The effects of technological change on labor markets: College wage premium in Europe.

Ángel Sánchez Daniel

Master in Labour Economics

Supervisor: Prof. Vahagn Jerbashian

June 2021

Abstract

Technology has affected the demand for skills and disrupted labor markets . In particular, the evidence suggests that technological change has led to job polarization by increasing the demand for high- and low-wage occupations at the expense of medium-wage occupations. This thesis builds on the hypothesis that different types of technologies can affect the evolution of skill premium differently. More specifically, it explores the effects of different types of technological capital on skill premium in 17 European countries from 2008 to 2017. Research on this topic is less abundant in Europe than in the US and usually utilizes older databases. The contribution of this study is the analysis of the skill premium with updated information and various types of technological capital. The results show that intangible assets have positive and statistically significant effect on skill premium. IT complements high-educated workers in retail, transportation, construction and health industries and CT substitutes high-educated workers in transportation, construction and in public administration industries. Moreover, this thesis explores a comparison of these with previous literature and presents an explanation for the differences and similarities with the results.

Keywords: skill premium, technological change, job polarization

JEL Codes: E24, I26, J31, O14, O33

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1.- Introduction

Technological change has disrupted labor markets. Technical change is behind the changes in the wage structure and employment in different countries, industries, and periods. For example, this process has affected income and consumption, not only labor market outcomes (Autor & Katz, 1999:1465). Inequality increased in the United States (US) in 1963-1993 period and Polarization of jobs expands inequality of earnings and increase employment for occupations at the bottom and top of the wage structure, while employment in the middle part of the distribution sinks. It is taking place in the last decades in the US and other developed countries changing the job structure (Autor et al., 2006:191). Research suggest that Information and communication technologies produce job polarization. There is evidence of a specific gender component due to women's increasing participation in the labor market (Cerina et al., 2021:2). In Europe, similar results for job polarization linked to technological change were found by Goos et al. (2009) for 16 countries from 1993 to 2006, but for Fernández-Macías (2012) the hypothesis of job polarization can be partially rejected, some countries experience this pattern while others experience opposite results.

Literature has focused in particular on the impact of Information Technologies (IT) on job polarization, even considering personal computers as a technological revolution (Beaudry et al., 2010). Some findings relate the falling in IT prices with a decline in middling occupation in Europe (Jerbshian, V. 2019:1095). These technologies increase inequality of earnings. They substitute middling occupations and routine tasks, but they complement low-paid occupations and non-routine tasks.

Then, other technologies impact labor markets in different ways than IT does. For example, Non-ICT and Communication technologies (CT) complement different skills. More recently software and Artificial Intelligence (AI) have effects on the labor market. The effect depends on the complementarity to skills of technical change induced by AI and the substitution elasticity between labor and capital. (Ernst et al., 2019:13).

This study explores the effects of different types of technological capital on university wage premium, constructed as the ratio between wages of high-educated workers to low- and medium-educated workers. Low-educated workers are those with primary studies or lower, medium educated workers are those with secondary or vocational studies and high-educated workers are those with tertiary studies, which is at least a university degree. My work contributes to the literature and complements it with this additional empirical analysis on the effects of various technologies on the demand for labor in European countries. Most of the literature revised focuses mainly on the US. It is more difficult to find analysis for European countries in this field, which remarks the relevance of this study. New technologies such as software, AI, and intangible technologies such as research and development and innovations are expected to complement university-educated workers and increase their labor demand and wage premium. ICT technologies can complement university-educated workers but also increase labor demand of less-educated workers.

The data is from the EUKLEMS 2019 database. The analysis of this study focuses on 17 European countries from 2008 to 2017.[1]Net capital stocks at current and nominal prices within industries and countries are necessary to compute the effects of technologies on skill premium. This study explains the effect of different capital technologies on college wage premium using a country- and industry-fixed effects empirical specification.

The conclusions section will explain the positive effects of intangible assets such as software, innovative properties, and research & development on skill premium. Information and communication technologies (ICT) and Non-ICT do not affect college wage premium during this period in the Eurozone.

2.- Literature revision

There exists an enormous debate about how the technological change can affect the labor market. Some fear the employment losses derived from the substitution of many jobs, while others are convinced that the increase in productivity will be related to increases in wages and employment shares. Literature investigating the relationship between technological change and wages gained importance several decades ago in the US, motivated by changes in the distribution of earnings and returns to college education (Acemoglu & Autor, 2011:1044). The returns to university education or wage premium to college are measured as the ratio between wages of workers with university education and wages of workers with lower education. The number of college-educated workers

[1] The sample of countries is the following: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Spain. All of them use the Euro as a local currency.

increased in the US in the 1960s and 1970s. When the availability of highly educated workers increases, we should expect a fall in the wage premium in the labor market due to the excess of supply of this group. Surprisingly, what happened was the opposite, returns to college grew up at the same time as the high-educated labor supply did.

Acemoglu (1998) developed his hypothesis for this counterintuitive behavior. Technological change played an important role by being biased in favor of high-educated workers. According to his hypothesis new college graduated workers available in the US labor market firstly shifted labor supply to a new equilibrium with a lower wage premium than in the initial situation. Then, when college-educated workers' supply started to grow, the market for skill-complementarity was larger and affected the production of technology by biasing it in favor of this group of workers. Technology firms found it profitable to build their technology in favor of this mass of new college graduated workers. Skill-biased technology produced an upwards shift in labor demand of this type of workers what affected positively the wage premium that increased at higher levels than in the initial situation. Changes in earnings may be motivated by the increase in the labor demand for college graduates seen in the late 1960s and 1970s in the US and induced by technology. (Acemoglu, 1998:1057). Michaels et al. (2010) tested this hypothesis and found that industries with faster growth of ICT had greater increases in relative demand for high educated workers.

When technology induces an increase in the relative demand for one type of worker (e.g. college-educated workers) the technological change is skill-biased. Acemoglu's hypothesis of the increase in wage premium is determined partly by a technical change biased towards skills complementing high-educated workers (Acemoglu, 2002:806).

But this is a hypothesis of a historical example of the US, technology can complement different skills and tasks. For example, as IT lower the cost of knowledge acquisition incurred by individuals, the relative wage or relative employment of individuals occupying a certain hierarchical layer may increase as they become less dependent on their superiors but may decrease as their subordinates become less dependent on them. Similarly, CT may increase relative wages of individuals because they can leverage their knowledge as a result of the greater dependence of subordinate workers on them but also can decrease relative wages of individuals because of an increase in their span of control of subordinates. The effects of technology can be different, and this is the reason why SBTC complements or substitutes the task composition of the different occupations.

Changes in task composition of occupations also affect the education attachment of the workers. They will increase their educational levels and their skills just in the case where technology complements more educated workers.

The skills are difficult to measure, but the economic literature usually accounts for skills depending on education level, for instance, primary studies, college degree, or university degree, but can be divided into many other different ways. In the case of this study, college-level is used as a proxy variable of skills. Different types of tasks are related to different skills. The research about how technological change affects employment is focused on what tasks can be complemented or substituted.

One of the pioneering studies about technology-skill complementarity is Autor et al. (2003). The authors of this study analyzed how computing capital substituted workers carrying out a limited and well-defined set of cognitive and manual activities but also complemented workers in carrying out problem-solving and complex communication activities (Autor et al., 2003:1280). The first set of activities are called routine tasks and include, for example, repetitive customer service (e.g. bank teller occupation), repetitive assembly, or calculation. Then, the second set of activities are called non-routine tasks and include, for example, supervision control, testing hypothesis, medical diagnosis, legal writing, or truck driving. Jobs are defined by tasks which are units of work activities that produce output (Acemoglu & Autor, 2011).

Studying technological change led to an explanation of which tasks can be complemented and which of them can be substituted. Different technologies complement or substitute tasks but not always in the same direction. Activities performed at work differ depending on the job and can be divided, not only between routine or non-routine they can be divided between cognitive and manual or interpersonal.

