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AGEING WORKFORCE IN THE DIGITAL ERA: OLDER WORKERS, DIGITALIZATION AND LABOUR PRODUCTIVITY WITHIN EUROPEAN UNION COUNTRIES

Master’s thesis

Programme TAAM, specialisation Economic Analysis

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and all works, important standpoints and data by other authors
have been properly referenced and the same paper
has not been previously presented for grading.
The document length is 10,307 words from the introduction to the end of conclusion.

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ABSTRACT

Current thesis aims to explore the relationship between workforce ageing and labour productivity in European Union (EU) countries and find how investments into ICT affect the labour productivity of older workers. Aggregated publicly available industry level data from EU KLEMS 2019 release makes up the small balanced panel used in the thesis covering 21 selected EU countries for 9 time periods from 2008 to 2016. The finite nature of the data is the main limitation of the work. The bulk of the empirical analysis draws on the static fixed effects model without time fixed effects. The robustness of the results is examined in four ways, one of which is estimating a a dynamic system generalized method of moments model. The baseline results indicate a positive relationship between the workforce ageing and labour productivity with a one percentage point increase in the share of hours worked by workers aged 50 or above bringing about 1.4 percent increase in the gross value added per hour worked compared to the reference group of labour inputs aged 15-29. Marginal effect of the share of hours worked by older workers aged 50 and above in total hours worked decreases with the increase in the share of ICT in total capital inputs which indicates that in countries where the share of investments into ICT is large ageing has a negative impact on labour productivity. Analysis results also point to a non-complementarity between low-educated older workers and ICT capital.

Keywords: Ageing workforce, older workers, digitalization, labour productivity, EU KLEMS

INTRODUCTION

Population within most developed countries including those in the European Union (EU) is in the long-term trend of ageing. Both higher life expectancy and low birth rates are the contributors to the higher share of older people in the total population. The Eurostat's (2022) article on population structure and ageing shows that more than one fifth of the EU's population was aged 65 and over in 2021, and the share of older people in the population is expected to rise to 31.3% (10.5 percentage points) by 2100. As the pressure on working-age populace increases due to rising social expenditure related to population ageing, it becomes increasingly important to support and facilitate employment amongst the elderly.

Older people are at risk of being excluded from the workforce in favour of younger workers due to allegedly lesser productivity. Aiyar *et al*. (2016) observed in their International Monetary Fund (IMF) working paper the impact of ageing on European productivity and noted that a higher share of older people in the workforce decreases the growth of labour productivity. A similar averse effect on Korean individual firm level was found by Lee *et al*. (2018) where the increase in the share of older workers had a negative effect on value added per worker.

In addition to younger workers, the automation of the digital era also threatens to replace elderly workers in the labour market. Yet, automation could also be the salvation of older workers as it could help them to be at the same or even higher productivity level as younger workers. (The Twin Threats… 2018) Evidence from Lee *et al*. (2021) suggests that producitivity decrease related to ageing can be mitigated by attainment of information and communications technology (ICT) skills.

This thesis aims to investigate the relationship between workforce ageing and labour productivity in selected EU countries, as well as how the education level of ageing workers affects their adaption to new technology in the workplace. Handled main research question is how investments into ICT affect the labour productivity of older workers.

Following, three hypotheses are studied in this thesis:

1. Workforce ageing has a negative effect on labour productivity in the selected sample of EU countries.
2. Ageing has positive impact on labour productivity in countries where the share of investments into ICT is large.
3. There is a complementary effect between older workers and ICT capital for both low- and high-educated workers.

To fulfil the aim of the thesis, the quantitative approach is used to conduct a static fixed effects regression analysis using panel data from the EU KLEMS 2019 release, which offers publicly available industry level data on economic growth, productivity, employment, capital formation, and technological change for all EU countries along with Japan and the United States. The letters in the EU KLEMS acronym are for capital, labour, energy, materials, and service inputs.

The main sample used in the current thesis covers twenty one countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom. Aggregated total economy data per country is pulled from all four divisions of the EU KLEMS statistical database. The balanced panel data from the EU KLEMS 2019 release covers years 2008-2016 with the main restrictor of the length of the time series being data unaivailability on either capital or labour inputs.

The robustness of static fixed effects regression results is checked in four ways. In order to account for potential multicollinearity, a model without the lagged natural logarithm of the share of low-educated labour in total labour input is estimated. Potential non-stationarity of variables is mitigated with first-differencing all the variables. The static fixed effects model is estimated using restricted country sample from which three outlier countries are removed. Finally, the sensitivity of results is checked with a dynamic system generalized method of moments (GMM) model.

The added value of the thesis is in the choice of EU countries and in examining the effect of workforce ageing on labour productivity using the balanced panel data from EU KLEMS 2019 release. The thesis combines methods from both Ilmakunnas and Miyakoshi (2013) and Lee and Song (2020) but it differs in terms of using aggregated total economy data and more recent time period. Moreover, both static and dynamic methods are used for analysis.

The thesis is structured as follows. The first chapter dives into the theoretical background of the relationship between productivity and labour ageing. This section of the thesis gives a brief overview of the importance and drivers of productivity, the economic effects of ageing population and ageing in the digital era. Last subchapter of the first chapter summarizes the previous literature on the interactions between ageing workers, digital skills, and productivity.

Second chapter contains information about the methodology and data used in this work. First, it gives an introduction into EU KLEMS data, then describes the methodology used for answering the research question. Selection criteria of the sample of the thesis, overview of the dataset based on the EU KLEMS 2019 release data and descriptive statistics are given in the last three parts of the second chapter.

The third chapter of the thesis outlines the empirical results. The first subchapter of the third part describes the correlation between the variables used in the analysis as well as tests for choosing between the different static panel data models. Static fixed effects regression results and robustness checks are respectively presented in the second and third subchapter. Fourth and final subchapter of the third part contains discusssion of the interaction effects and overall results. Final chapter concludes the whole work.

1. THEORETICAL AND EMPIRICAL OVERVIEW

1.1. The importance and drivers of productivity

Productivity, or in other words, the efficiency with which inputs such as labour and capital are turned into outputs, is widely recognized as the key ingredient in economy's growth and competitiveness. Increased living standards today as compared to the past are largely due to productivity growth- we are now able to produce more goods and services than before with the same amount of inputs. The most prominent effects of productivity growth on an individual-level include more time for leisure, greater number of both market and public goods and services, and lower labour cost of goods and services.

The work by Schreyer and Pilat (2001) includes several different productivity measures that can be broadly categorized into single or multifactor productivity measures. Single factor productivity measures like labour or capital productivity relate output to a single measure of input. Multifactor productivity also known as total factor productivity (TFP) measures however relate output to a bundle of inputs. Another way to classify productivity measures is by how they capture movement of output, either by relating some measure of gross output to inputs or by using the concept of value-added.

Syverson (2011) notes in his article that all empirical studies which he covered found large tenacious differences in measured productivity even between firms which were quite similar with each other (positioned in the same narrowly defined industry). Del Gatto *et al.* (2011) point out that quantifying productivity is difficult due to the variety of approaches available. Factors that cause productivity differences at the micro level can be roughly divided into two categories of internal and external. Firm-level drivers of productivity include the level of trade integration, access to finance, education and training, innovation and ageing (Karpowicz, Suphaphiphat 2020).

