IMPACT OF QUALIFICATIONS IN THE ECONOMY

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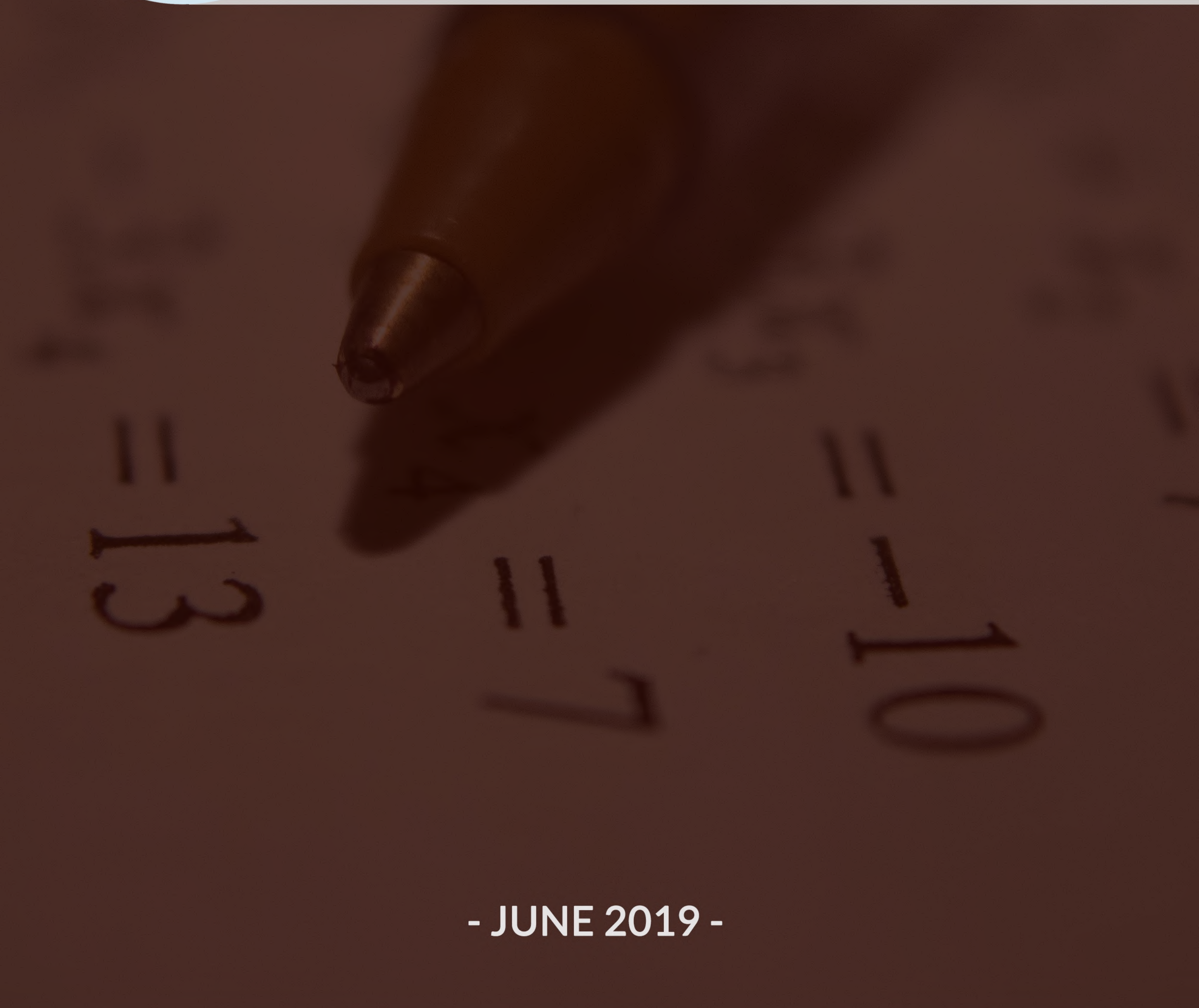

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Main determinants of labor productivity: the impact of qualifications in the economy

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Abstract: This paper aims to explore deeply the relations between distinct types of workers' qualifications and the average productivity of labor. To do so, we used cross-sector data on 6 different countries, including Portugal. The Portuguese situation is, indeed, the origin of the paper. We dealt with some constraints while collecting cross-sector data. Even the one available for Portugal is not abundant in terms of time length and we could not collect it for some countries that were more similar such as Spain, Greece and Ireland which would probably fit better and allow for the construction of a more robust model. Portugal has, as we detail further in the paper, huge discrepancies in terms of both economic performance and qualifications regarding the other five countries chosen. However, the model built gave some interesting insight regarding the impact of qualifications in labor productivity. It was confirmed the positive impact of non-formal qualifications, despite in a smaller magnitude than that we were expecting. Some interesting outcomes were also collected regarding the separated impact of ICT and non-ICT capital in the economy.

Contents

Introduction

The developed economies have been, since the financial crisis, in a constant debate over the reasons why the average labor productivity does not grow as fast as it did in previous times such as the 90s. From 2010 to 2018, the GDP per hour worked in the European Union grew by 8%, which results in a yearly 0.97% growth in labor productivity. If we ignore the EU as a whole and look to more developed countries (G7) individually, Canada is the one with the higher growth rate (7.7% in 7 years), followed by Germany with 7.6% in the same period. Departing for the Portuguese reality, the numbers are even more alarming. According to the OECD[1], average labor productivity in Portugal was, in 2018, 2.3% above that of 2010 and this value is smaller than the one registered in 2012. This has been a constraint for many developed countries. When the average productivity of labor does not increase, the real wages tend to stagnate or even decrease, leading to more and more outrage coming from the civil society.

However, each problem brings something positive and this one gave economists a stronger incentive to find out what other sources rather than formal education can stimulate the most the labor productivity. While qualifications have a well-known effect behind the ability to promote economic growth, this paper tries to analyze them deeply, separating both formal and non-formal education (training) in order to unveil the extent up to which the European and, more particularly, Portuguese labor productivity can be differently affected by both types of skills.

Purpose

This paper arose from the necessity of evaluating in a more rigorous and analytical way the impact of the qualification of employees (specifically Portuguese) in the productivity of their countries' economies. Such purpose translated into a cross-country and cross-sector analysis and led us to the construction of an econometric model, supported by previous literature and influenced by the availability of data, which tries to explain how formal qualifications and training throughout life impact the evolution of labor productivity in a country. Such evolution is intimately linked to the concept of capital accumulation and, thus, such measures are unavoidable in an analysis like the one presented. Furthermore, we wanted to build on the most recent work done in this field and, thus, we decided to distinguish between ICT and non-ICT

[1] All data regarding GDP per hour worked derives from OECD database.

capital, as such work supports the idea that the former type of capital enhances the productivity of workers when combined with investments in training.

Before initiating such inferential and econometrical examination, we believe it is of greatest interest to start by studying what has been written regarding this subject, as a mean of supporting our own work and enhancing it. In that sense, Section 1 departs from a literature review of some papers presented in this area of expertise. Section 2 elaborates and centers on a descriptive analysis of the data collected from the EU KLEMS database, in an attempt to capture trends and explain persistent behaviors in the figures across time. It also covers a brief explanation on how data was collected and processed. Finally, Section 3 presents our econometric model and its results after running a regression of labor productivity on various explanatory variables, using the OLS method. Section 4 exposes our concluding remarks, suggesting improvements to the results achieved and the methodologies to reach them and preparing future work in this field.