Routine tasks are those that involve clear rules to be executed by a machine, and non-routine tasks do not have clear rules, and they usually have a huge component of interpersonal skills that are more difficult to be modeled. Routine tasks can be performed by different types of workers. For example, ICT has complemented non-routine analytic tasks but substituted for routine tasks while not affecting non-routine tasks (Michaels et al. 2010). Moreover, the assembling of car pieces is usually performed by low-skilled workers, and the accountability of a firm is usually performed by a high-skilled worker. Both have clear rules. Some authors call this Routine-biased technological change rather than skill-biased because it replaces this type of task. In general, routine tasks are concentrated in the middle of the skill distribution and they are more likely to be substituted by technologies.

Similarly, non-routine tasks can be performed by different types of workers. For example, the waiter occupation is usually performed by low-skilled workers, and most firm managers are highly skilled. This kind of job does not have clear rules and an interpersonal component.

Different technologies perform different tasks, for example, literature usually analyzes which of these tasks can be performed by computers using the Dictionary of Occupational Titles. For example, ICT complement non-routine tasks and displace routine ones. Moreover, it formalizes why computers increase the demand for educated workers in a task framework (Autor et al., 2003). These technologies have expanded for the last forty years, and the reduction of its costs produced a technological change, complementing skills and polarizing jobs. But in recent years, both technologies have different effects on employment. IT decrease relative demand for medium-skilled and younger workers and increase labor demand for high-skilled, low-skilled, and oldest workers. CT exerts opposite effects, it complements medium-skilled workers, and replaces high- and low-skilled tasks (Blanas, 2019).

ICT operates increasing the labor demand for high skill-employees, replacing other workers from their tasks (Autor, 2013). In this case, we need to include manual or cognitive tasks for the analysis of how technology affects skills. The key here is if the job contains some routine tasks and how displaceable they are. IT led to an increase in the demand for high skilled workers because they only displaced routine tasks performed mainly (but not completely) by medium-skill workers.

Routinization is a hypothesis in which routine tasks are replaced by technology. These tasks are mostly performed by medium-paid workers. Routinization produces low employment shares in the middle of the wage distribution and an increase in high- and low-paid occupations. For example, computing technology complements non-routine tasks and increases high-skill labor demand. In this case, improvements in computing technology substitutes for routine tasks, which are mostly located in the middle of the distribution will lead to a polarization of jobs, employment shares will increase at both extremes and reduce at the middle of the distribution.

In the past, traditional technologies were used to complement routine tasks. For instance, workers in a factory improve their productivity when a machine was added to the production process. This led to employment gains for workers in this kind of task. Adding technology to the firm increased the productivity of the workers and due to this their labor demand was high. But an increase in the power of computation and the storage capacity (Ernst et al., 2019:13; Naudé, 2019:7) is leading to a strong decline in ICT costs lead to an increase in the adoption of new technologies.

In summary, ICT will increase labor demand for high- and low-skilled workers but decrease labor demand for medium-skilled workers. In the other cases, there will be changes in the wage structure and employment shares, labor demand can increase for some workers and decrease for others.

But Skill biased technological change (SBTC) hypothesis cannot fully explain job polarization by itself, it is necessary to include routinization. Skill-biased technological change (SBTC) explains how the demand for skills is linked to technology generating a bias in favor of some groups with the same skills (Acemoglu & Autor, 2011:1044) and routinization explains how technology relace more routine tasks and complement non-routine ones.

Polarization of jobs increases employment shares among the low and high skilled but not among medium-skilled workers. This leads to increases in wages at the extremes of the wage distribution, at the bottom and the top, which could imply an ongoing increase in inequality (Autor & Dorn, 2013:2; Buyst et al., 2018).

This is also happening in Europe, since the early 1990s Europe, like the United States and the United Kingdom, has experienced this process (Goos, et al., 2009:62). Their work develops a model for the effects of RBTC and offshorability on job polarization. Both are positively correlated, which implies that more routine occupations are more likely to be routinized. These occupations are usually those that are in the middle of the wage structure.

Jerbashian, (2019), explores changes in shares of employment associated with the fall in IT prices due to technological change. His results corroborate the polarization hypothesis (Jerbashian, 2019:1113). Furthermore, differences among gender and age groups are found.

For Fernández-Macías (2012), the European case seems to be different. This author argues that job polarization in Europe is less clear. In his work, he shifts the unit of analysis from individuals to jobs using the same methods as Goos et al. (2009). The author concludes job polarization just for the Netherlands, France, Germany, and Belgium. There appears an upgrading tendency with improvements in employment shares just for high-paid occupations in Finland, Luxembourg, Sweden. This behavior is more consistent with SBTC in favor of high skilled workers. Then, Mediterranean European countries and Ireland show a mid-upgrading tendency. In this area, employment shares in low-paid occupations are declining or increasing slightly while in middle and high-paid occupations are increasing strongly (Fernández-Macías, 2012:173).

This study concludes with very different patterns within countries. All of them face an increase in the employment shares on the top of the wage distribution, but what occurs in the middle and the bottom of the distribution depends on each country. Continental countries are associated with polarization, Scandinavian ones with upgrading, and southern countries with an increase in middling occupations too.

Some authors as Revenga (1992) argue that offshorability also affects labor demand in the same direction as routinization, increasing employment shares at the top and the bottom of the wage structure and decreasing it at the middle. During the 70's and the 80's in the US manufacturing employment and standards of living fell steadily while the ratio of imports to total domestic supply almost doubled. (Revenga, 1992:1) This pattern seems to be behind the call for more protectionist policies.

ICT allow workers to perform the same tasks in different ways than they are usually performed. This technology also make some tasks easier to perform. For example, some internet networks and computers allow for connections without being in the same place. Labor import competition and new technologies expand labor supply for the firms, they can hire personnel outside the borders. Most of the top offshorable jobs are medium-paid, which is consistent with the job polarization.

Task offshoring explains part of SBTC joined with the replacement of routine tasks, but some argue that both are correlated. Goos et al. (2014) found a correlation coefficient of 0.46 and statistically significant, which implies that routine tasks are more likely to be offshored.

Offshorability is changing traditional trade, nowadays services can be also traded. Productivity can enhance with the set of tasks able to be offshored. (Grossman & Rossi-Hansberg, 2008).

Revenga (1992) studied empirically the impact of offshorability on wages and employment. He used the fall in the price of imports between 1975 to 1985 as a natural experiment to show how it negatively affected both. Changes in import prices have had a significant effect on both employment and wages.

Technological change will probably displace some workers in the short run from their jobs. This will turn into lower levels of employment (Blanas et al., 2019:1). This new technology induces a structural break in the labor market.

Mobility across sectors and places will increase and in the short run, this change will translate into job losses. To avoid this impact, workers in displaced sectors should re-train themselves and re-allocate their effort into the new tasks complemented by the technology.

Changes in employment shares may differ depending on the industry. More routinized industries will account for job losses as their tasks will be replaced by technology. There is evidence about a decrease in employment shares in manufacturing, which is a routine industry, but an increase in employment in services industry, which is a non-routine industry (Blanas et al., 2019:1). In the case of non-routinized industries, the pattern will be the opposite. Technology complementarities derive in an labor supply increase. This has effects on the mobility of employees across sectors. Workers replaced by technology will become active in looking for public or private training programs to perform better in their new industry due to occupational mobility.

Employees who are not replaced from their jobs or those whose marginal product is not affected by technology should train themselves in different types of tasks. Furthermore, labor demand is more likely to improve in some sectors, while in others it can be reduced. Replaced workers, who are usually medium-skilled must look for new job opportunities at occupations at the top or the bottom of the wage structure. This will imply training themselves in different tasks than those that they had been performing before.

Even with gains and losses of jobs in the short run, there is the expectation that in the long run, the result will be positive for most of the workers, and employment rates should increase. The spread of new technologies does not necessarily imply a general decline in the well-being of workers, for example in terms of labor conditions (deCanio, 2016:289).

In the short run, the effects of technological change will depend on the type of worker, the tasks involved in his job, his skill level, and the sector. Workers involved in routine manual tasks, but workers involved in non-routine interpersonal tasks will be benefited a lot. In the long run, the increase in productivity and the reallocation of workers will rebalance the equation and the result will be higher benefits from AI to unemployment (Autor, 2019:1).