Korkmaz and Korkmaz (2016) state in their study about the relationship between productivity and economic growth that the most frequent metric for evaluating productivity is labour productivity, which is defined as output equivalent to input gained from the workforce or in other words added value per hour worked. Labour productivity is broadly determined by three factors. The first is human capital which is comprised of an average employee's cumulative knowledge (education and experience), talent, and competence. The second factor is advancement in technology as new inventions and innovations stimulate the development of new products and services which boost productivity. The third is economies of scale, which cut production costs.

1.2. Economic effects of ageing population

Participation in the labour force usually declines when people age however the trend towards early retirement has been reversed since the late 1990s (Martin 2018). This is partly due to the governments of ageing countries trying to bring older workers back into employment to relieve the pressure of financing most of the consumption of older citizens (World Population… 2019). As increasingly more older people are actively working, it arises the question about how this affects the overall economy.

According to Feyrer (2007) changes in the workforce demographic structure lead to changes in aggregate human capital, which in turn affect the total output of the economy. There are two opposing branches in the literature about age effects on productivity. One branch dates back to Becker’s (1962) opinion that accumulated experience and skills make older workers more productive. The other stresses that since both cognitive and physical abilities decrease with age, the older workers cannot compete with their younger counterparts in terms of productivity (Desjardins, Warnke 2012).

Tang and MacLeod (2006) show that in Canada, labour force ageing has had an increasing negative impact on productivity growth since the middle of the 1990s. The results of the analysis conducted by Walewski (2008) indicate that the relative productivity of older workers is lower for the EU member states that joined the EU on 1 May 2004 than for EU-15, which may also be the reason for the lower employment rates of the older workers in these countries. Maestas *et al*. (2016) associate a 10% increase in the share of population aged 60 and above with a 5.5 percentage decrease in Gross Domestic Product (GDP) with slower labour productivity growth accounting for two-thirds of the reduction and one-third occurring due to slower labour force growth.

Vogel *et al*. (2017) point out that the decrease in the share of population in working age decreases the future welfare for middle aged asset rich households as the rates of return to capital will decrease and wages increase making the return on assets low. In the long run, population ageing will bring about a reduction in consumption and an increase in work effort as in steady-state consumption per worker must equal the output per worker (Sheiner 2014).

On the other hand, Göbel and Zwick (2009) find by estimating firm-level age-productivity profile that the average age productivity is essentially flat. This means that there is little indication that an ageing workforce will inevitably lead to a deterioration in the welfare of industrialised nations. In the long-run context neither higher life expectancy nor a decline in fertility affect economic growth if population ageing is allowed to affect capital- and labour-saving technical change (Irmen 2017).

1.3. Ageing in the digital era

Acemoglu and Restrepo (2018) show in their paper that ageing brings about greater industrial automation. Battisti and Gravina (2021) investigate the complementary effects of robotic capital by age group and find that younger workers suffer more from higher robotization. Their results seem counter intuitive as older workers generally have fewer digital skills and, in a previous study by Mariano *et al.* (2020), stereotype threat of lacking technological ability undermines acquiring computer skills in late adulthood. Peng *et al.* (2017) find that the impact of ICT on the wage share of highly skilled workers is positive and significant across all age-groups.

Cataldi *et al*. (2011) reveal after disentangling the age-productivity-wage problem that even though workers above 49 years are significantly less productive than their younger colleagues, older workers are paid above their marginal productivity regardless of the ICT environment of the company. This is in line with the findings of Ilmakunnas and Maliranta (2005) who showed, using plant-level employer-employee data, that while education increases productivity, wage under-compensates productivity.

Schleife (2008) analyzes the relationship between firm-provided IT training and the firm's proportion of older workers using data from the Leibniz Centre for European Economic Research (ZEW) ICT surveys. She observes that while IT-intensive firms employ less older workers compared to firms who do not use IT as intensively, higher participation rates of older workers in IT training are connected to a larger share of older workers within firms.

1.4. Ageing workers, digital skills, and productivity in the previous literature

There are number of empirical works dealing with productivity, digitalization and older workers. Older individuals retain a relatively high productivity level in tasks where experience and verbal abilities matter more compared to tasks where problem solving, learning and speed are crucial (Skirbekk 2004). Therefore, the productivity decline related to age is not homogeneous and is dependent on, for example, the level and quality of education, the characteristics of industries and jobs and the pace of technological change (Walewski 2008).

Ariu and Vandenberghe (2014) stress that the TFP slowdown in Belgium in 1998-2006 was induced by ageing and, educational composition of the workforce did not affect the TFP growth. Remes *et al*. (2018) on the other hand, detail three waves that collided to drive productivity growth for US, Germany, France, UK, Italy, Spain, and Sweden. The first two waves of the waining of the impact of the 1990s information technology revolution and financial crisis aftereffects decreased the productivity growth by 1.9 percentage points across the countries. Authors expect the productivity growth to recover and see productivity growth potential of at least 2 per cent per year over the next decade due to the third wave of digital distruption.

The importance of ICT capital investment in productivity growth is emphasized by Strauss and Samkharadze (2011). They show that while the growth contributions from ICT are found to be smaller than those from TFP for both EU-15 and the US, the ICT has made smaller contributions to labour productivity growth in the EU-15. Trpeski *et al*. (2021) find that while the impact of ICT investments on labour productivity for European developed countries in the post Great Recession period is positive, it is also insignificant.

2. DATA AND METHODOLOGY

2.1. About EU KLEMS project

Initially European Commission's industry level growth and productivity research project, EU KLEMS started with an aim of creating a database of high quality statistics for the assessment of competitiveness and economic growth potential as stated in the Lisbon and Barcelona summit goals. The initial project lasted from 2003 to 2008 during which it was developed under the guidance of the University of Groningen by 18 European research institutes. The original database was updated multiple times after the end of the Framework Project: in 2009, 2011, 2012, and 2016[1].

There have been three new releases of the dataset in the past five years. The first one in 2017 was revised in July 2018. The second dates back to 2019 while the latest Growth and Productivity Database (GPD) by the Vienna Institute for International Economic Studies (wiiw) was released in December 2021[2]. Though a successor of previous EU KLEMS releases the 2021 dataset should not be linked with the older datasets due to different methodology and problems with data availability.

The EU KLEMS release 2019 utilized in the current thesis includes industry level information about economic growth, productivity, employment, capital formation, and technological change for all European Union members as well as Japan and the United States. This information is divided between two datasets: statistical and analytical. Statistical database is built on the National Accounts data found in Eurostat providing a detailed differentiation of growth contributions of tangible and intangible capital. The analytical database incorporates data on additional asset types not available in the National Accounts. This work uses data from the statistical dataset.

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[1] Previous EU KLEMS database up until 2017 release is available at http://www.euklems.net/.

[2] For more information about the latest 2019 and 2021 releases, please visit https://euklems.eu/ and https://euklems-intanprod-llee.luiss.it/. Alternatively, consult Adarov and Stehrer (2019), Stehrer *et al*. (2019) and Stehrer (2021) directly.

The data for 40 detailed NACE Revision 2 industries and twelve industry aggregates in the 2019 release covers the period 1995-2017. The time series lengths, however, vary across the countries and indicators available. For example, the 2019 release database includes the shares of employment by type in total industry employment only from 2008 onwards.