Section 1 – The beginning of a journey

Literature Review

Our work was initially based mainly in two papers regarding this matter. The first one is a report by CEDEFOP (2014), which focuses on the "macroeconomic benefits" of Vocational Education and Training (VET), comparing it with skills acquired through other types of education. The effort to distinguish and work with five different qualification groups (higher, upper-intermediate vocational, lower-intermediate vocational, lower intermediate general, and low-skilled) and the deepness and richness of the methods used to decompose the growth of labor productivity throughout time are the two main advantages of the work made by the European organization. Nevertheless, the demanding procedures and accessibility to data presented in this document revealed to outweigh the benefits of following its approach. Therefore, we decided to use only three qualification levels (the ones presented in the EU KLEMS dataset). However, we did not neglect the usefulness and quality of the methods employed in the report and, with some adaptations, adopt them in some sections of this paper. CEDEFOP's work presents another innovative aspect, which regards the evaluation of complementarities between vocational and general skills. Based on the premise that "growth accounting tends to underestimate the contributions made by all types of skill to productivity performance because it cannot take account of complementarities", the report attempts to capture such complementarities. Its conclusions are quite important, in terms of policy analysis, as they suggest that “relying too heavily on the expansion of higher education at the expense of intermediate skills development” can be prejudicial for the economy. It further extends its analyses, to conclude that complementarities are enhanced when VET systems are apprenticeship based. As one can imagine, due to the lack of data, we were unable to proceed with a such deep analysis and we focused on the complementarities between Training and ICT Capital and less on the complementarities between skill levels.

O’Mahony (2011) also supported our analysis and we will follow much of the approach followed by this paper, focusing on Portugal. In this work, some of the problems related to measuring uncertified skills are dealt in an innovative way and its approach allows the extraction of some interesting conclusions, especially regarding the complementarities between ICT Capital (Capital Stocks related with Information and Communication Technologies, a broad category which comprises most of capital related to technology, communication and the digital networks) and Training, advocating that a higher stock of ICT Capital has greater effects on productivity, when investment in training is increased and everything else is held constant. We will try to verify if the same applies to the group of countries chosen by us and especially to Portugal.

Finally, it is important to point out that we are working under the assumption of perfectly competitive markets, where real wages equate to the marginal productivity of workers. In that sense, the theoretical background is set up by Barro (2005).

Dataset

Following the approach of O’Mahony, we decided to work with data retrieved from the EU KLEMS database. Such source collects data for most European countries and it is widely used in the papers related to productivity, due to its variety of variables and easiness to work. Despite lacking the accuracy and richness of microdata, it contains rather valuable information which can be withdrawn with the proper analysis and modelling. EU KLEMS is divided into economic sectors, which go from Agriculture and Forestry to Financial Intermediation. The main idea is that one can focus on production and service sectors and ignore non-market sectors, whose output is difficult to measure. Furthermore, such division of data allows for the possibility of deeper and deeper analysis of this subject.

It is important to point out one methodological issue that influenced the entire analysis and further exploration of the data collected. There was a change in the classification of the sectors into which economic activity can be divided (NACE 1 and NACE 2 are the two classification systems we are referring to). Such alteration of the paradigm disabled us to work with a single temporal framework, since the correspondence between sectors of the different systems isn't perfect, compromising the linking of values from one temporal framework to the other. Therefore, we decided to deal with these two systems separately. Since NACE 1 aggregated data from more years and more accurately, we considered this as the most adequate dataset to use in a multi-variate regression analysis. Nevertheless, we did not want to ignore more recent data (from NACE 2 dataset) and decided to include these in a deeper descriptive analysis.

In the EU KLEMS database, three levels of education are presented: high, medium and low. These 3 levels of education try to comprise different education systems, whose characteristics may difficult the division between the three categories. Nevertheless, it is commonly assumed that the higher level of education corresponds to tertiary education (of long and short-cycle). In our analysis, we will assume that a worker with a level of "High Education" in Portugal is as qualified, in terms of certified skills, as a worker with a level of "High Education" in Germany. Further and necessary explanations regarding data will be explained throughout the paper. Age is also divided into three groups: from 15-29 years old, from 30-49 years and 50 years or older.

Section - Descriptive Analysis

1992-2005 (NACE 1)

In the late 90s and beginning of the 21st century, there was a clear trend of improvement in the share of workers with high education skills and a decrease in the share of the ones with low education. In fact, of the 6 countries analyzed, Germany was the only exception to this "rule" since the share of low educated workers in services went up from 28% to 33%. However, even in this situation, the correspondent share of highly educated improved. The sector that more intensively uses low educated workers is, usually, agriculture, hunting, forestry and fishing, whilst renting and business activities is, clearly, the one that is the most intensive in high educated workforce.

As for Portugal particularly, it is by far the country, out of the six, that has the least educated workers. The highly educated workers represented 3% and 9% of the production and services' workers, respectively, in 1992 The correspondent values in 2005 were 5% and 11%. Regarding the share of intermediate education in the workforce, it increased 2 p.p. to 9% in the production sectors and 5 p.p. to 20% in the service sectors. Finally, the share of low educated workers in the production sector went down from 90% to 86% between 1992 and 2005. Finally, the proportion of low educate workers in the services sectors fell from 76% to 69% in the same period (figure1).

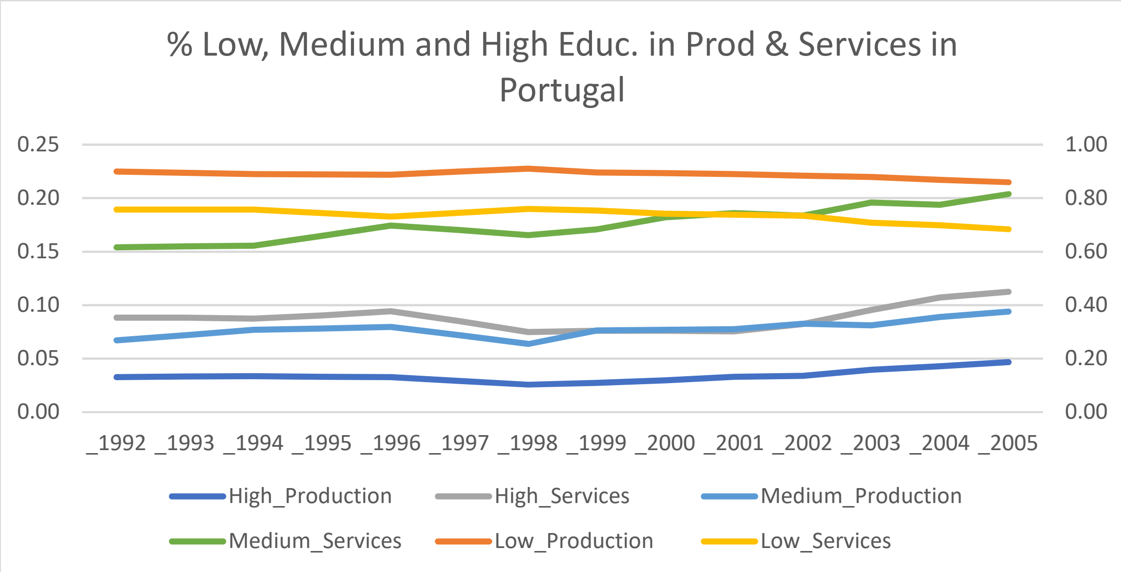

Figure 1. % of low educated workers on the right scale. Authors' calculations based on EU KLEMS database

2008-2015 (NACE 2)

On more recent periods, and after the change from NACE 1 sectors' classification to NACE 2, the unavailability of significant amount of data does not allow to gather enough observations in order to replicate the method followed for the period 1970-2005 using NACE 1.