Then, the effect of technological change on wages will depend on task-based models. They include significant declines in real wages of low-skill workers and non-monotone changes in different parts of the earnings distribution, accompanied by shifts in the composition of employment (Acemoglu et al., 2016:1046). Notably, while factor-augmenting technical change progress always increases wages in general, it can reduce wages of certain groups. This issue impact skill premium, the decline in real hourly wages of low-skill workers provide an scenario in which technology increase the difference between earnings of high-educated workers and earnings of low-educated workers.

The composition of skills available in the labor market and the allocation of skills have changed in the US and European Union. The explanatory power of this fact in accounting for wage differences is increasing. Labor supply of skills is strongly related to wage premium, for example, an increase in the supply of a group of workers may turn into an excess of supply what makes the supply of the other groups scarcer.

Relative wages of high to low skill workers are determined by relative supplies, labor demand and task allocations. Wage inequality across the earnings distribution increased over the past decades in the United States (Acemoglu et al., 2016). There exists a positive trend for wages at the top and the bottom of the income distribution (Autor et al., 2006:1). It appears the opposite tendency for medium-paid occupations.

Wage distribution and income shares of different types of workers are changing dramatically with technological change. This implicates an increase in total inequality. Adachi et al. (2020) empirically study automation in Japan from 1978 to 2017, and in this case, they found positive effects of automation on employment. They argue that the differences with literature are due to scale effects in each industry.

In summary, technology may lead to changes in employment and wages depending on the routineness and the level of offshorability. The impact of the technology will depend on the type of tasks, for example, routine or non-routine, in which it is involved. But most of the literature argues that technological change has the potential to increase the “size of the pie”. As different workers have different skills and abilities, each type of job contains different tasks. The market will demand different types of workers as technology changes.

3.- Data

EU KLEMS database is managed by the Vienna Institute for the International Economic Studies (wiiw) and was financed by the European Commission DG Economic and Financial Affairs. Its repository includes information about economic output, productivity, capital formation, employment, and technological change for all European Union members, Japan, United States, and the United Kingdom. Technological change, capital formation and wages data provided by EUKLEMS 2019 ensure a correct creation of college wage premium and the effects of different capital assets on it.

Data is available for the country, year, and industries for most of the series and also contains information about gender, age, and skill level of workers in labor statistics. It also contains differences for five groups of capital assets (Stehrer et al., 2019).

This database provides the necessary elements for the study of the college wage premium in Europe in recent years. It also uses the NACE Rev.2 industry classification. For example, it contains data for capital formation and capital stocks by asset types for all industries. EUKLEMS 2019 consists of different databases: the capital input account containing gross fixed capital formation and capital stocks; the national account containing values, prices, and volumes for gross value-added, gross output, intermediate inputs, compensation of employees, number of workers, and hours worked; the growth account containing information of value-added. These files include country, industry, and year information. Finally, the labor account contains wage and employment shares for gender, age group, and educational attainment.

This study uses information from 17 Eurozone members from 2008 to 2017 to analyze the relationship between net capital stocks and college wage premium.

EUKLEMS 2019 repository provides data for all assets capital stocks. Assets are disaggregated between computing and communications equipment, cultivated assets, computing equipment, non-residential investment, research and development, residential structures, computer software and database, transport equipment, other machinery investment, and other innovative productive products (IPP) assets.

Furthermore, disaggregated Gross Fixed Capital Formation, prices indices, and volumes are also available for these types of capital what makes EUKLEMS 2019, which has a large and complete database in capital formation and technology, a proper database for analyzing the effects of different types of capital.

Information on gross value-added, capital and labor compensation, the total amount of hours worked and employees, allows for the analysis of the effects of different technologies on the economy; and the information on employment and labor shares by education level, gender, and country allows us for checking SBTC in European countries.

4.- Theoretical framework

I provide a simple model based on (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018). The model uses their approach, but it is developed to include the possibility of different technologies to affect wages. We are in an economy where workers and technology are needed to produce a unit of output. The environment in all markets, including the labor market, is competitive.

A set of tasks are allocated in the production process to production. There are three different types of workers, high-skilled, medium-skilled, and low-skilled which are imperfect substitutes.

$$Y = \tilde{B} \int_0^1 y(i) di$$

Where Y is the unique final good, and y(i) the production of works in task i and reflects the continuum of tasks in the unit interval [0, 1] whose combination produces the output. This is a simplistic vision of the production, just depending on tasks. $\tilde{B}$>0 is the path of growth for the production.

We have the aforementioned three types of factors of production, high, medium, and low-skilled workers, L, M, and H, respectively. Furthermore, technology and capital are introduced in the model.

Each task pursues the following production function:

$$y(i) = \tilde{B}[A_L\alpha_L(i) + A_M\alpha_M(i) + A_H\alpha_H(i) + A_K\alpha_K(i)k(i)]$$

In this equation A terms represent the technology augmenting the production from each type of workers, and α terms are the productivities parameters for the different factors of production in task i.

First, we ignore capital and technology, so $\alpha_K(.)$=0. Let denote the price of services of the task. If we set the price of the final unique good to one, we have:

$$\int_0^1 p(i)di = 1$$

Where p(i) are the price services of task i. Finally, in equilibrium in competitive markets from the production function we obtain salaries for different factors of production:

$$w_L = p(i)A_L\alpha_L(i) \text{ for any } i<I_L$$

$$w_M = p(i)A_M\alpha_M(i) \text{ for any } I_L<i<I_H$$

$$w_H = p(i)A_H\alpha_H(i) \text{ for any } i>I_H$$

Where I is the threshold in which one type of worker has a productive advantage and these tasks will be performed by that type of worker. This threshold will appear in equilibrium for the structure of comparative advantages.

But this theoretical framework based on Acemoglu & Autor (2011) and Acemoglu & Restrepo (2018) does not allow for different technologies within the same group of workers. Different technologies can augment the output in different ways. It is necessary to consider k types of capital to formalize the effect on wages. Technology has different effects on production depending on the task in which is introduced and the skill level of the worker, they can augment production for low-, medium-, and high-skilled workers in different ways. Production of each type of worker will depend on skills, tasks, and technology.

$$y(i) = \tilde{B}\left[A_L^k\alpha_L(i) + A_M^k\alpha_M(i) + A_H^k\alpha_H(i) + A_K\alpha_K(i)k(i)\right]$$

Following this equation, wages will depend on the productivity parameter of different factors of production, the price of services in task i, and in k types of technology. Now, there is more than one type of technology.

$$w_L = p(i)A_L^k \alpha_L(i) \text{ for any } i<I_L$$

$$w_M = p(i)A_M^k \alpha_M(i) \text{ for any } I_L<i<I_H$$

$$w_H = p(i)A_H^k \alpha_H(i) \text{ for any } i>I_H$$

In this case, I threshold will differ depending on which technology is used. The ratio between wages of different workers will change with technology. This work aims to study the evolution of college wage premium when allowing for different types of capital. Factor augmenting technology will be different for each technology and each type of worker. Wage premium will change depending on which type of workers augment more their production relative to the others.

Wage premium is the ratio between wages of high to low skilled workers. If we consider low- and medium-skilled workers in the same group and constant prices, we have the following equation for college wage premium:

$$Wage\ premium = \frac{w_H}{w_L} = \frac{A_k \alpha_H}{A_k \alpha_L}$$

In summary, wage premium to college will depend on the productivity of each group of workers but also on the technology. There would be technologies complementing low-skilled occupations that reduce wage premium or the opposite, technologies complementing high-skilled occupations that increase wage premium.

5.- Descriptive analysis

This study analyses the impact of different types of net capital stocks at current and nominal prices in economic and labor market outputs from the information of 17 European Union members during the period from 2008 to 2017, focusing on the evolution of wage premium in the last years.

Technological change is elated to ICT, which in this framework are communications and computing equipment. Capital stocks depend on the technology in which the country or industry is specialized as well as in prices and currency.