2.2. Research design and methodology

The research design and methodology of this work follows both Ilmakunnas and Miyakoshi (2013) and Lee and Song (2020). These articles center around the effect of workforce ageing on productivity using EU KLEMS and in the case of Lee and Song (2020), also WORLD KLEMS[3] data. Ilmakunnas and Miyakoshi (2013) focus on examining the relationship between workforce ageing and productivity in the aggregate manufacturing for thirteen Organisation for Economic Co-operation and Development (OECD) countries while Lee and Song (2020) investigate how the growing share of older workers affects labour productivity utilizing industry-level data of two Asian countries: Japan and Korea.

The baseline empirical model is a logarithmic form of the production function of firms in country *c* at time *t* with *k* number of lags as in Ilmakunnas and Miyakoshi (2013) and Lee and Song (2020). The equation is as following:

$$ln(Y/L)_{ct} = \theta + \alpha \ln(K/L)_{ct-k} + \beta_l \ln(L_l/L)_{ct-k} + \beta_h \ln(L_h/L)_{ct-k} + \varphi^*_{mid} Sh_{mid,ct-k} + \varphi^*_{old} Sh_{old,ct-k} + \varphi^*_{ICT} \ln(K_{ICT})_{ct-k} + \mu_c + f_t + \varepsilon_{ct} \quad (1)$$

where
$(Y/L)_{ct}$ − labour productivity (output per unit of labour)
$(K/L)_{ct-k}$ − capital-to-labour ratio
$(L_l/L)_{ct-k}$ − the share of low-educated labour in total labour input
$(L_h/L)_{ct-k}$ − the share of high-educated labour in total labour input
$Sh_{mid,ct-k}$ − the share of labour inputs aged 30-49
$Sh_{old,ct-k}$ − the share of labour inputs aged 50 or above
$K_{ICT,ct-k}$ − the share of ICT capital in the total capital input
μ_c − country fixed effects
f_t − year fixed effects
ε_{ct} − error term.

[3] WORLD KLEMS hosts data on United States, Japan, Canada, and Russia. For more information about WORLD KLEMS please refer to https://www.worldklems.net/wkhome.

The main parameter of interest in the baseline model depicted in Equation 1 is φ^*_{old}, as the first hypothesis of this work focuses on the direction of the relationship between workforce ageing and labour productivity. Parameter φ^*_{ICT} is also examined to estimate the effect of ICT investments on productivity without added interaction terms. The methodology used is a secondary analysis of balanced panel data and the reference in the model is the group of young labour inputs aged 15-29.

The second hypothesis states that ageing has a positive impact on labour productivity in countries where the share of ICT investment is large. The model used for inspecting the validity of this statement is presented in Equation 2 which differs compared to Equation 1. It adds the interaction terms between the share of ICT capital in the total capital input and the shares of labour inputs aged 30-49 and 50 or above.

$$ln(Y/L)_{ct} = \theta + \alpha\, ln(K/L)_{ct-k} + \beta_l\, ln(L_l/L)_{ct-k} + \beta_h\, ln(L_h/L)_{ct-k} + \varphi^*_{mid} Sh_{mid,ct-k} + \varphi^*_{old} Sh_{old,ct-k} + \varphi^*_{ICT}\, ln(K_{ICT})_{ct-k} + \varphi^*_{midICT}\, ln(K_{ICT})_{ct-k}\, Sh_{mid,ct-k} + \varphi^*_{oldICT}\, ln(K_{ICT})_{ct-k}\, Sh_{old,ct-k} + \mu_c + f_t + \varepsilon_{ct} \tag{2}$$

Parameters of interest in Equation 2 are φ^*_{old}, φ^*_{ICT} and φ^*_{oldICT} since the handled main research question is how investments into ICT affect the labour productivity of older workers. Again, the reference group is young labour inputs aged 15-29.

Interactions between ageing, education, and ICT capital are added into the model in Equation 3. Analysing this model gives information about the existence of complementary effect between both low- and high-educated older workers and ICT capital.

$$ln(Y/L)_{ct} = \theta + \alpha \ln(K/L)_{ct-k} + \beta_l \ln(L_l/L)_{ct-k} + \beta_h \ln(L_h/L)_{ct-k} + \varphi^*_{lmid} Sh_{lmid,ct-k} + \varphi^*_{lold} Sh_{lold,ct-k} + \varphi^*_{hmid} Sh_{hmid,ct-k} + \varphi^*_{hold} Sh_{hold,ct-k} + \varphi^*_{ICT} \ln(K_{ICT})_{ct-k} + \varphi^*_{lmidICT} \ln(K_{ICT})_{ct-k}\, Sh_{lmid,ct-k} + \varphi^*_{loldICT} \ln(K_{ICT})_{ct-k}\, Sh_{lold,ct-k} + \varphi^*_{hmidICT} \ln(K_{ICT})_{ct-k}\, Sh_{hmid,ct-k} + \varphi^*_{holdICT} \ln(K_{ICT})_{ct-k}\, Sh_{hold,ct-k} + \mu_c + f_t + \varepsilon_{ct} \tag{3}$$

where
$Sh_{lmid,ct-k}$ – the share of low-educated labour inputs aged 30-49 in all low-educated
$Sh_{lold,ct-k}$ – the share of low-educated labour inputs aged 50 or above in all low-educated
$Sh_{hmid,ct-k}$ – the share of high-educated labour inputs aged 30-49 in all high-educated
$Sh_{hold,ct-k}$ – the share of high-educated labour inputs aged 50 or above in all high-educated

Low- and high-educated labour inputs are divided by the age group. For example, the share of young workers aged 15-29 in the low-educated group is calculated as $Sh_{lyoung} = \frac{L_{lyoung}}{L_l}$ and in the high-educated $Sh_{hyoung} = \frac{L_{hyoung}}{L_l}$. The shares for both middle and old age groups are calculated analogously. The parameters of interest in Equation 3 are φ^*_{lold}, φ^*_{hold}, φ^*_{ICT}, $\varphi^*_{loldICT}$ and $\varphi^*_{holdICT}$.

Country fixed effects are included in the models to account for country-specific unobserved factors which might correlate with the inputs. Addition of country fixed effects, therefore, helps to alleviate the bias occurring from time-invariant country-specific confounding factors. Due to adding country fixed effects, the estimates are based on variation within the countries meaning that instead of comparing outcomes in different countries using variation between countries, outcomes in the same country at different time periods are compared.

Time fixed effects are added to mitigate the effects of potential aggregate-level time shocks. Another time related potential problem could be simultaneity bias. To avoid that, lagged explanatory variables with $k = 1$ are used in all of the estimations instead of contemporaneous explanatory variables. Finally, the error term accounts for left-out variables and stochastic shocks.

Ilmakunnas and Miyakoshi (2013) point out that the models described in Equations 1, 2 and 3 would not be suitable for estimating the labour productivity for a random selected group of elderly compared to young individuals. There would be an upward bias in the estimated age-productivity relationship as older workers with lower productivity leave the labour force more likely than older workers with high productivity. The emphasis of this thesis is, however, on how the variation in the shares of different groups who are actually working, can explain the changes in productivity.