While using the database of EU KLEMS with NACE 2, the better period that can be covered is 2008-2015 and there is also no data per sector on capital stocks. Thus, the descriptive analysis that follows will focus on the evolution of Apparent Productivity of Labor and the two variables education and age. Education is still separated in the 3 same levels – high, medium and low – and employees are discriminated 3 age groups – 15-29, 30-49 and 50+.

Regarding productivity of labor in the production sectors (figure 2), it has been relatively stagnated along the observed period. During 2008-2015, The Netherlands kept being the more productive economy despite being the one with the lower growth in percentage points. As of Portugal, it is by far the country with lower productivity, however it was the second with the most significant growth (10%) just behind Denmark (18%) that surpassed Germany as the second most productive country. The British and the Italian levels of labor productivity in terms of production have been following each other closely for the last years, below those of Germany and Denmark, but still way above the Portuguese.

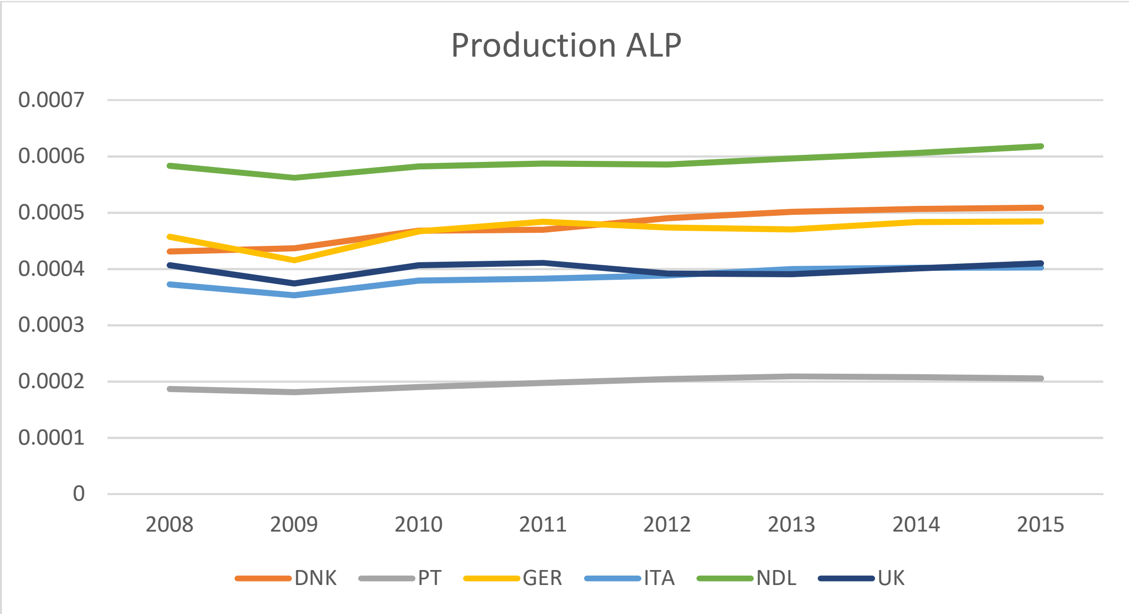

Figure 2. Average labor productivity in the production sectors. Authors' calculations based on EU KLEMS database

As for services (figure 3), Portugal was the country where the labor productivity grew the most (16%), followed by the 13% growth rate of Denmark. Although, the extreme positions of The Netherlands and Portugal coincide with those observed in the production sectors, while Italy appear right below, but close to, the German and Danish levels.

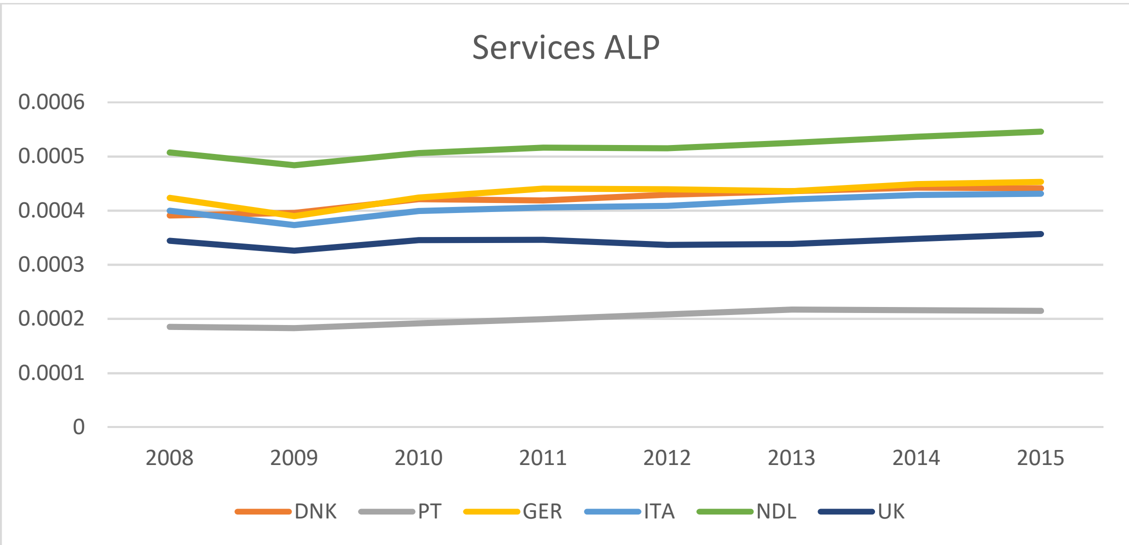

Figure 3. Average labor productivity in the services sectors. Authors' calculations based on EU KLEMS database

On what concerns education, as expected, the share of low education workers in the work force declined in all countries and all sectors analyzed. In most cases, this fall was caused by the increase in both medium and low educated workers' shares. In Denmark, the country that showed the stronger growth in APL, the share of highly educated workers only decreased for the *agriculture, forestry and fishing* and the *construction* sectors, having registered a maximum increase of 90% in the share of workers in *food service activities.* In the overall production sectors, the share of low educated workers fell from 32% to 24%. The share of medium educated workers increased by 5.5 p.p. to approximately 56% and the share of high educated by the remaining 2.5 p.p. to 20%. For the service sectors, the upgrade in education was significantly different. Low educated workers went down from 33% to 27% but almost 5 p.p. affected the increase of high educated share and only 1 p.p. is respective to the medium educated workforce. Having this information, we can already guess some correlation between these two indicators. There's a strong positive correlation between the share of highly educated workers in services and market economy's sectors (R=0.89 and R=0.95, respectively). On the other hand, the share of low educated workers reveals a strong negative correlation with labor productivity along the services, production and market economy sectors (all the correlation coefficients present values below -0.95). Finally, it's interesting to note that the correlation between the productivity of the production sectors and the share of medium educated class (R=0.91) is stronger than that for the highly educated one (figure 9).

Isolating now the analysis of Portugal one can state that, despite the still reduced relative levels of labor productivity, the country showed the 2nd and 1st best performances in the production and services' sectors, respectively. For all sectors, the Portuguese were able to increase the share of both high and medium educated workers and reduce that of low educated. For the overall market economy, the share of workers with no formal qualifications fell from 76% in 2008 to 58% in 2015. Inversely, the ones with medium education went up from 15% to 25% of the population and the upper qualified workforce rose from 9% to 18%. Other noticeable fact is the strong correlation between all the levels of education and the production and services' sectors, being, once again, positive for high and medium and negative for low. However, it can't be said that the same happens for the overall market economy (figure 9).