The purpose of the empirical model is to provide the effect of different technologies on wage premium using real hourly wages. The EUKLEMS 2019 database provides information on capital stocks for ICT which include both communication and computing equipment, and non-ICT which include Residential structures, total non-residential investment, machinery equipment, transport equipment, and cultivated assets, and finally, intangible assets which include Research and development, Computer software and database, and Other IPP assets. The split in the aggregation may be useful to conclude better which of the capital stocks have effects on wage premium. For example, is may be the case that ICT technologies do not affect wage premium, but IT and CT have statistically significant effects.

5.1.- Capital stocks and countries.

The relationship between technology and labor outcomes differs across countries as can be seen in the dataset. Capital stock values are displayed in millions of Euros. All countries in the sample belong to the Eurozone and they use the Euro as a currency for the measurement of these capital stocks.

Table 1.- Capital stocks for 19 Eurozone countries

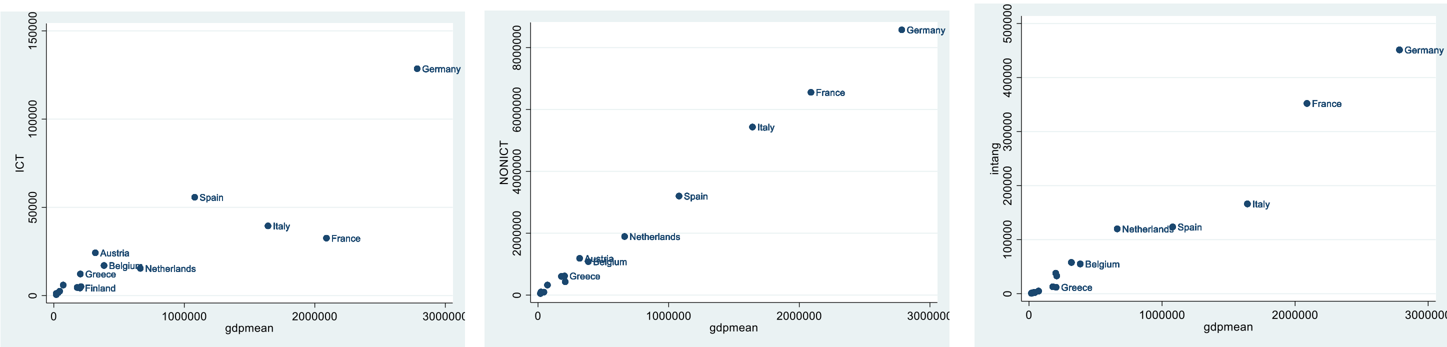
country	K_ICT	K_NONICT	K_CT	K_IT	K_Cult	K_OCon	K_OMach	K_RStruc	K_TraEq	K_OIPP	K_RD	K_Soft~B	K_GFCF
Austria	4377.593	191472.3	3694.604	682.989	254.3276	101825.1	20461.99	63659.31	5271.54	174.0257	7367.363	2843.589	206234.8
Belgium	2761.142	144944.5	1196.147	1564.994	43.59617	53076.55	25614.26	59996.94	6213.204	263.0191	6035.961	1328.613	155333.3
Cyprus	578	53987.35	213.25	58.2127	8.279365	3084.257	5710.45	4331.543	576.6762	141.25	447.5778	328.2889	58335.72
Estonia	214.6751	8413.615	181.0677	33.60741	6.152381	4072.179	1095.131	2696.234	543.9196	13.89312	129.7153	53.66243	8825.568
Finland	799.7429	92674.06	535.6524	264.0905	32.57143	39207.22	10815.16	39868.73	2750.371	301.5667	5656.367	951.5476	100383.3
France	6037.543	989686.7	4369.276	1668.267	4414.571	302271.4	82520.42	575537.2	24943.12	1000.538	40118.38	24458.42	1061317
Germany	23528.48	1342369	10445.61	13082.88	1776.305	503573.6	138230.4	637510.1	61278.79	2735.238	68879.93	11312.73	1448826
Greece	2235.304	97209.44	1618.561	616.7423	112.5016	31103.06	8656.152	46957.55	10380.17	557.4079	946.9487	455.4127	101404.9
Ireland	5082.722	430243.2	1966.256	3116.467	434.273	20081.22	24461.41	30837.98	13082.46	805.9778	29673.49	2504.956	75617.24
Italy	7221.591	865774.8	3997.391	3224.2	1185.188	359415.7	99989.53	380453.9	24730.5	1904.474	16546.64	10959.94	902510.6
Latvia	170.5476	16615.42	105.9212	64.62646	12.96455	9115.072	1589.996	5100.49	796.8931	226.6778	638.2	55.16142	103259.7
Lithuania	293.0704	15254.38	158.9841	134.0862	23.06243	9328.263	1398.338	3615.232	889.4862	154.132	118.8598	118.8598	15902.03
Luxembourg	457.7376	15544.69	129.8095	327.9281	6.300952	8684.88	1171.402	3804.184	1877.927	9.94619	236.8071	149.5767	16400.02
Netherlands	2713.31	1442105	364.9	2348.41	2332.3	117331.9	38436.75	387096.6	10948.4	1336.112	12579.02	7586.662	320408.7
Portugal	4606.7	604030	3078.922	1527.778	1302.694	50763.82	17996.57	39051.68	2051.889	874.7111	9413.778	2542.133	99505.36
Slovakia	1086.094	54535.24	544.7071	541.3867	1654.574	32333.89	7289.412	11063.64	2193.719	151.7538	410.2181	235.8467	56419.11
Spain	11619.64	631098.4	8522.594	3097.049	1632.819	267295.2	57374.44	282649	22146.96	1643.282	14884.26	9062.245	668307.9
Total	4386.4	344834.1	2410.699	1863.945	786.8475	110454.4	35037.51	139772.5	11045.66	742.8125	13057.02	4747.533	339219.4

Source: EUKLEMS 2019

Table 1 shows the levels of different types of capital stocks by country. Differences appear depending on the type of capital stock, the country, and the capital technology specialization of each country. For example, Cyprus has a lower level of capital stock compared to the rest of the countries when computing all assets. On the contrary, Cyprus do not have the lowest value in some technologies such as innovative properties. This fact can be related to a multitude of variables, such as, for example, the size of the country, the economic development, or maybe the public and private expenditure on capital could drive their capital stocks.

Then, Germany is the country with the highest capital stock for all assets. Numerous variables can drive their results such as GDP or country size. It is the country with the highest GDP in Europe. Graph 1 shows how different assets are distributed depending on the GDP if the country. The relationship is positive for ICT, non-ICT and intangible assets. In the case of non-ICT assets this relationship is almost linear, while for intangible and ICT assets, there are more dispersion.

Graph 1.- ICT, non-ICT, and intangible assets by GDP.



Source.- EUKLMES 2019 and Eurostat

Table 2 shows these two countries with differences in terms of capital stocks. The quantity of the differences can drive most of the regressions. The table shows the test for the difference in means of these two countries as an example to explain that countries are different, and these differences can drive the results of the empirical model.

Table 2.- Test for the mean differences of Germany and Cyprus.