2.3. Selection of the sample

The main sample of this work consists of the EU KLEMS 2019 release data of twenty one countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom. The map of European area in Figure 1 illustrates the country composition of the sample.

USA and Japan, which are also covered by the EU KLEMS 2019 release but not shown on Figure 1, are excluded from the thesis sample due to specific interest in how investments into ICT affect the productivity of older workers in EU countries. The specific interest in European Union countries follows from both the persistent long-term trend of labour-force ageing in the area as well as the seeming failure of the main initiative of the Lisbon European Council in 2000- becoming the most competitive knowledge-based economy in the world.

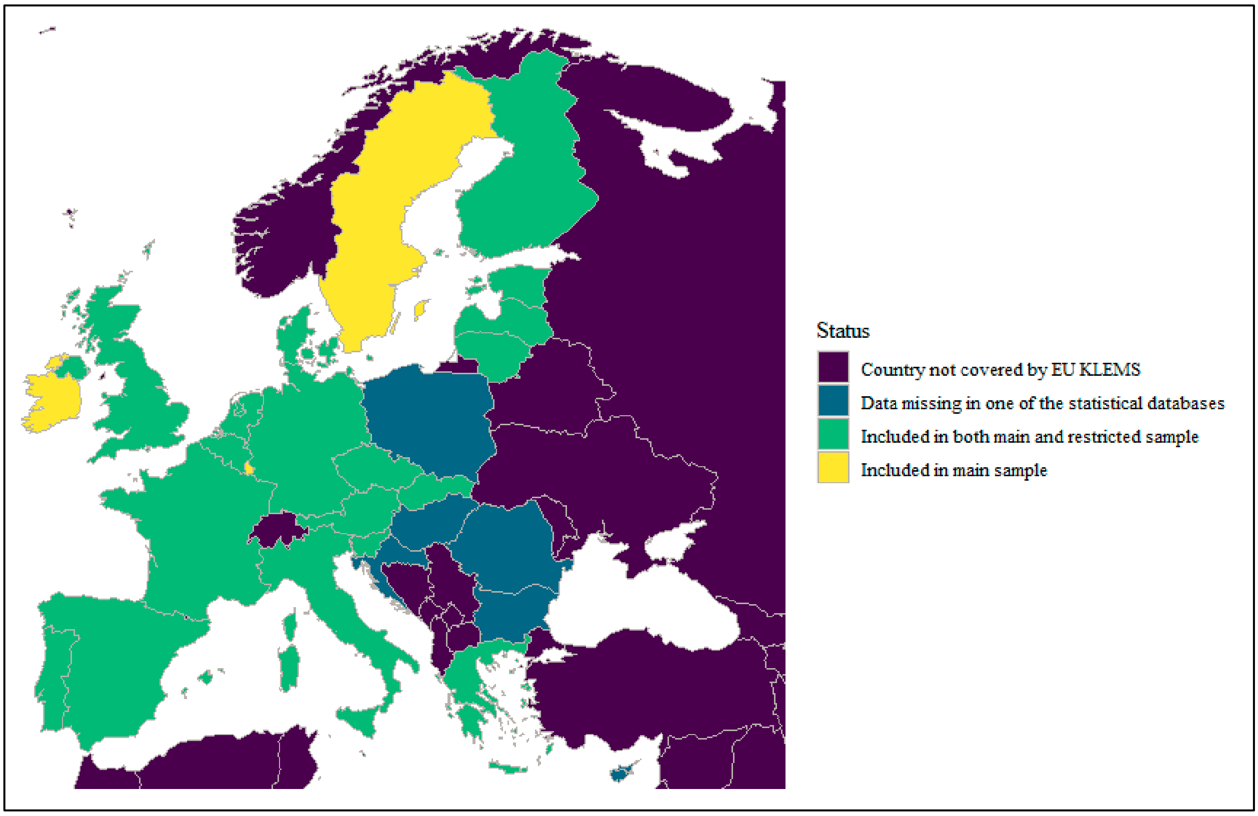

Figure 1. European area map filled in by the sample status of the country
Source: Created by author in R based on information acquired from the EU KLEMS 2019 release

The immediate elimination of seven EU countries ties into data unavailability. For Bulgaria, Croatia, Cyprus, Hungary, Malta, Poland, and Romania displayed as blue on the map in Figure 1, there was missing information for all the covered years of 1995-2017 in at least one variable from the four (Growth Accounts, National Accounts, Labour, Capital) statistical databases. More detailed view of the data availability by country for the EU KLEMS 2019 release is provided in Appendix 1.

The twenty one main sample countries are represented in Figure 1 in green or yellow. Even though United Kingdom separated from the EU in January 2020, it is still included in the sample as it was a member during the period covered by EU KLEMS 2019 release data. Three countries marked with yellow (Ireland, Luxembourg, Sweden) are included only in the main sample and removed from restricted sample for sensitivity analysis.

2.4. Overview of the dataset

EU KLEMS 2019 release data for all countries from 1995 was downloaded from the wiiw homepage in rds file format which is R data file format. The necessary variables for this work were scattered across the four EU KLEMS statistical databases, hence the download was done in four parts. After selecting only European Union countries and information for total economy in all four data files, extra variables were removed from the data.

Table 1 compiles the information about the EU KLEMS 2019 release names, labels and the statistical database of the variables used for deriving the variables for the models described earlier in Equations 1, 2 and 3. Dependent variable of labour productivity is measured using gross value added (GVA) per hour worked while capital-to-labour ratio is the quotient of capital and labour services.

Different labour shares are based on total hours worked by type. The share of high-educated labour is made up from workers who have graduated with college degree, while low-educated labour includes those with high school diploma and below. Another dimension used to divide labour into different groups is age. Young, middle and old age groups include labour aged 15-29, 30-49, and 50 and above, respectively. Net capital stock of ICT assets and all assets are used to calculate the share of ICT capital in the total capital input. ICT assets encompass computing equipment, communications equipment, and software.

After removing the seven countries where there was missing information for all the covered years of 1995-2017 in at least one variable, the time period was restricted to 2008-2016 due to the information for labour shares by type beginning only in 2008 in 20 out of 21 remaining sample countries[4]. Year 2017 was eliminated from the analysis as there was a gap in capital inputs data availability for Estonia, Greece, Ireland, Latvia, Lithuania, Portugal, Spain, and Sweden.

[4] The only country where the information about the labour shares by type is available earlier than 2008 is Belgium for which the labour time series start in 1999.

Therefore, the final main sample without accounting for the lag $k = 1$ consists of balanced panel data with 189 observations ($T = 9, N = 21$).