Opposing what happened in these fastest growing productivity economies, the ones of the United Kingdom and Germany, more stagnated, show little correlation between the three aggregates and the three levels of education (all but one correlation coefficient show absolute values below 0.8, even this exception only applies to Germany).

For the Netherlands, there are strong correlations between the high and low levels of education (positive and negative, respectively) and the productivity of labor in all aggregates.

Considering a different aspect of the workforce, these years resulted, for every country but Denmark, in a decrease of the share of workers between 15 and 29 years old. Following the ageing of the European population, all the countries saw an increase in the proportion of employees with more than 50 years old.

For Portugal, there is a strong negative correlation between the 15-29 years old share and labor productivity for all the aggregates. Relevant as well may be the positive strong correlation between the middle age share and the productivity in services' sectors. This last correlation is a peculiarity only observed in Portugal. In the other five countries, it is negative; being, in some of them, a strong one. Finally, it can also be highlighted that, except for Germany and the United Kingdom, the coefficient of correlation between the 50+ class and productivity in the production sectors is superior to 0.84, thus, a strongly positive one.

Another way to understand the impact of uncertified skills (acquired not through formal education) is to analyze the relation between the average wage of employees with distinct education levels. From theoretical analysis, we know that the wage of a worker must reflect its marginal productivity which, with decreasing returns to scale, is also a measure of average labor productivity. Thus, if wage can be used as a proxy of average labor productivity, a wage ratio between two classes of workers with different education levels, is also a proxy of their relative productivity.

By computing the average wage ratio for Portugal relative to low wage workers, there were only two deviations from what would be expected. In 2008, the high educated workers in the *agriculture, forestry and fishing* sector and the medium educated ones in the *food service activities* received less per hour worked than the low educated workers in the respective sector. As these may be interpreted as specific deviations from the norm that were corrected in the following years, what is interesting to observe is that, in sector *agriculture, forestry and fishing*, the average hourly wage of medium educated worker seems to be persistently superior than that of high educated ones (the relative wage of high-medium educated was inferior to 1 in 2008, 2009, 2013-2015). Indeed, a similar trend was also observed in the last two years (2014 and 2015) in *mining and quarrying*. One strong explanation for the impact of non-formal education in these sectors can derive from the fact that these are jobs that require a lot of repetitiveness. Hence, the capability to perform the same task is acquired with experience and in-job training, relegating the impact of formal education to a secondary role. Although, not having education at all will most probably jeopardize labor productivity since the wage relative to low educated workers is almost always above 1 (figures 4 and 10).

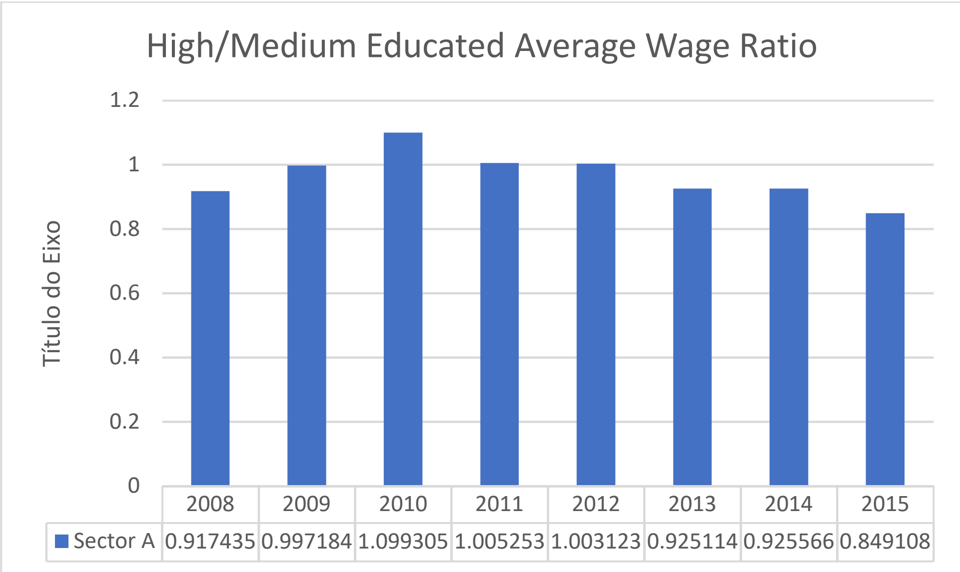

Figure 4. High educated/Medium educated average wage per hour. Average labor productivity in the production sectors. Authors' calculations based on EU KLEMS database

Section 3 – You can't make lemonade without econometric models

The model

The descriptive analysis of the variables aforementioned reveals some fragilities that cannot be overcome without resorting to an econometric model, which tries to capture the impact of the different regressors chosen on productivity. The approach followed by us is the one used by O'Mahony (2011). Nevertheless, due to the shortage of data available, we had to adapt some of the procedures used to measure the explanatory variables. Moreover, we focused our analysis in sectors previously mentioned and used only NACE 1 data. Non-market sectors were excluded due to difficulties in measuring output and productivity. Due to the lack of specific data for Portugal, we limited the temporal framework to 1995-2005, with observations for each country and each sector. In that sense, we arrived to the following model:

$$\ln(lp)_{cit} = \beta_1 Ed\_High_{cit} + \beta_2 Ed\_Medium_{cit} + \beta_3 Age\_29_{cit} + \beta_4 Age29\_49_{cit} + \beta_5 Male_{cit} + \beta_c + \beta_i + \beta_t + \beta_6 \ln(intkh)_{cit} + \beta_7 \ln(capithcit)_{cit} + \beta_8 \ln(capnithcit)_{cit}$$

Where ln(lp) stands for the logarithmic form of the average labor productivity, ln(intkh) denotes stocks of Training Capital and ln(capithcit) and ln(capnithcit) represent the logarithm of the stock of ICT and Non-ICT Capital, respectively.

In the following subsections, we will explain each variable used in more detail.

Education High

This variable corresponds to the proportion of workers with a high level of education. As explained in the subsection “Dataset”, there are 3 levels of education in the EU-KLEMS database. There are some differences between countries regarding which components of general education are included in which category. Nevertheless, we consider that these differences did not influence the conclusions of our analysis. Therefore, we assume that the same level of certified skills is obtained by a worker in Portugal or in the United Kingdom if he is included in the category “High”.

Education Medium

This variable corresponds to the proportion of workers with a medium level of education. Both variables regarding levels of education were employed as dummies[2] to control for the impact of certified skills, this is, they try to capture the effect of school-based education (both general and vocational) on labor productivity.

Age Under 29 Years

This variable corresponds to the proportion of workers with less than 29 years old. With the exception of Portugal, the data used in the calculations of such proportions were retrieved from the Labour Input Files of the March 2008 release of the EU KLEMS page. Since Portugal did not have such file available, information regarding age groups was taken from the Eurostat database.

Age Between 29 and 49 Years

This variable corresponds to the proportion of workers whose age is between 29 and 49 years old. The methodology used to calculate such proportion was the same as in the variable

[2] Proportion of Workers with Low Education being the base group

above. Both were used as dummies[3] to control for the impact of experience on labor productivity. In that sense, age is seen as a proxy for experience.

Male

This variable corresponds to the proportion of workers that are male. Once again, data was collected from EU KLEMS, except for Portugal, whose values were retrieved from Eurostat. This variable is used to capture any differences in productivity between the two genders. This is analyzed based on the idea that wages are equated to the marginal productivity of workers. Nonetheless, we believe such assumption is sometimes unrealistic and, therefore, a positive or negative coefficient can reflect social and economic conditions that can't be easily observed in data.