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Cyprus	9	58335.72	833.8323	2501.497	56412.9	60258.54
Germany	10	9154536	239507.5	757389.3	8612733	9696340
combined	19	4845810	1077539	4696886	2581983	7109636
diff		-9096201	253205.8		-9630418	-8561983

```
    diff = mean(Cyprus) - mean(Germany)                      t = -35.9241
Ho: diff = 0                                degrees of freedom =       17

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Source: EUKLEMS 2019

It is necessary to include these differences in the model. Otherwise, the error term of the equation will increase, and coefficients will be biased.

Fixed effects allow the model to include dummies for each country and compute the effect of capital stocks in college wage premium. Differences between countries imply the need to control and account for that in our model. Country-fixed effects allow for controlling between differences. This ensures that the results are not driven by some countries with higher or lower values for each. The motivation for this specification is according to this prior analysis about the variability in the values across countries and industries. Unobserved variables such as the size of the country or public investment affect capital stocks and using random-effects include this variability in the error term.

5.2.- Capital stocks and industries

Table 3.- Capital stocks for each industry.

industry	K_ICT	K_NONICT	K_CT	K_IT	K_Cult	K_OCon	K_OMach	K_RStruc	K_TraEq	K_OIPP	K_RD	K_Soft~B	K_GFCF
Accommodation & food	568.5972	33035.98	298.9927	257.9196	6.677512	57422.39	10998.23	144.1995	1209.81	3.672495	43.47703	387.311	74624.7
Agriculture, forestry & fishing	329.8209	81445.83	117.5683	202.823	18979.67	203665.2	62770.23	272.956	15656.58	71.75138	1070.583	237.7647	317165.4
Arts, entertainment & recreation	893.1212	41455.33	438.0915	434.0184	424.6248	40286.16	4919.342	30.07487	551.9832	2173.824	1246.228	563.3951	53684.64
Construction	680.5735	64052.18	218.7602	441.4567	13.45072	89177.37	24131.81	13631.74	13459.44	105.2898	624.0138	816.6134	149308.6
Education	1256.216	106497.2	355.2708	862.3026	8.766986	188362.4	15167.57	1115.211	1420.702	16.13135	16426.43	1760.318	238091.8
Energy supply	2136.377	130696.4	1649.624	464.3204	69.437	185929.8	86196.91	65.76021	1886.567	5.636402	975.3798	1839.656	289348.2
Finances & insurance	1842.7	40613.81	532.3108	1254.324	3.891388	63011.81	9645.189	3240.739	2594.401	15.09905	1117.722	13224.44	98215.08
Health and social work	1720.208	96149.9	647.3857	1025.268	7.882297	122955.9	26094.03	3373.025	2324.467	27.97798	3022.907	1255.022	168488.2
Information and communication	7283.739	55234.09	4884.908	2293.907	12.20287	200444.3	58363.39	6.1265	4660.439	14561.05	8477.969	19079.4	321993.2
Market economy	36990.96	6007935	18487.03	17774.09	19745.99	3179941	968059.7	1700886	265331.9	19890.34	175100.3	71917.18	6582048
Mining and quarrying	187.0196	21157.89	74.35467	107.6502	1.954545	22589.45	14137.09	35.8215	741.3138	1986.994	240.8288	130.6355	41001.82
Other service activities	510.8166	19045.85	126.2118	366.7372	1.359	90951.47	4884.714	185.2801	1400.226	.3855978	928.6443	772.3785	106879.9
Professionals and scientifics	5806.406	84600.66	2372.487	3282.037	32.93437	96725.05	36356.9	11472.77	29548.28	262.6057	45092.88	8797.432	233792.5
Public administration & defence	2478.954	373630.8	887.168	1525.997	30.50966	1104032	73205.18	3382.819	10201.3	47.59567	5220.705	5899.41	1288786
Real estate activities	833.4118	1647610	367.3548	445.3178	18.53971	191811.8	11272.72	2439847	2447.239	119.6008	247.1089	692.0609	2859053
Total manufacturing	7823.963	278111.4	4011.085	3643.423	201.0301	383929.8	465230	365.696	21159.53	2117.696	101674.3	13175.66	992079.8
Transportation and storage	2135.741	242401.3	1115.272	975.3589	22.53397	354054.9	55284.38	33.913	119754.9	13.31209	790.9047	3147.96	568655.7
Water supply & derivates	642.8889	70218.11	448.4652	185.3889	3.9435	140239.6	15750.67	76.81832	4008.309	2.167754	473.4889	528.787	172730
Wholesale & retail; repairs	3066.968	110627.7	1163.883	1819.44	57.02344	190639	69841.62	207.195	38166.19	471.7874	8550.664	6709.122	329716.2
Total	7401.055	1166293	3679.377	3559.349	4207.408	635470.4	193075.8	405797.5	51172.9	4068.852	36213.99	14639.08	1366109

Source: EUKLEMS 2019

Following the same pattern as in the previous subsection, table 3 shows different capital stocks depending on the industry. There can be found differences depending on the type of capital stock, the industry, and the type of technology associated with each industry. For example, mining and quarrying have a lower level of capital stock when computing all assets. This industry needs few capital stocks to operate. Huge differences are depending on the industry. Real estate activities are the industry with the highest capital stock. The reason for this high value may be the high value of the services provided in this industry, related to buying or selling land or commercial and residential properties.

Then, for instance, the agricultural sector has the highest cultivated assets capital stock and the information and communication sector have high computing technologies capital stock.

Table 4 shows the differences between mining and quarrying and real estate activities in terms of capital stocks. These industries are chosen as an example to show the inequalities depending on the sector.

Table 4.- Test for the mean differences of mining and quarrying and real estate activities.

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Mining a	153	7888.55	868.0171	10736.78	6173.614	9603.486
Real est	153	1114058	125220.1	1548888	866661.2	1361455
combined	306	560973.2	70073.64	1225788	423084.2	698862.2
diff		-1106169	125223.1		-1352583	-859755.4

diff = mean(Mining a) - mean(Real est) t = -8.8336
Ho: diff = 0 degrees of freedom = 304

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000

Source: EUKLEMS 2019.

There are also strong differences between industries that systematically appear. This is the reason why models in this paper will additionally include industry-fixed effects. On top of that, fixed effect for industries allows to avoid biased estimators of the effects in the empirical equation and reduce the error term. This strategy improves the consistency of the coefficients. To do so, the analysis will include a coefficient, excluding all assets group for each industry.

5.3.- Control variables

The empirical equation includes different types of capital stocks. According to the economic model, Tables 5 & 6 show the compensation of employees in millions at current prices, the number of persons employed, the number of employees, both in thousands, gross output and gross value-added, both at current prices, total hours worked by person engaged in thousands, and labor, and capital compensation.

Table 5.- Economic outputs activities depending on the country.

country	COMP	EMP	EMPE	GO	H_EMP	VA	LAB	CAP
Austria	27134.76	752.1354	648.0414	109339.1	1246422	51203.53	32820.71	18382.83
Belgium	28710.76	733.4544	605.5069	122514.7	1158666	51474.04	32088.72	19385.32
Cyprus	1486.543	67.24805	58.20376	6047.382	122941.1	2875.688	1793.876	1081.812
Estonia	1562.116	108.0837	97.72995	6781.936	203720	2877.853	1735.034	1142.82