Table 1. EU KLEMS 2019 release variables names, labels and the statistical database of the variables used for deriving the variables for the analysis

Name in EU KLEMS	Label in EU KLEMS	Statistical database
	Labour productivity (output per unit of labour) Y/L	
LP_QI	GVA per hour worked, volume 2010=100	National Accounts
	Capital-to-labour ratio K/L	
CAP_QI	Capital services, volume indices, 2010=100	Growth Accounts
LAB_QI	Labour services, volume indices, 2010=100	Growth Accounts
	Labour shares L_l/L, L_h/L, Sh_{young}, Sh_{mid}, Sh_{old}, Sh_{lyoung}, Sh_{lmid}, Sh_{lold}, Sh_{hyoung}, Sh_{hmid}, Sh_{hold}	
H_shares	Shares of employment by type	Labour Accounts
	The share of ICT capital in the total capital input K_{ICT}	
Kq_IT	Computing equipment, volume 2010 reference prices, NAC mn	Capital Accounts
Kq_CT	Communications equipment, volume 2010 reference prices, NAC mn	Capital Accounts
Kq_Soft_DB	Computer software and databases, volume 2010 reference prices, NAC mn	Capital Accounts
Kq_GFCF	All assets, volume 2010 reference prices, NAC mn	Capital Accounts

Source: Compiled by the author
Notes:

1. Variable names and labels in EU KLEMS 2019 release can be found on the wiiw Growth and Productivity Data Release Jan 2022 webpage using the query data archive under section Archive & History.
2. "NAC mn"- millions of units of national currency.

Data for analysis could in theory be expanded to cover 1995-2016 for ten EU countries ($T = 22, N = 10$) by using the EU KLEMS 2008 and 2012 releases. The potential usage of data from different releases is mapped out in the table in Appendix 2, however there are a number of complications in this route including data gap for some countries for years 2006 and 2007, indexes mismatch, and data incompatibility between the releases (values for the same variable in different releases are inconsistent). The first two problems could be solved by applying interpolation techniques and rebasing, respectively, while the third is extremely difficult to overcome. Therefore, to eliminate the possibility of data inconsistencies driving the analysis results, this approach is left unexplored in current work.

2.5. Descriptive statistics

Descriptive stratistics of the variables used in the analysis are given in Table 2. The mean values, standard deviations and the minimum and maximum values in the table cover 21 EU countries' data from 2008 to 2016. Some variables are included into the analysis as natural logarithms which descriptive statistics can be found in Appendix 3.

Table 2. Descriptive statistics of the variables used in the analysis

Variable	Mean	Standard Deviation	Minimum	Maximum
GVA per hour worked, volume 2010=100, Y/L	102.34	5.80	86.32	138.52
Capital-to-labour ratio (%), K/L	99.76	4.85	79.26	112.70
Share of low-educated labour in total labour input (%), L_l/L	68.00	8.19	50.76	85.10
Share of high-educated labour in total labour input (%), L_h/L	32.00	8.19	14.90	49.24
Share of hours worked by workers aged 15-29 (%), Sh_{young}	19.61	3.22	11.70	29.27
Share of hours worked by workers aged 30-49 (%), Sh_{mid}	52.27	4.46	44.80	60.85
Share of hours worked by workers aged 50 or above (%), Sh_{old}	28.12	3.25	20.41	34.80
The share of ICT capital in the total capital input (%),K_{ICT}	2.36	0.80	0.94	5.65
Share of low-educated labour aged 15-29 in low-educated (%), Sh_{lyoung}	21.02	4.52	12.29	29.67
Share of low-educated labour aged 30-49 in low-educated (%), Sh_{lmid}	49.54	5.41	38.76	60.33
Share of low-educated labour aged 50 or above in low-educated (%), Sh_{lold}	29.44	3.46	20.57	37.17
Share of high-educated labour aged 15-29 in high-educated (%), Sh_{hyoung}	16.84	3.97	9.45	29.53
Share of high-educated labour aged 30-49 in high-educated (%), Sh_{hmid}	57.57	4.46	48.42	66.19
Share of high-educated labour aged 50 or above in high-educated (%), Sh_{hold}	25.59	5.09	15.60	37.01

Source: Author's calculations based on data obtained from EU KLEMS 2019 release
Notes:

1. Descriptive statistics of logarithmic variables can be found in the Appendix 3.
2. Sample covers 189 observations from 21 EU countries for period 2008-2016.

Over the sample period, the average volume index for GVA per hour worked was 102.34 which means that during the period 2008-2016 the gross value added per hour worked increased on average 2.34% compared to the base year of 2010. The choice of 2010 as the base year was directly influenced by the fact that the variables were already included that way in the original unaltered dataset. Average capital-to-labour ratio was 99.76% showing that for the sample period the overall capital and labour use in EU for years 2008-2016 were almost equal in volume.

Share of low-educated labour inputs over the sample period is 68%, the largest share of high-educated workers 49.24% describes Luxembourg in 2014. Age division for low-educated and high-educated displays mostly expected patterns, with the share of young labour inputs in high-educated 16.84% being on average 4 percentage points lower than in low-educated while for the mid age workers, the share in high-educated is approximately 7 percentage points higher compared to their share in low-educated. Interestingly, the overall share of older workers in high-educated labour inputs is smaller than in low-educated.

On average, older workers worked 28.1% of the total hours worked in the labour market which was 8.5 percentage points higher than the share of hours worked (19.6%) by young labour inputs. Hours put into by the middle age workers made up a little more than half of the total hours worked. The share of hours worked by workers aged 50 or above was the highest (34.8%) in Germany in 2015 and the lowest (20.4%) in Luxembourg in 2008. The lowest share of hours worked by workers aged 15-29 (11.7%) illustrates the Italian labour market in 2015.

Looking at the minimum and maximum values of the share of ICT, it is clear that there are notable differences in ICT capital between countries and time. The share of ICT capital in total capital over the sample was the smallest with the value of 0.94 percent for Latvia in 2013 and biggest at 5.65 percent for Luxembourg in 2016. On average, ICT capital makes up 2.4 percent of the total capital input over the sample.

The following figures illustrate entity heterogeneity of the variables GVA per hour worked (Figure 2), share of hours worked by workers aged 50 or above (Figure 3) and the share of ICT capital in the total capital input (Figure 4). The meanings of the country abbreviations used in the figures can be found in Appendix 1. All three figures also include time dimension, however time heterogeneity figures where time is on the horizontal axis are found in Appendices 4, 5 and 6 for more comprehensive view of time variability.

Figure 2 shows that for the variable GVA per hour worked, country mean values are relatively similar and for all other sample countries aside from Greece, the labour productivity has increased over the time period 2008-2016. Country with the most variability across years in GVA per hour worked is Ireland, for which the labour productivity measured with GVA volume index has increased drastically from 86.3 in 2008 to 138.5 in 2016. This means that by 2016, the GVA had increased by 38.5% compared to base year 2010. The main reason for Ireland's extremity compared to other sample countries lies in its "tax haven" status for some of the biggest technology and life science companies.