Country, Sector and Year

These are control variables, used to "control the unobservable time-invariant effects and the business cycle".[4] In this case, Portugal was considered the benchmark country (country represented with number 0). The benchmark sector was Atb (Agriculture and Forestry) and the base year was 1995. It is important to point out that, due to the lack of data there are 7 missing values for the sector C (Mining and Quarrying) and for the sector E (Electricity and Water Supply) for the country Portugal.

Training Stocks

Following the approach of O'Mahony and the Cedefop report, we decided to consider training (proxy for uncertified skills) as an intangible asset and estimated real investments in training. This was made resorting to data from the Continuous Vocational Training Survey from 2005 and 1999. It was impossible to have access to the proportion of workers trained by skill level, age and gender. Therefore, adaptations to the procedure used by O'Mahony were necessary. In that sense, we could not adjust the opportunity cost to the characteristics of the population that received training. Nevertheless, we decided to proceed with our analysis and used the variable "Cost of CVT courses per training hour, by type of cost and NACE Rev. 1.1", measured in Purchasing Power Standard. These variables include three type of costs: direct, labor related and net contributions (the latter is only available in the 2005 survey)[5]. We

[3] Proportion of workers with 50 years or older being the base group

[4] O'Mahony (2011)

[5] Direct course costs include: fees and payments for CVT courses; travel and subsistence payments related to CVT courses; the labor costs of internal trainers for CVT courses (direct and indirect costs); the costs for training centres, training rooms and teaching materials. Participants' labor costs (personal absence costs) refer to the labor costs of participants for CVT courses that take place during paid working time. The net

considered that labor costs corresponded to the opportunity cost of workers, as computed in O'Mahony. Assuming as unit PPS guarantees that differences in costs are real and not the result of different currency units and their personal evolution. Next and resorting to the variables "Participants in CVT courses by sex and NACE Rev. 1.1 activity - % of persons employed in all enterprises" and "Hours spent in CVT courses by NACE Rev. 1.1 activity - hours per participant", also available in the Eurostat database, we computed total number of hours spent receiving training per sector and per year. We were then able to compute total costs of training for the year of 1999 and 2005. The average of the two values was considered the real investment in training in each year. We assumed real investment was constant throughout time. Since training received doesn't exhaust its benefits in terms of enhancing productivity in one year, this isn't a problematic assumption, this is, training received creates a quasi-permanent increase in productivity and not a temporary one (quasi-permanent, because technologies associated with the training received become obsolete after some years). What matters is the accumulation of capital itself and not the pace at which is accumulated. Having the flow of investments in each year, we needed to convert such flows into stocks. To compute the of stock of training capital, we first had to assume a given depreciation rate. We decided to use the one applied in the O'Mahony and the CEDEFOP papers (25%). Literature on this topic is vast and diverse and was thoroughly examined in the aforementioned works, conferring credibility to the value chosen6. The most common assumption regarding the form of the depreciation function is geometric decay:

$$K_t = I_t + (1 - \delta) \times K_{t-1}$$

where I represents Investment, K denotes capital and δ the depreciation rate.

The main difficulty here was to define an initial capital stock. We had to assume a year where capital stock would be 0 and compute the accumulation of capital as described above from that point onwards7. The definition of this starting point was based on previous papers on

contribution to training funds is made up of the amount of contributions made by the enterprise to collective funding arrangements through government and intermediary organizations minus receipts from collective funding arrangements, subsidies and financial assistance from government and other sources.

[6] For a more complete analysis and a study of the sensibility of the results to changes in the depreciation rate, see O'Mahony (2012)

[7] "The assumption that initial capital stocks are zero (rather than an unknown positive value) has little effect on our growth accounting analysis because all of the depreciation rates are relatively high and the true value of the benchmark will have depreciated away by the date that we start our growth accounting analysis" – Corrado (2009): https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1475-4991.2009.00343.x

this topic, namely Corrado (2009). Furthermore, to distinguish more developed countries that may have started accumulating this type of capital earlier than poorer countries, we also established a criterium based on GDP per capita levels (at constant prices)[8]. Figure 5, schematized below, indicates the base year for each county:

Country	Initial Year (Capital Stock = 0)
Portugal	1970
Germany	1960
Italy	1960
Denmark	1950
United Kingdom	1955
Netherlands	1950

Figure 5. Initial Year of Training Capital Stock

Real stocks were then computed taking this into account. Two final transformations were made: on the one hand, capital stocks were divided by the total number of hours worked in each sector and in each country, in order to get real training capital per hour worked; on the other hand, a logarithmic transformation was applied to this final value reached, as it is usual when variables are expressed in a given currency unit or are of big dimension.

ICT and Non-ICT Capital Stocks

These variables represent the stock of ICT and Non-ICT capital in different sectors. This data was collected directly from the EU KLEMS dataset and its unavailability for some countries constrained the span of countries that we could have used for the regression. We found the separation crucial in order to test if there was any complementarity, suggested by previous literature, between ICT capital and upper education levels which could enhance the positive effects that both indicators have individually in the average productivity of labor. These capital stocks are given in real terms and then adjusted to Purchasing Power Parity. Finally, they are divided by the total number of hours worked in each sector in order to gather real capital stocks per working hour. In the end, this value suffers a logarithmic transformation.

[8] The base year corresponds roughly to the year where GDP per capita reach a level above 2500$ (at 2010 prices).

Average Productivity of Labor

The average productivity of labor is entirely calculated, once again, based on the EU KLEMS database. In order to account for the true productivity of the workers, data is first gathered for the Gross Value Added at current prices in the countries' correspondent national currency. Furthermore, all the values are divided by the correspondent price index (per year and per sector) in order to eliminate other than volume effects. Once again, it is adjusted to Purchasing Power Parity (even because both Denmark and United Kingdom have a different currency) and divided by the total number of hours worked. Hence, we reach the values correspondent to the evolution of real gross value added per working hour in PPP, which is the dependent variable of the model. Finally, a logarithmic transformation is applied to this variable in order to ease the comprehension of the OLS results.

OLS Results

Figure 6 shows the results of the regression of our explanatory variables (described above) on the logarithm of labor productivity. Performing the Breusch-Pagan Test, data revealed heteroskedasticity (strong rejection of the null hypothesis of constant variance) and, thus, robust standard errors were applied to deal with heteroskedasticity of observations.

The results show all variables except two (Country and Age 29_49) are significant at a 1% level. To highlight some of the results, one could say:

- An increase of 1% in the proportion of workers with high education leads to an increase in the ALP of approximately 1,59%, everything else held constant;
- On average, an increase of 1% in the proportion of workers with less than 29 years old leads to a decrease of approximately 1,31% in the ALP, *ceteris paribus*;
- An increase of 1% in the training capital stock leads to an increase of 0,04% in the ALP, everything else held constant;
- An increase in the stock of ICT capital by 1% leads to an increase of 0,14% in ALP, *ceteris paribus*;
- An increase in the stock of non-ICT capital by 1% leads to an increase of 0,27% in ALP.