Finland	17291.99	443.2386	387.35	68228.59	735460.5	30501.66	20583.38	9918.279
France	192103.9	4756.242	4268.437	668955.8	7339531	327603.9	228312.7	99291.13
Germany	252080.5	7421.21	6606.857	939620.9	1.03e+07	448945.2	297696.4	151248.8
Greece	11743.93	770.3173	498.6814	56456.83	1592785	30276.28	18453.64	11822.65
Ireland	13156.19	350.0867	287.7921	80362.22	623603.3	34322.19	16438.5	17883.7
Italy	112365.9	4269.495	3092.596	568034.7	7586914	256097	167753.1	88343.84
Latvia	1774.875	160.4277	140.6479	8133.506	310808.6	3537.572	2027.874	1509.699
Lithuania	2538.378	235.6585	206.6004	10935.16	441263.8	5559.941	2890.536	2669.404
Luxembourg	4035.072	68.80686	64.59243	27409.03	104708.4	7369.43	4284.637	3084.792
Netherlands	57146.94	1565.09	1302.7	231167.9	2247919	106448	71620.47	34827.48
Portugal	13997.29	833.8518	689.8574	58259.38	1571048	27186.14	16676.34	10509.8
Slovakia	4980.32	404.0829	339.6954	31581.03	718842.4	12086.47	6225.462	5861.007
Spain	91601.35	3347.361	2863.017	370523	5788773	173361.1	109194.4	64166.7
Total	47922.48	1501.531	1265.005	193752.5	2405785	90198.26	59052.3	31145.96

Source: EUKLEMS 2019.

Table 6.- Economic outputs activities depending on the industry.

industry	COMP	EMP	EMPE	GO	H_EMP	VA	LAB	CAP
Accommodation & food	8145.694	430.4086	342.4394	29071.3	713750.2	15226.57	11557.78	3668.793
Activities of households as empl	509.5263	51.37463	51.37463	509.5316	71733.22	509.5316	509.5263	0
Agriculture, forestry & fishing	2156.589	287.5135	117.8771	19403.41	603958	8579.199	6555.54	2023.659
Arts, entertainment & recreation	3587.346	140.2521	111.945	12511.8	207857.8	6733.218	4828.332	1904.886
Construction	15749.51	556.8331	428.1374	73423.86	991784.2	27772.85	21524.05	6248.809
Education	21842.69	554.3076	526.6342	31850.7	718252.2	26080.67	23301.97	2778.701
Energy supply	2756.828	40.1402	39.77149	29287.6	65327.07	9755.519	2798.865	6956.654
Finances & insurance	13449.55	230.6536	208.4301	55834.91	372466.7	25754.81	15250.84	10503.97
Health and social work	27597.18	914.3913	821.2822	55674.86	1302222	37567.43	31552.5	6014.923
Information and communication	11900.21	231.9059	205.4441	50203.77	385765.2	23867.72	13770.23	10097.49
Market economy	246492.8	7758.808	6522.324	1004775	1.25e+07	462964.2	306904.4	156059.8
Mining and quarrying	598.5512	12.34078	11.86862	3710.801	21550.19	2071.211	624.674	1446.537
Other service activities	4994.304	254.1899	181.9125	13956.44	386768.8	8794.213	7356.343	1437.87
Professionals and scientifics	31325.98	1105.337	871.755	102214.5	1715256	55419.87	41145.12	14274.74
Public administration & defence	26903.48	599.6731	599.556	51010.03	919578.5	35619.95	26909.65	8710.299
Real estate activities	2423.573	86.13386	67.94664	74506.58	135756.5	58615.66	3247.37	55368.29
Total manufacturing	49391.73	1204.662	1125.651	293818	1956979	85568.05	53543.14	32024.91
Transportation and storage	14276.05	420.1972	378.4645	60419.58	704321.3	25385.16	16340.27	9044.884
Water supply & derivates	2196.603	55.88706	54.46387	11652.16	93859.02	4674.482	2271.919	2402.563
Wholesale & retail; repairs	32630.24	1284.828	1033.38	106437	2104252	57304.42	43020.53	14283.89
Total	47922.48	1501.531	1265.005	193752.5	2405785	90198.26	59052.3	31145.96

Source: EUKLEMS 2019

For instance, Germany is the country with the highest compensation of employees, and Cyprus, as a small country has the lowest compensation of employees. There are also differences depending on the industry.

Table 7.- Coefficients for the effects of capital stock on labor outcomes (ICT and NON-ICT aggregated)

	(1) COMP	(2) H_EMP	(3) EMP	(4) VA	(5) GO	(6) LAB	(7) CAP
K_ICT	1.869***	152.888***	0.088***	1.067**	1.573	0.167	0.900***
	(0.266)	(18.420)	(0.011)	(0.349)	(0.969)	(0.192)	(0.220)
K_NONICT	0.063***	7.990***	0.004***	0.215***	0.478***	0.138***	0.077***
	(0.005)	(0.327)	(0.000)	(0.006)	(0.017)	(0.003)	(0.004)
K_OIPP	-2.326	293.921**	0.193***	8.844***	26.192***	4.826***	4.018***
	(1.323)	(91.475)	(0.054)	(1.732)	(4.811)	(0.952)	(1.092)
K_RD	1.405***	-95.724***	-0.018***	0.962***	1.197***	0.871***	0.090
	(0.082)	(5.651)	(0.003)	(0.107)	(0.297)	(0.059)	(0.067)
K_Soft_DB	2.424***	13.152	0.002	1.377***	0.902	1.331***	0.046
	(0.181)	(12.538)	(0.007)	(0.237)	(0.659)	(0.131)	(0.150)
_cons	235.876	6.6e+05***	88.822	2259.627	3.0e+04**	-3.6e+03	5827.716**
	(2614.669)	(1.8e+05)	(107.525)	(3422.542)	(9508.735)	(1882.378)	(2157.487)
r2	0.996	0.990	0.993	0.998	0.996	0.999	0.993

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Source: EUKLEMS 2019

This table explores the correlations of capital stocks on labor outcomes, which will be added to the model as control variables. ICT and non-ICT have positive effects for most of them and they are statistically significant. Research and development capital stock have statistically significant negative effects on hours worked and employment.

6.- Empirical strategy

Wage premium depends on the education level, and it is necessary to explain the difference to correctly build the ratio between earnings of high- and low-educated individuals. High-educated workers are those who at least have an university degree and low-educated workers are those with less than college education.

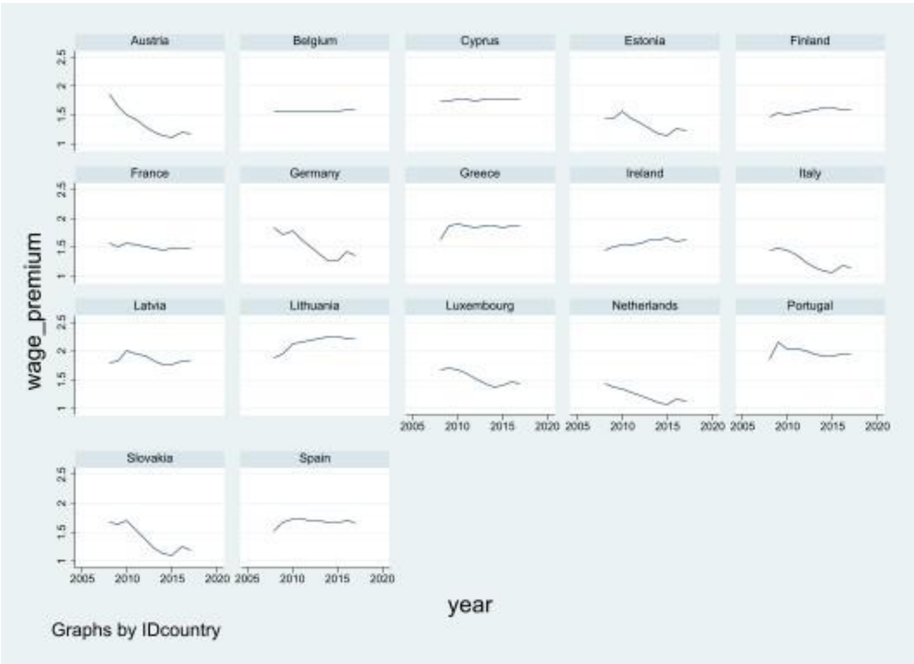
Real hourly wages of high- and low-skilled workers are constructed as follows: total nominal labor compensation divided by wage shares of these two groups. Then, this value is divided by the number of hours worked. Finally, price index for gross value added is included to account for real values. Wage premium is the ratio between the high-skilled real hourly wages and low-skilled real hourly wages.

College wage premium is higher than 1 what implies higher wages for more educated workers. For example, when wage premium increases, salaries of high-educated workers are improving relative to salaries of low-educated salaries and vice versa.

Wage premium is above 1 for all sample countries and industries. Graph 2 illustrates the levels of wage premium and its dynamics by country. The average of wage premium is around 1.5. However, there are countries where it is above 2 in recent years such as Lithuania, and other countries near 1, which is the case of Estonia, Netherlands, and Slovakia in some periods. The dynamics in wage premium varies significantly across in sample countries. There is a negative trend in Austria, Estonia, Germany, Italy, Luxembourg, Netherlands, and Slovakia. The trend is stable for Belgium, Cyprus, Finland, France, Latvia, Portugal, and Spain. The trend seems to be positive for Greece, Lithuania, and Ireland.

This evolution is consistent with Fernández Macías' (2012) paper which found different patterns depending on country. For center and eastern European countries wage premium is declining. The tendency for southern European countries, and Ireland is the opposite. Their wage premium is slightly increasing.

Graph 2.- College wage premium evolution by country from 2008 to 2017.

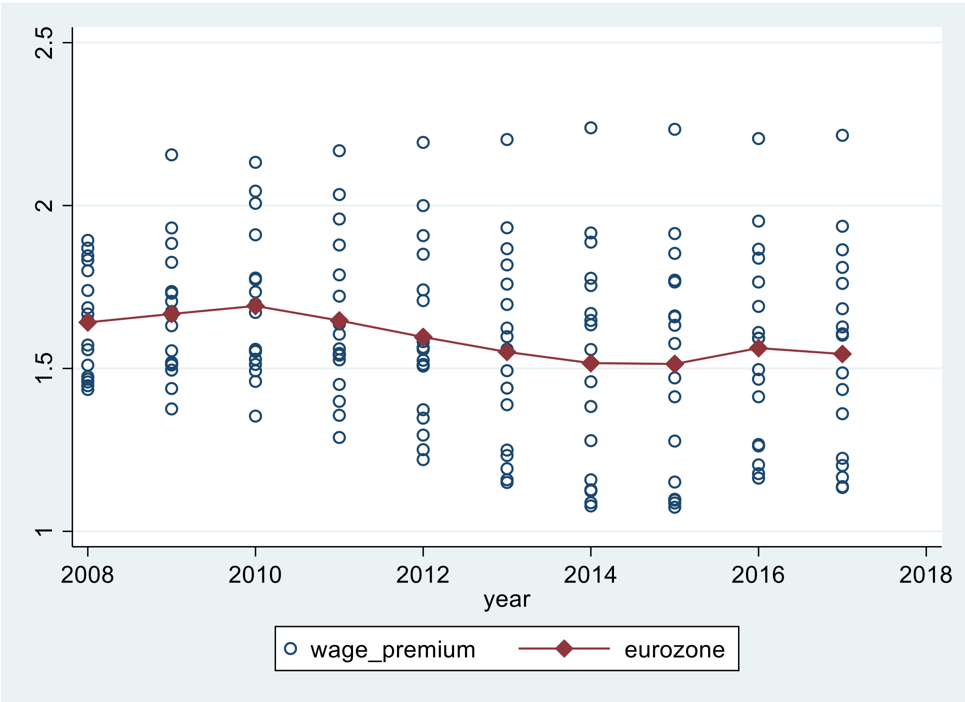


Source: EUKLEMS 2019

Graph 3 shows the mean wage premium in the Eurozone and the dispersion compared to this value of the sample countries. College wage premium increased in mean from 2008 to 2010, the period after the financial crisis. It decreased until 2015 reaching the value of 1.5 and after that period increased a bit again.