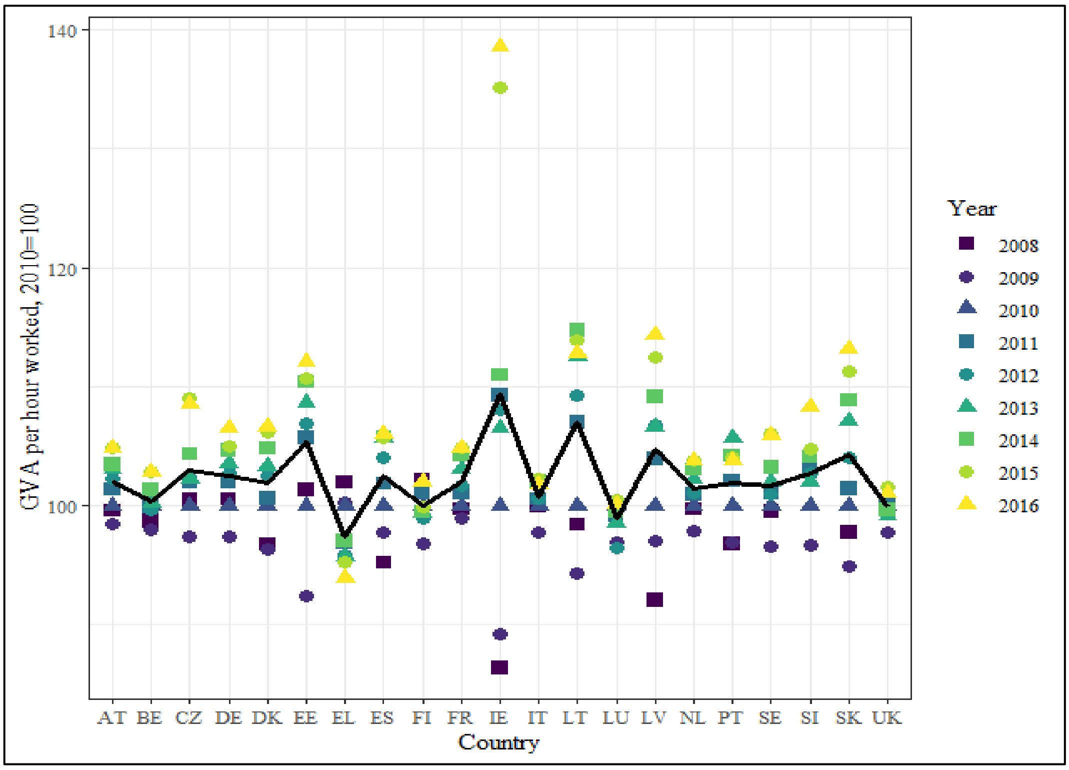

Figure 2. Country heterogeneity of the variable gross value added per hour worked
Source: Created by author in R based on data from the EU KLEMS 2019 release

Country heterogeneity of share of hours worked by workers aged 50 or above is displayed on Figure 3. Compared to the country heterogeneity of the variable GVA per hour worked illustrated on Figure 2, now it is clear that the share of older workers varies between countries and years more than the labour productivity. Looking at the time trend, the share of hours worked by workers 50 or above increased for most countries from 2008 to 2015 and then dropped back to 2013 levels in 2016 when the EU economy was shaken by the Chinese stock market crash and UK's decision to leave the Union. The time trend can also be seen on time heterogeneity figure in Appendix 5.

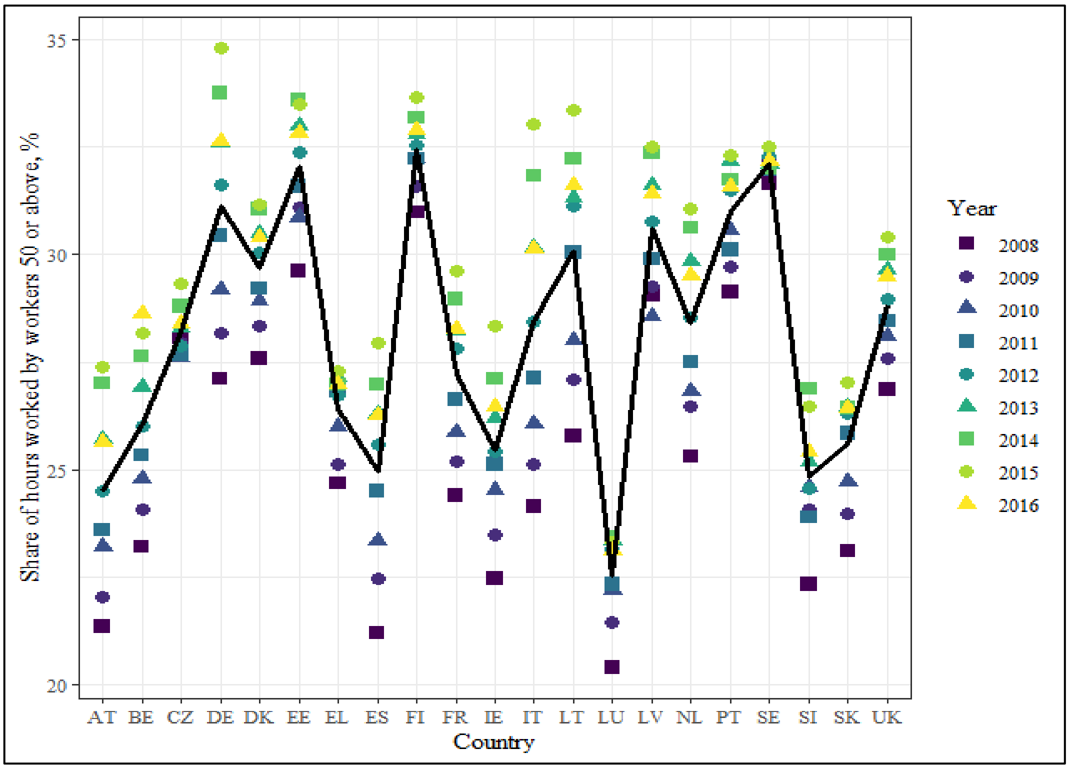

Figure 3. Country heterogeneity of share of hours worked by workers aged 50 or above
Source: Created by author in R based on data from the EU KLEMS 2019 release

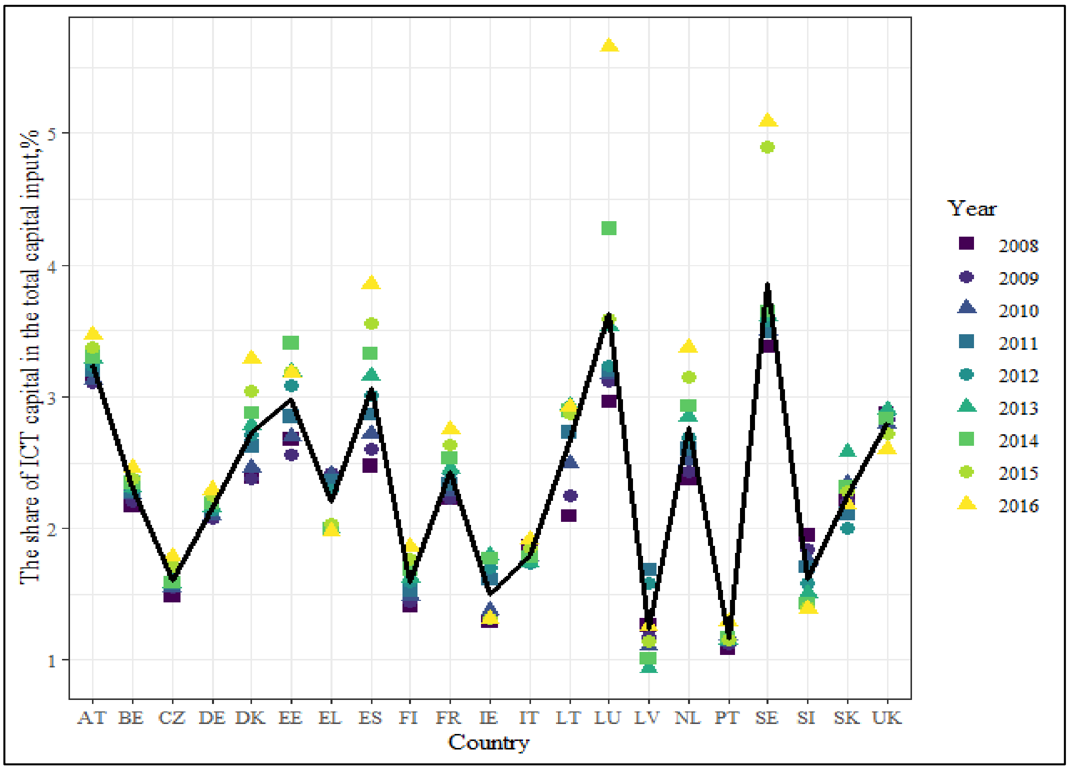

Figure 4. Country heterogeneity of share of ICT capital in the total capital input
Source: Created by author in R based on data from the EU KLEMS 2019 release