Literature on this matter shows that ICT capital enhances productivity when combined with Training. Therefore, it makes sense to estimate this same regression including such interaction term. However, results aren't satisfactory, as the variable "Logarithm of Training Stocks" is no longer significant, not even at a 10% level. Nevertheless, we decided to further explore this idea of interaction between regressors and ICT capital. In that sense, we also included an interaction term between ICT capital and the variable “Education High”, as well as with the variable “Age below 29 years”. The reasoning behind such exercise follows from the idea that highly educated workers and younger people are better prepared to work with ICT. A regression was made using the 3 interaction terms, but its bad performance, in terms of the statistical significance and economic significance of the variables, made us neglect it in the analysis.

WLS Results

In order to evaluate the robustness of the coefficients computed using OLS and robust standard errors, we decided to estimate the intrinsic function associated to the error variance, attributing to each observation a given weight – Weighted Least Squares method. Starting by regression the same equation as before, but this time excluding robust standard errors, we then computed fitted values, as well as the residuals, regress the absolute value of the residuals on the fitted values calculated before and collected the fitted values of this new regression. Finally, we defined as weight the inverse of the square of this last collection of fitted values, using this weight in the initial regression to get the WLS coefficients. Results are presented below and, as one can see, differences in coefficient values aren’t significant. Furthermore, the analysis of statistically significant variables isn’t affected by this method change. The biggest changes regard the capital related variables.

Production versus Service Sectors

Due to the small sample size, a regression including only observations for Portugal seems inappropriate and inaccurate. We ran such regression and understood it quickly, by getting most of the coefficients statistical insignificant. Nevertheless, we wanted to extend our discussion and decided to estimate coefficients for the model described above using, for starters, only Production related sectors and then only Services related sectors. For each group, we estimated a regression without the interaction term that joins ICT Capital and Training Capital and a regression with this interaction term. OLS coefficient estimates are presented below (robust standard errors were applied), as well as estimates for the initial regression with all sectors included:

	Total Sample		Production Sectors		Service Sectors	
Training Capital*ICT Capital		0.038***		0.018**		-0.017
Training Capital	0.041***	- 0.012	0.039***	0.017	0.093***	0.121***
ICT Capital	0.140***	0.168***	0.137***	0.143***	0.215***	0.213***
Non-ICT Capital	0.268***	0.258***	0.406***	0.393***	0.183***	0.181***
Education High	0.0159***	0.017***	- 0.002	0.002	0.022***	0.022***
Education Medium	0.003***	0.005***	- 0.003**	- 0.002	0.008***	0.008***
Age < 29	- 0.013***	- 0.114***	- 0.007**	- 0.007**	- 0.013***	- 0.014***
Age 29-49	0.001	- 0.000	- 0.004	- 0.003	0.004	0.005
Male	0.005***	0.005***	0.013***	0.012***	- 0.003**	- 0.004**
R^2	0.8186	0.8277	0.8674	0.8696	0.8277	0.8284
N	710	710	314	314	396	396
Obs:	The * above the coefficient denotes the significance level of the variable - ***, ** and * indicate that variable is significant at the 1%, 5% and 10% level, respectively					

Figure 6. Regression Results (Regressing Ln(lp) with and without the interaction term in the total sample, production and service sectors

Marginal effects of training proportions at percentile levels of ICT capital for Portugal

	Total sample				
ln (ICT Capital)	Min (-2.023)	25% (-1.041)	50% (-0.695)	75% (-0.167)	Max (0.038)
Marginal effects	-0.089	-0.052	-0.038	-0.018	-0.011
	Production Sectors				
ln (ICT Capital)	Min (-2.024)	25% (-1.76)	50% (-1.02)	75% (-0.84)	Max (-0.08)
Marginal effects	-0.019	-0.015	-0.001	0.002	0.016
	Service Sectors				
ln (ICT Capital)	Min (-1.26)	25% (-0.71)	50% (-0.36)	75% (-0.11)	Max (0.04)
Marginal effects	0.142	0.133	0.127	0.123	0.12

Figure 7. Marginal effects of training proportions at percentile levels of ICT capital for Portugal for the total sample, production and service sectors

This analysis shows some difference between production and service sectors. As it would be expected, ICT Capital tends to have a greater positive impact on productivity on service sectors rather than production sectors. On the contrary, the same increase in non-ICT Capital leads to a higher productivity on production sectors. Furthermore, a bigger proportion of highly-educated workers increases average labor productivity more in service sectors. It is also interesting to point out that in service sectors, the coefficient for the variable "Male" (although small) is negative and in production sectors is positive. This is probably the reflex of the characteristics of workers in each category and the characteristics of the jobs themselves (more physically demanding in production sectors). Finally, it is interesting to analyze differences in the estimates of Training Capital and, more precisely, in the differences in the interaction term estimate. To achieve such goal, we considered that predicting the marginal effect of training on productivity for Portugal was the best option. In that sense, and for each category, we computed the minimum stock of training capital, the first, the second and the third quartile, as well as the maximum stock. The impact of training on productivity was then calculated, resorting to the coefficients obtained in the regression9. Table x presents these computations and reveals that the impact of training on productivity is positive in the service sectors, but it decreases with the increase in ICT Capital (although this coefficient is statistically insignificant at any level of interest, which can bias our analysis). On the other hand, the combination of training with ICT Capital increases the productivity of workers in production sectors (the same occurs when the total sample is considered). However, since the coefficient for training is negative, the overall effect is also negative for more than 50% of the observations (being negative for all observations in the case where the total sample is considered).

Final Notes

The results at which we arrived revealed some fragilities when compared to what has been proposed by literature on the topic. Nonetheless, it is important to reflect on these and to explore some of the reasons why such differences were present. For starters, the lack of accessibility to further data disabled us of measuring certain inputs of the model the way most papers measure nowadays. Necessary adaptations can fail to capture some of the variance in the variables of interest. Furthermore, this lack of data didn't allow us to proceed with the application of instruments that tackle some issues related with the use of panel data using fixed-effects estimators.[10] Future works on this matter should consider this when designing their own

[9] Considering that $\frac{dln(lp)}{dln(intkh)} = \beta_1 + \beta_2 * \ln(capithcit)$, where β_1 corresponds to the coefficient associated with the variable "Logarithm of Training Capital Stock" and β_2 to the coefficient of the interaction term.

[10] "Although the fixed-effects estimator corrects for the omitted-variable bias associated with unobserved time-invariant factors in the cross-section estimation, the fact that current values of training may be simultaneously determined with output can lead to biased estimates." – O'Mahony (2011)

econometric model. Finally, differences in terms of the number and list of countries used, as well as in the time span chosen can lead to these differences in the results.

Conclusions

Despite the negative impact of workers younger than 30 years old in productivity, overall, the results of the model confirm the relations between the different variables and average productivity of labor that would be expected for someone that had previously gone through a descriptive analysis of the data available. However, they create value added to the discussion of factors enhancing labor productivity by giving a sense of the magnitudes that are implied and which factors can be a complement to each other.

We must highlight the following outcomes:

When analyzed independently and everything else held constant, a 1% increase in the share of highly educated workers, in the value of non-ICT capital, ICT capital or training stock leads to a 1.59%, 0.27%, 0.14% or 0.04% increase in the level of average labor productivity;

Ceteris paribus, a 1% increase in the share of workers younger than 30 years old results in a 1.31% decrease in average labor productivity;

No differences of big dimension were found when using OLS or WLS estimators.