2008 is a peculiar year with lower dispersion around the mean. Then, the dispersion increases. In 2008, there were few countries where their wage premium was below 1.5, while in more recent periods these values are near one. Moreover, there are countries near a college wage premium of 2, which means that college-educated workers earn two times the amount that the non-college-educated workers earn.

Graph 3.-College premium evolution around the mean.

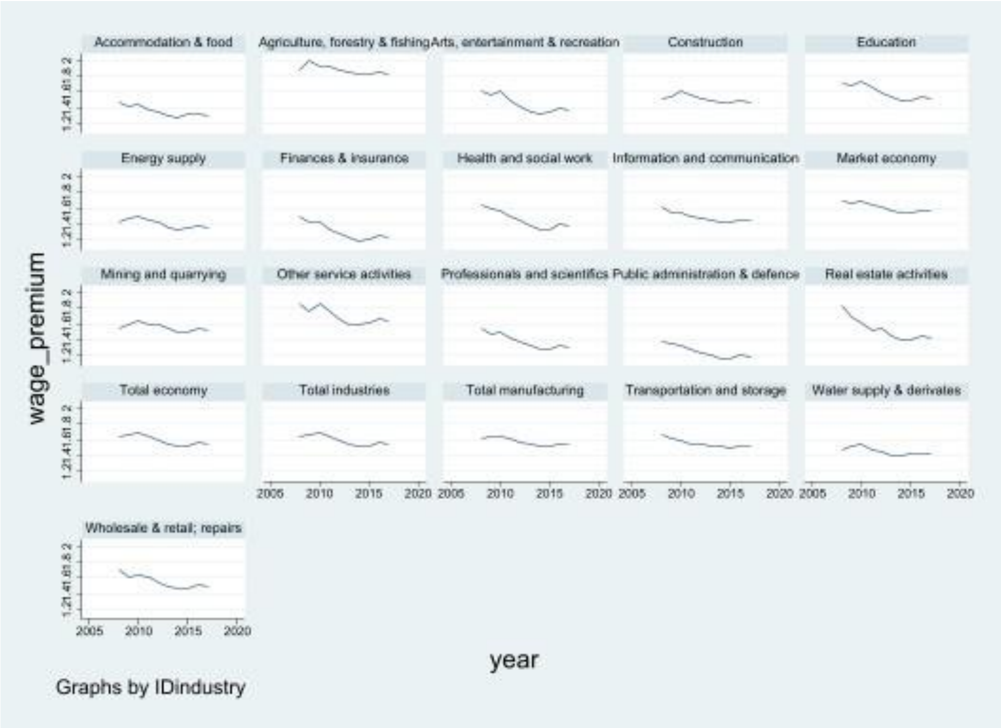


Source: EUKLEMS 2019

Then, there are differences in the wage premium across industries. Graph 4 shows the evolution of the wage premium on the sample of countries from 2008 to 2017 depending in the industry.

It can be observed that the agriculture industry is the one with the highest wage premium near a value of 2. Finances and public administration are the industries with the lowest value, slightly higher than 1.2. There is a generalized negative tendency for wage premium in almost every industry, and the highest drop is seen for real estate activities industry, which fell from 1.8 in 2008 to 1.4 in 2017.

Graph 4.- College wage premium evolution by industry from 2008 to 2017.



Source.- EUKLEMS 2019

This study builds an empirical specification for wage premium including the impact of country- and industry-fixed effects. The empirical equation is estimated by ordinary least squares (OLS):

$$Wage\ premium_{ij} = \beta_0 + \beta_k(\log(Capital\ stock_{kij})) + \delta_i + \gamma_j + \epsilon_{kij}$$

Where $wage\ premium_{ij}$ is the ratio between real earnings of high-skilled workers related to real earnings of low-skilled workers in industry j in country i. β_0 is the constant of the specification. $Capital\ stock_{kij}$ comprises the explanatory variables which are different capital stocks in industry j in country i. β_k are the coefficients for the impact of different capital stocks on wage premium.[2] Positive coefficients for capital stock means that increasing the asset increase the wage premium. δ_i are the time-invariant country-

[2] k ϵ (Communications equipment, computing equipment, computer software and database, cultivated assets, other IPP assets, other machinery equipment, research and development, residential structures, transport equipment, and total non-residential investment). The first model includes aggregated assets in ICT, NON-ICT, and intangible assets.

fixed effects and γ_j are the time-invariant industry-fixed effects. Given the specification, $\beta_k$capture the effect of each capital stock in each industry and country on college wage premium.

Capital stock variables provide the necessary information to include different technologies and account for their impact on college wage premium. A positive and statistically significant coefficient is related to increases in wage premium, which suggests that this type of technology to be biased in favor of high-educated workers, and when it is negative and statistically significant, that type of technology is biased in favor of low-educated workers.

Fixed effects are needed to capture time-invariant differences related to the country and the industry. This helps with the specification by capturing differences that appear systematically in the panel data by country and industry. Blanas et al., 2019 uses a similar empirical strategy into investigate income and wage shares. They add country invariant and industry-country fixed effects to control for other characteristics determined at the national level or the initial level of technology and pattern of specialization.

Values of capital stocks and the rest of explanatory variables are much higher than the values for wage premium which are higher but close to one. Variables are scaled in logarithms to avoid this difference. The first specification includes the logarithms of ICT, Non-ICT, and intangible assets, and its results are shown in the first 2 columns of table 7. The first column contains the aggregated model with ICT, Non-ICT, and intangible assets. I observe positive and significant effects for intangible assets at 1% level and non-ICT at 10% level. Non-ICT is not significant, so I cannot conclude that the effect is different from zero. Other IPP assets and research and development affect wage premium positively at a 10% level.

Then, in the second column, there is the disaggregated model, the main observation is that the positive coefficient for intangible assets was driven by computer software & databases and other IPP assets, while Research and development do not have effects. The rest of the capital stocks are non-significant except for cultivated assets that increase college wage premium at a 1% level of significance.

But these results are different when studying different industries. ICT and non-ICT have different effects depending on the industry, even the effects of IT and CT are different. For example, college wage premium in agriculture diminishes significatively with IT but it has positive effects for transportation, construction, retail, and health services. Non-ICT is strongly negative in almost every industry.

Intangible assets increase wage premium as mentioned above, but not for all industries. In the case of water supply sector, the effect is negative, which means that increasing research, software, or IPP assets complement low-skilled workers and reduce the ratio between college- to noncollege-educated workers.

Table 8.- Regressions for wage premium

	(1)	(2)	(3)	(4)
	rw_HL	rw_HL	rw_HL	rw_HL
logK_ICT	-0.006		-0.007	
	(0.008)		(0.009)	
logK_NON-T	-0.026*		0.003	
	(0.012)		(0.014)	
logK_int-g	0.038***		0.054***	
	(0.008)		(0.008)	
logK_IT		-0.008		-0.012
		(0.009)		(0.009)
logK_CT		-0.001		0.004
		(0.006)		(0.006)
logK_Cult		0.031***		0.026***
		(0.007)		(0.007)
logK_OCon		-0.013		-0.010
		(0.010)		(0.011)
logK_OIPP		0.019***		0.024***
		(0.004)		(0.005)
logK_OMach		0.016		0.024*
		(0.012)		(0.012)
logK_RD		0.008		0.009*
		(0.004)		(0.004)
logK_RSt-c		0.002		0.005
		(0.004)		(0.004)
logK_Sof-B		0.020*		0.026**
		(0.008)		(0.008)
logK_TraEq		-0.009		-0.006
		(0.008)		(0.008)
logCOMP			0.022	0.000
			(0.060)	(0.061)
logEMP			-0.062	-0.059
			(0.089)	(0.095)
logEMPE			-0.039	-0.011
			(0.065)	(0.067)
logGO			-0.152***	-0.183***
			(0.038)	(0.038)
logH_EMP			0.213**	0.182*
			(0.070)	(0.075)
logVA			-0.046	0.017
			(0.043)	(0.042)
logLAB			0.025	0.026
			(0.049)	(0.049)
_cons	1.158***	1.038***	0.084	0.333
	(0.116)	(0.104)	(0.536)	(0.570)
r2	0.350	0.362	0.369	0.380

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Source: EUKLEMS 2019

Columns 3 and 4 show the model with control variables, what increase R^2. Control variables are those included in EUKLEMS 2019 repository which may affect wage premium in basis of the literature presented in Section 2 and those presented in section 5. The effect of gross output on wage premium to college is statistically significant at 1%

level, and total hours worked by person engaged is statistically significant at least at a 5% level. The rest of control variables are non-statistically significant, we cannot conclude that their effect is different from zero.

