0,046	1,81	a
Period dummy 2005-2009	0,018	1,87	a	0,024	2,14	b	0,028	1,51	
Period dummy 2010-2014	omitted			omitted			omitted		
Period dummy 2015-2019	0,004	0,37		-0,001	-0,07		-0,002	- 0,29	
Constant	0,907	7,07	b	0,770	3,28	b	0,067	0,11	
Hansen test of overidentifying restrictions (p-value)		0,209			0,136			0,202	
AB test for AR(1) (p-value)		0,046			0,036			0,026	
AB test for AR(2) (p-value)		0,807			0,638			0,389	
No. of observations (no. of countries)		97			97			97	
Wald-test: EDU = BERDXGDP = INNOV=0					F(3, 28) = 3,47 Prob > F = 0,0292				
Wald-test: BERDHT = EDU = BERDXGDP =INNOV= 0								F(4, 28) = 6,49 Prob > F = 0,0008	
Wald-test: BERDHT == BERDXGDP =INNOV= 0								F(3, 28) = 7,90 Prob > F = 0,0006	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPHW, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU, lnINNOV.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-0/t-1	t-1/t-2	t-1/t-1
Lags in the level equation	t-0/t-1	t-0/t-1	t-1/t-2

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Table 26: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1995-2019, dependent variable: ln GDP per hour worked in PPP)			
	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,310	1,12	
ln Average years of education (EDU)	1,763	0,76	

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).
a Statistically significant at the 10% level.
b Statistically significant at the 5% level.

Table 27: Estimation results for the two-step system GMM estimator (5-year averages over 1995-2019, dependent variable: ln GDP per employed person in PPP)

Specification		(i)			(ii)			(iii)	
	Coeff.	t	Signif.	Coeff.	t	Signif.	Coeff.	t	Signif.
Lagged ln GDP per employed person (GDPEP)	0,914	20,18	b	0,870	18,22	b	0,861	16,89	b
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,020	3,15	b				0,023	2,55	b
ln Business sector R&D expenditures (BERD) % GDP				0,015	0,68		0,011	0,62	
ln Average years of education (EDU)				0,090	1,97	a	0,105	2,92	b
ln Investment Ratio (%) (INV)	0,094	2,24	b	0,084	1,22		0,079	1,17	
ln Innovindex (INNOV)	-0,004	-0,94		-0,007	-1,01		-0,011	-1,80	a
Period dummy 2000-2004	0,030	2,78	b	0,039	3,13	b	0,028	1,77	a
Period dummy 2005-2009	0,018	1,86	a	0,025	2,44	b	0,015	1,12	
Period dummy 2010-2014	-0,001	-0,19		0,002	0,33		-0,002	-0,32	
Period dummy 2015-2019	omitted			omitted			omitted		
Constant	1,182	2,25	b	1,467	2,43	b	1,539	2,32	b
Hansen test of overidentifying restrictions (p-value)		0,158			0,240			0,141	
AB test for AR(1) (p-value)		0,052			0,043			0,042	
AB test for AR(2) (p-value)		0,552			0,927			0,609	
No. of observations (no. of countries)		97			97			97	
Wald-test: EDU = BERDXGDP = INNOV= 0					F(3, 28) = 1,53 Prob > F = 0,2281				
Wald-test: BERDHT = EDU = BERDXGDP = INNOV= 0								F(4, 28) = 8,12 Prob > F = 0,0002	
Wald-test: BERDHT == BERDXGDP = INNOV= 0								F(3, 28) = 10,45 Prob > F = 0,0001	

t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity.

The model uses data averaged over periods 1995–1999, 2000–2004, 2005-2009, 2010-2014 and 2015-2019. For each period, we treat right-hand variables as endogenous in all regressions. Internal instruments: l.1 ln GDPEP, ln INV. External instruments: ln BERDHT, ln BERDXGDP, lnEDU, lnINNOV.

	(i)	(ii)	(iii)
Lags in the first-differenced equation	t-0/t-1	t-0/t-0	t-1/t-2
Lags in the level equation	t-0/t-1	t-0/t-2	t-0/t-1

a Statistically significant at the 10% level.
b Statistically significant at the 5% level.
Source: OECD, World Bank, own calculations.

Table 28: Long-run coefficients utilizing a fixed-effects model (5-year averages over 1995-2019, dependent variable: ln GDP per employed person in PPP)

	Coeff.	z	Signif.
ln Share of BERD in the high-tech sector in total manufacturing BERD (%)	0,166	2,09	b
ln Innovindex (INNOV)	-0,077	-1,17	
ln Average years of education (EDU)	0,756	1,84	a

The estimations concern only the explanatory variables that are statistically significant at least at 10% level in the short run (two-step system GMM estimator).

a Statistically significant at the 10% level.

b Statistically significant at the 5% level.