Having this said, it is important to look at the results and try to infer what are their main implications in terms of policies to incentivize higher levels of productivity. It seems crystal clear that, in the long-run, formal education is the main determinant of labor performance. However, improving the share of highly educated takes significant costs and a lot of time to produce real enhancing effects in productivity. Proof of that is the effort that has been made in Portugal to increase education levels and the country still lags considerably below the other five countries analyzed, as observed below. Furthermore, when investing in education, it would be important to drive the focus to the sectors that have the lower shares of highly educated students since increasing the share of a workers with a certain characteristic is easier in sectors where they are not abundant, everything else equal. In what concerns formal education, it is also important to point out that it is important to develop different types of skills and not only to promote the highest level of education, as there might be complementarities between levels of skills which couldn't be captured with the data available but that are referred in some of the literature analyzed in this paper.

It is also important to highlight the differences between Service and Production Sectors, an in the former ICT Capital is more preponderant to enhance productivity and in the latter Non-ICT Capital occupies this role. It was also interesting to observe that, despite this conclusion, the higher the level of ICT Capital the more positive the effect of training on productivity for production sectors and vice-versa for service sectors.

Since the time span that each policy takes to have effect is also important, considering an increase in the stocks of physical capital or training is more attractive from the short-time effects point of view. While investing in a student takes more than 20 years to have an effect in the market, investing in capital (tangible or not) has effects in the following year. From that point of view, an investment in non-ICT capital may seem, at first sight, more attractive than in ICT due to its greater coefficient. However, it is important to notice that the stock of ICT is about one tenth of that of non-ICT capital. Thus, the cost of investing 1% of existing non-ICT capital is 10 times higher than the cost of investing 1% of existing ICT capital, whilst the returns are a 0.27% increase or a 0.14% increase in ALP, respectively. Thus, the nominal value of these three variables is preponderant to understand which one is most likely to increase net gains from investment. The same happens for the investment in training capital. Despite the lower relative low coefficient, the fact that a 1% investment in training is also relatively cheaper when compared with other variables, may also justify the investment in this intangible capital. Moreover, training capital is likely to have even shorter-term effects than physical stocks that, sometime, require some awaiting after ordering and time for installing the new machines.

A further step to build on this work would be, therefore, to make a cost benefit analysis regarding the most profitable investments that each pursued policy could represent, bearing also in mind the spillovers that an investment in ICT capital could have on the productivity of the workforce with less than 30 years old.

Finally, in the following years, if more recent data is released regarding the existence of ICT and non-ICT capital, as well as more reliable and consistent data on non-formal education for more countries, will allow to gather a pool of countries more similar to the Portuguese economy and build a more robust model that would, maybe, reveal some additional interconnections between the variables and the average productivity of labor.

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Appendix

Average 1992-2005		High	Medium	Low
Portugal	AtB	1%	2%	98%
	C	7%	16%	77%
	D	4%	9%	87%
	E	7%	16%	77%
	F	3%	5%	91%
	G	4%	15%	82%
	H	4%	15%	81%
	I	10%	19%	71%
	J	25%	43%	32%
	K (no real estate)	29%	26%	45%
	O	6%	10%	84%
United Kingdom	AtB	4%	61%	35%
	C	17%	73%	9%
	D	10%	69%	21%
	E	17%	73%	9%
	F	6%	79%	15%
	G	5%	73%	21%
	H	5%	74%	21%
	I	7%	79%	14%
	J	22%	73%	5%
	K (no real estate)	30%	59%	10%
	O	16%	67%	17%
Germany	AtB	3%	64%	33%
	C	8%	67%	25%
	D	7%	63%	29%
	E	8%	67%	25%
	F	4%	69%	27%
	G	3%	66%	31%
	H	3%	66%	31%
	I	3%	69%	28%
	J	10%	79%	11%
	K (no real estate)	14%	52%	34%
	O	11%	53%	37%
Italy	AtB	1%	87%	12%
	C	4%	93%	2%
	D	3%	96%	1%
	E	6%	94%	0%
	F	1%	95%	3%
	G	3%	95%	2%
	H	1%	97%	2%
	I	3%	96%	1%
	J	15%	85%	0%
	K (no real estate)	34%	66%	1%
	O	5%	93%	1%
Denmark	AtB	1%	40%	59%
	C	5%	52%	43%
	D	4%	59%	38%
	E	5%	71%	24%
	F	1%	67%	32%
	G	3%	63%	34%

	H	2%	47%	51%
	I	3%	56%	41%
	J	8%	79%	13%
	K (no real estate)	18%	59%	24%
	O	9%	60%	31%
Netherlands	AtB	2%	89%	9%
	C	8%	88%	5%
	D	5%	83%	12%
	E	7%	88%	5%
	F	1%	87%	11%
	G	2%	88%	9%
	H	2%	88%	9%
	I	4%	85%	11%
	J	13%	85%	2%
	K (no real estate)	20%	75%	5%
	O	13%	81%	6%

Figure 8. Average education level by sector. Some sectors may not add up to 100% due to rounding. Authors' calculations based on EU KLEMS database

Correlation Coefficient	Portugal			Denmark			Germany			Italy			Netherlands			United Kingdom		
Education Level	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low
MARKT	0.75	0.83	-0.80	0.95	0.86	-0.96	0.62	0.04	-0.75	0.56	0.62	-0.61	0.88	0.69	-0.86	0.47	-0.34	-0.52
Production	0.92	0.90	-0.91	0.52	0.91	-0.96	0.56	0.28	-0.74	0.86	0.85	-0.87	0.86	0.75	-0.88	0.32	-0.22	-0.36
Services	0.93	0.97	-0.96	0.89	0.79	-0.97	0.74	-0.06	-0.85	0.87	0.69	-0.89	0.86	0.67	-0.85	0.42	-0.15	-0.51
Age	15-29	30-49	50+	15-29	30-49	50+	15-29	30-49	50+	15-29	30-49	50+	15-29	30-49	50+	15-29	30-49	50+
MARKT	-0.91	0.82	0.82	0.17	-0.87	0.93	-0.80	-0.73	0.76	-0.60	-0.45	0.56	-0.87	-0.85	0.90	-0.25	-0.53	0.42
Production	-0.88	-0.37	0.85	-0.60	-0.72	0.93	-0.75	-0.63	0.67	-0.88	-0.72	0.88	-0.75	-0.88	0.88	0.42	-0.36	0.09
Services	-0.98	0.96	0.69	0.76	-0.88	0.86	-0.88	-0.73	0.80	-0.85	-0.85	0.88	-0.83	-0.76	0.85	-0.31	-0.53	0.45

Figure 9. Authors calculations based on EU KLEMS data

Education level	year/sector	A	B	C	F	G	H	I	J	K	R	S	MARKT
High	2008	0.99	1.15	2.42	2.37	2.49	3.65	2.46	2.55	1.61	2.79	3.65	2.20
Medium	2008	1.08	1.05	1.58	1.31	1.16	1.42	0.98	1.27	1.00	1.26	1.25	1.01
High	2009	1.73	1.45	2.58	2.52	2.53	3.74	2.98	2.80	1.97	3.44	3.96	2.74
Medium	2009	1.73	1.11	1.73	1.43	1.26	1.54	1.09	1.39	1.14	1.30	1.34	1.29
High	2010	1.72	1.42	2.45	2.39	2.48	3.24	2.88	2.89	2.00	3.54	4.14	2.62
Medium	2010	1.56	1.06	1.50	1.36	1.32	1.71	1.09	1.54	1.20	1.50	1.37	1.31
High	2011	1.59	1.38	2.41	2.31	2.61	3.81	2.37	3.07	1.72	2.93	3.94	2.62
Medium	2011	1.58	1.07	1.55	1.36	1.36	1.75	1.18	1.52	1.21	1.60	1.36	1.36
High	2012	1.67	1.54	2.22	2.23	2.47	4.07	2.35	3.34	1.80	2.84	3.55	2.62
Medium	2012	1.66	1.20	1.60	1.41	1.42	1.84	1.23	1.48	1.32	1.57	1.36	1.41
High	2013	1.55	1.45	2.01	2.05	2.44	4.10	2.22	3.44	1.92	2.80	3.31	2.60
Medium	2013	1.68	1.28	1.66	1.47	1.53	1.97	1.26	1.57	1.55	1.40	1.29	1.48
High	2014	1.51	1.13	1.91	1.80	2.76	4.59	2.43	3.75	1.76	2.77	3.82	2.62
Medium	2014	1.64	1.37	1.74	1.59	1.65	2.10	1.28	1.74	1.78	1.34	1.34	1.60
High	2015	1.45	1.03	1.96	1.91	2.69	4.25	2.51	3.49	1.85	2.86	3.98	2.64
Medium	2015	1.71	1.30	1.77	1.58	1.64	2.15	1.30	1.74	1.76	1.42	1.33	1.64