7.- Results

The college wage premium found in this study is 1.59 and is affected positively by intangible assets such and research and development, Software and databases, and intellectual property assets. ICT have negative effects, but they are non-significant, and non-ICT have negative effects statistically significant at a 10% level.

These results are different from Autor et al., (1998), in that case, wage premium increased due to the effects of Information and Communication technologies, while in the case of this study this type of technology seems not to affect wage premium in Europe in the last years. The college wage premium found by Katz and Murphy (1992) for US in 1963-1987 period was 1.41 which is lower than the wage premium found by Cerina et al. (2021). The college wage premium found in their theoretical and empirical study was 1.54 for females and 1.57 for males in the data, and 1.62 and 1.65 in their model, respectively. They are consistent with the findings of a wage premium between 1.3 and 1.7 by Autor et al. (1998).

This wage premium increased in the US from 1984 to 1993 due to the spread of computer use but this may not be the case for all countries and periods. The college wage premium found in this study is 1.59, which similar but slightly higher than in the cases mentioned above. In this case, the effects of IC technologies are non-significant, which can be interpreted like it is intangible assets which are the technologies increasing wage premium.

But the results for intangible assets, which are research and development, software, and databases and other IPP assets are consistent with Ernst et al., 2019. Intangible assets such as AI are leading to an increase in wage premium and wage polarization, complementing college-educated workers. This paper forecast high wage and high level of employment for those related to this technology.

Moreover, these results have similarities with the results from Fernández-Macías, 2012 there are different conclusions about job polarization in Europe than in US; In Europe, there are different labor markets while in US, the labor market follows the same tendency.

In contrast, ICT technologies reduce wage premium what is the opposite as observed for the US in the 60's and 70's, and with the spread of computer use (Acemoglu & Autor, 2011:1044). In those cases ICT increased wage premium. A reason behind these differences may be that ICT is not complementing high educated workers anymore, and intangible assets are increasing wage premium as other technologies did in the past.

Including control variables increased the R^2 of the model, and the results of this model are similar to the first one. In this case, non-ICT assets turn to be non-significant. When the capital stocks are including disaggregating the assets, cultivated assets, computer software & databases, and other IPP software increase college wage premium. Intangible assets, which are research & development, innovative property products, and software & databases have strong and positive effect on college wage premium at a 1% level.

The main driver of college wage premium is intangible assets, mainly computer software and innovative property products, but not for all industries. In general, non-ICT reduce college wage premium in almost all industries, but when accounting for the aggregation, their effects are non-significant. ICT usually have non-significant effects, but IT enhance college wage premium for at least 5 sectors. IT only have negative effects on the agriculture industry. CT have negative effects on construction, transportation, and public administration. These differences in the effects between IT and CT may be the cause for the non-significant coefficient for ICT assets.

Finally, for the control variables, the number of hours worked by person engaged negatively affects college wage premium in both models, gross output negatively affects college wage premium also in both models. R^2 increases with new control variables.

In summary, college wage premium depends positively on computer software, research and development and innovative property products, this technology complements college-educated workers. But the effects are different depending on the industry, the type of tasks performed may have effects. CT and IT affect the output in different ways. CT have negative effects on the wage premium in transportation, construction and defense and public administration, but IT have positive effects on wage premium in retail, transportation, and construction.

8.- Conclusions

Technical change is disrupting labor markets and leading to job polarization. Low- and high-skilled occupations face improvements in their employment share while medium-skilled occupations tend to decrease in employment shares. Wage premium to skills is increasing in the US and Europe. Acemoglu (1998) proposed induced biased technological change to explain how technology affects the labor market, different technologies seem to affect in different ways depending on their bias.

This study incorporates different technologies to explain college wage premium. Moreover, it provides a contribution to literature about the impact of technology in labor markets, focusing on college wage premium. I use EUKLEMS 2019 database which includes information for 19 European countries from 2008 to 2017, which is relevant to study the effects of different technologies more recently.

The empirical strategy follows a fixed-effects model to explain college wage premium with different types of capital stocks such as ICT, Non-ICT, and intangible assets, and including country- and industry-fixed effects to control for time-invariant changes. The empirical model includes aggregated and disaggregated types of capital stock and with or without control variables.

Results suggest that intangible assets such as research & development, software and IPP assets are the main driver of college wage premium. This is consistent with recent literature arguing that these new technologies are complementing high educated workers, improving wage premium, and leading to job polarization. ICT and Non-ICT assets do not affect wage premium when including country- and industry-fixed effects, but their coefficients are statistically significant in some industries. IT and CT complement college-educated workers in different industries. This result is different from previous research in which ICT affects positively wage premium.

Fixed effects strategy allows us to capture invariant unobserved characteristics within countries and industries that may interfere in concluding valid causal effects. This approach is following as mean differences for those groups are significatively different.

The empirical specification could be improved by including more countries in the sample wat was difficult in this case due to less availability of data in some cases, and differences in currencies in other cases. Then, including a higher number of periods could be positive. This allows exploring the effects of capital stock on wage premium with a large database.

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