In contrast to the share of hours worked by older workers, the share of ICT capital in total capital inputs has been relatively stable over the sample period. This can be seen by looking at the closely located points representing different years for each country on Figure 4, and the mean value line graph in Appendix 6.

Countries for which the share of ICT noticeably increased during the sample period include Denmark, Spain, Luxembourg, Netherlands, and Sweden. The ICT share in 2008-2016 decreased in Greece and Slovenia. Sudden drop in ICT shares in 2016 took place in Estonia, Ireland, Latvia, Slovakia, and United Kingdom.

Comparing Figures 2, 3 and 4 tentative overall pattern emerges: with the average share of ICT capital in total capital input remaining relatively static one of the possible drivers of the average labour productivity growth could be the observed rise in the share of hours worked by older workers. Still no concrete conclusion can be drawn at this point.

3. EMPIRICAL ANALYSIS

3.1. Correlation and testing for the best static model

Correlation plot in Figure 5 illustrates the relationships between the variables used for pinpointing productivity effects of labour ageing. All variables, except the natural logarithm of gross value added per hour worked ($ln(Y/L)$), in the plot are first-order lagged. Correlation between two variables is marked with a cross if statistically insignificant on .05 level. The very high negative correlation between the natural logarithms of the share of low-educated labour in total labour input ($ln(L_l/L)$) and the share of high-educated labour in total labour input ($ln(L_h/L)$) is expected as the two together make up all total labour input.

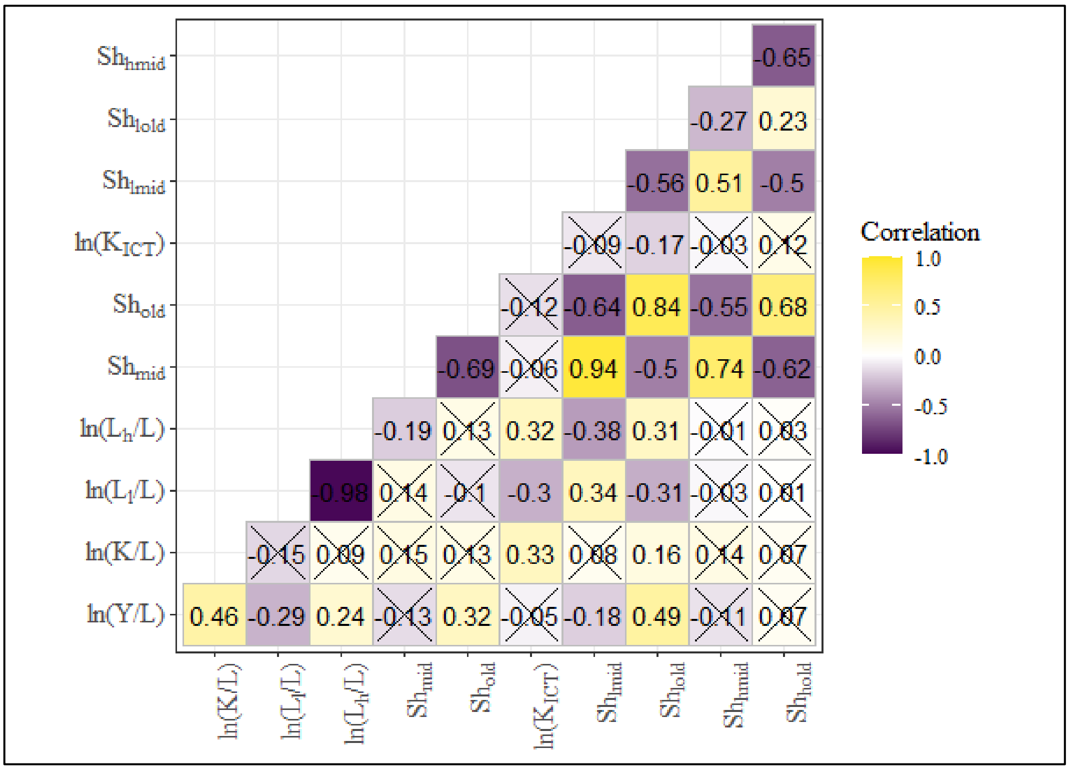

Figure 5. Correlation plot for variables used in the analysis
Source: Created by author in R based on data from the EU KLEMS 2019 release

The highest negative correlation considering those between dependent variable and independent variable is -0.29 which shows that GVA per hour worked ($ln(Y/L)$) and the share of low-educated labour in total labour input ($ln(L_l/L)$) move together but in opposite directions. The highest positive correlation 0.49 is between dependent variable ($ln(Y/L)$) and the share of low-educated labour aged 50 or above in low-educated (Sh_{lold}).

Results of tests used to specify the best model for regression between pooled ordinary least squares (OLS), fixed effects (FE), FE with time effects and random effects (RE) are available for more detailed perusal in Appendix 7. Test for fixed effects with the null hypothesis that pooled OLS is better than FE is conducted by using an F-test for individual effects with pFtest() function. The null hypothesis is rejected in favour of the alternative and therefore fixed-effects model is better than the pooled OLS. To help to decide between a RE model and pooled OLS, the Breusch-Pagan Lagrange multiplier (LM) test is used which shows that there are significant differences across the countries (null hypothesis that the variance across entities is zero is rejected at .01 level) and therefore, the RE model is superior to pooled OLS.

Decision between a FE and RE model is made with Hausman test. Hausman test checks individual error terms correlation with the regressors. The null hypothesis is that there is no correlation between individual error terms and the regressors, which means that RE model should be preferred. The alternative hypothesis asserts that individual error terms and regressors are correlated and FE model should be used. Hausman test's p-value is sufficiently small to reject the null hypothesis at .1 level for four models. Still FE model results are interpreted for all models due to the assumption that labour productivity varies between countries due to some time invariant country-specific unobserved factors.

The need for time fixed effects is tested with an F-test for twoways effects. The model with time fixed effects is compared to the one without, the null hypothesis is that no time fixed effects need to be added to the model. The null hypothesis is not rejected and the fixed effects model without time fixed effects is used.