Figure 10. Ratio of Relative wage earned compared to low educated workers. Authors' calculations based on EU KLEMS database

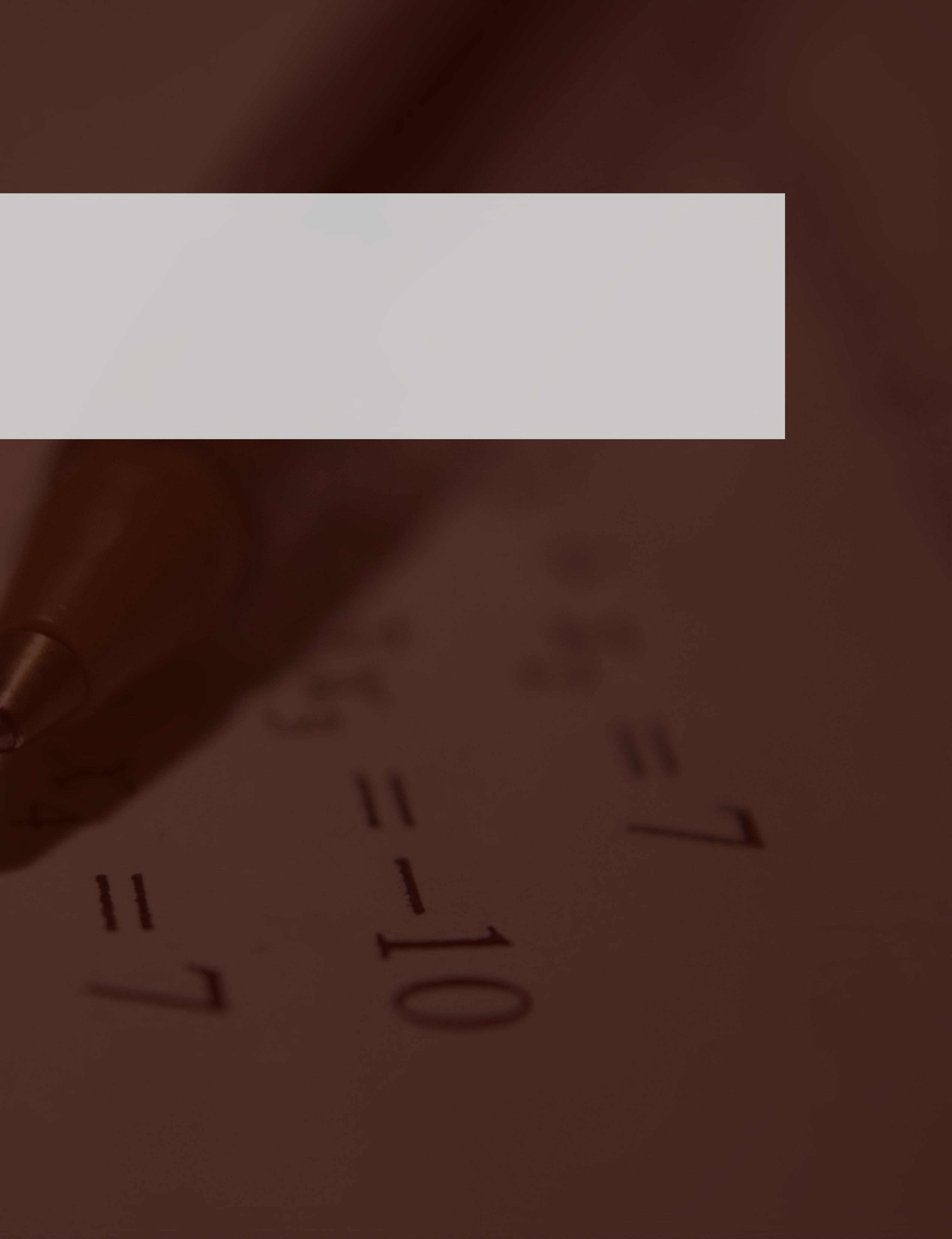
year/sector	A	B	C	F	G	H	I	J	K	R	S	MARKT
2008	0.92	1.09	1.53	1.81	2.15	2.57	2.51	2.00	1.61	2.21	2.92	2.17
2009	1.00	1.30	1.49	1.76	2.00	2.43	2.73	2.02	1.73	2.65	2.95	2.13
2010	1.10	1.34	1.63	1.76	1.88	1.89	2.64	1.87	1.66	2.36	3.01	2.00
2011	1.01	1.29	1.56	1.70	1.91	2.17	2.01	2.02	1.42	1.83	2.90	1.93
2012	1.00	1.28	1.38	1.58	1.74	2.21	1.91	2.27	1.36	1.81	2.62	1.86
2013	0.93	1.13	1.21	1.39	1.59	2.08	1.76	2.19	1.23	2.01	2.56	1.76
2014	0.93	0.82	1.10	1.13	1.68	2.18	1.90	2.16	0.99	2.06	2.85	1.64
2015	0.85	0.79	1.10	1.21	1.64	1.98	1.93	2.00	1.05	2.01	2.99	1.61

Figure 11. Ratio of Relative Wage earned by high educated vs medium educated workers. Authors' calcualtions based on EU KLEMS database

Source	SS	df	MS			
				Number of obs	=	710
				F(11, 698)	=	287.64
Model	309.16796	11	28.1061782	Prob > F	=	0.0000
Residual	68.2038398	698	.097713237	R-squared	=	0.8193
				Adj R-squared	=	0.8164
Total	377.371799	709	.532259238	Root MSE	=	.31259

lnlp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Ed_High	.015856	.0019874	7.98	0.000	.0119539	.019758
Ed_Medium	.0037623	.0008206	4.58	0.000	.0021511	.0053735
Year	-.0184432	.0041349	-4.46	0.000	-.0265615	-.010325
Age_29	-.0123068	.002134	-5.77	0.000	-.0164967	-.008117
Age_29_49	-.0007223	.0027884	-0.26	0.796	-.0061969	.0047524
Male	.0064973	.0009809	6.62	0.000	.0045715	.0084231
Country	-.0049797	.0122665	-0.41	0.685	-.0290635	.019104
Sector	-.0364193	.0060522	-6.02	0.000	-.048302	-.0245365
lnintkh	.0542232	.0130263	4.16	0.000	.0286477	.0797986
lncapithcit	.1183837	.0119091	9.94	0.000	.0950018	.1417656
lncapnithcit	.2751699	.015162	18.15	0.000	.2454014	.3049385
_cons	-2.475721	.1804376	-13.72	0.000	-2.829986	-2.121455

Figure 12. Regression Results, when using WLS estimators



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