Breusch-Pagan test against heteroskedasticity's p-values, for all models, is small enough to reject the null hypothesis of homoskedasticity at the .01 level. Testing against serial correlation with Breusch-Godfrey/Wooldridge test also gives small p-values so the null hypothesis of no serial correlation is rejected at the .01 level. Therefore, there is strong evidence for the presence of both heteroskedasticity and serial correlation in all models and clustered standard errors are used.

3.2. Fixed effects regression results

The fixed effects regression results without time effects based on the models in Equations 1, 2 and 3 are displayed in Table 3. All models are significant at .01 level and cover total economy data on 21 European Union countries from 2008 to 2016. Standard errors in parentheses are both heteroskedasticity and serial correlation (in other words autocorrelation) robust. Regression results for pooled OLS, RE and FE with time effects added can be found in Appendices 8, 9 and 10 respectively for comparison.

The FE estimation results based on the Equation 1 are in the first column in Table 3 and show that the estimated coefficient for share of labour aged 50 or above is positive and statistically significant at .1 level. This implies that contrary to the previous assumptions based on the literature, there could be a positive relationship between ageing and labour productivity in the selected sample as one precentage point increase in the share of hours worked by workers aged 50 or above brings about 1.4 percent increase in the gross value added per hour worked. The statistically insignificant estimated coefficient for the natural logarithm of the ICT share is negative which means that without the interaction between ICT and labour share by age, ICT capital share has, on average, an insignificant effect on labour productivity in EU countries.

Column 2 of Table 3 reports the regression results based on the model in Equation 2 with the interaction of age group shares with a logarithm value of the ICT capital share in total capital input. Looking at the interaction terms both estimated coefficients are negative and statistically significant at .01 level. Relative to young labour inputs, the increase in the share of labour aged 30-49 has a negative[5] and the share of labour aged 50 or above a positive[6] effect on labour productivity at the mean of the logarithm of the ICT capital share. One-standard-deviation increase of 4.46 percentage points in the share of labour aged 30-49 would therefore lead to a decrease in labour productivity (relative to the labour productivity of young workers) of 0.004 and one-standard-deviation increase of 3.25 percentage points in the share of labour aged 50 or above to

[5] $\varphi^*_{mid} + \varphi^*_{midICT} \times \overline{\ln\,(K_{ICT})} = 0.015 + (-0.020) \times 0.80 = -0.001$

[6] $\varphi^*_{old} + \varphi^*_{oldICT} \times \overline{\ln\,(K_{ICT})} = 0.032 + (-0.028) \times 0.80 = 0.0096$

an increase of 0.031 at the mean value of the logarithm of the ICT capital share. These respectively amount to -0.4% and 3.1% of the labour productivity.

Table 3. Fixed effects regression results based on the models presented in Equations 1, 2 and 3

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.434***	0.457***	0.478***	0.465***	0.441***	0.409***
	(0.091)	(0.087)	(0.085)	(0.081)	(0.113)	(0.076)
$\ln(L_l/L)$	-0.136	-0.144	-0.589*	-0.347	0.022	-0.242
	(0.319)	(0.292)	(0.346)	(0.408)	(0.324)	(0.346)
$\ln(L_h/L)$	-0.050	-0.073	0.014	-0.049	-0.063	-0.149
	(0.138)	(0.103)	(0.110)	(0.096)	(0.129)	(0.116)
Sh_{mid}	0.005	0.015**	0.000	0.013**	–	–
	(0.007)	(0.006)	(0.006)	(0.006)		
Sh_{old}	0.014*	0.032***	0.011	0.026**	–	–
	(0.007)	(0.009)	(0.007)	(0.012)		
$\ln(K_{ICT})$	-0.014	1.830***	0.979***	1.932***	-0.031	1.279***
	(0.051)	(0.346)	(0.325)	(0.397)	(0.048)	(0.324)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.020***	–	-0.018***	–	–
		(0.004)		(0.004)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.028***	–	-0.021*	–	–
		(0.009)		(0.011)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.283***	-0.121	–	–
			(0.090)	(0.101)		
Sh_{lmid}	–	–	–	–	-0.001	0.001
					(0.005)	(0.008)
Sh_{lold}	–	–	–	–	0.013**	0.029***
					(0.006)	(0.008)
Sh_{hmid}	–	–	–	–	0.006**	0.009
					(0.003)	(0.006)
Sh_{hold}	–	–	–	–	-0.001	-0.006
					(0.003)	(0.004)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	-0.004
						(0.007)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.022***
						(0.006)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	-0.008
						(0.007)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	0.003
						(0.004)
Observations	168	168	168	168	168	168
R^2	0.615	0.698	0.664	0.703	0.664	0.738
Adjusted R^2	0.544	0.637	0.600	0.641	0.597	0.676

Source: Author’s calculations based on data obtained from EU KLEMS 2019 release

Notes:

1. Robust standard errors clustered by country in parentheses.
2. All explanatory variables inserted into the models with a one-period lag.
3. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
4. All models significant on 1% level.

The estimated coefficients on the logarithm of the share of the ICT capital and its interaction terms with the labour share by age group indicate that the logarithm of the share of the ICT capital has, similarily with Lee *et al.* (2020), a negative[7] effect on labour productivity at the mean of the interaction terms. It should be noted that for this analysis of EU countries, the effect of ICT capital share in labour productivity becomes even more negative when the average share of either middle aged or older workers increases.

The share of ICT capital influences the magnitude of the labour productivity effect of labour ageing. For example, if a country has a higher value of the logarithm of the share of ICT capital by one-standard-deviation of 0.35, the marginal effect of population ageing on labour productivity decreases to -0.0002. A one-standard-deviation increase in the share of older workers of 3.25 percentage points would then lead to decrease in labour productivity of -0.00065. Such a result indicates that an increase in ICT capital share does not improve the productivity of older workers relative to that of young workers but rather impairs it.

Regression results based on the model presented in Equation 1 with added interaction term between the logarithm of the share of ICT and share of high-educated workers is displayed in column 3 of Table 3. The coefficient estimate of the logarithm of the share of ICT capital is statistically significant at .01 level and positive while the interaction term with the share of high-educated workers has a negative and also at .01 level significant estimate of -0.283. This indicates that an EU country with a high share of high-educated labour lessens the labour productivity by investing in more ICT capital refuting complementary between ICT capital and high-educated labour for EU countries.

Regression results based on the model presented in Equation 2, with added interaction term between the logarithm of the share of ICT and share of high-educated workers, are displayed in column 4. Estimates for the coefficients of interest support the non-complementarity between ICT capital and older workers implied by the results in column 2. The coefficient of the interaction between ICT capital and high-educated labour inputs is negative but not statistically significant. This indicates that the adverse effect between ICT capital and high-educated workers is not robust after the non-complementarity between ICT capital and workers aged 50 or above is controlled for.

[7] $\varphi^*_{ICT} + \varphi^*_{midICT} \times \overline{Sh_{mid}} + \varphi^*_{oldICT} \times \overline{Sh_{old}} = 1.83 + (-0.020) \times 52.27 + (-0.028) \times 28.12 = -0.00276$

Column 5 of Table 3 presents regression results based on the model presented in Equation 3 without the interactions between the logarithm of the share of ICT and shares of low- and high-educated workers by age group. The positive statistically significant coefficient for the share of low-educated labour aged 50 or above in low-educated shows that an increase in the share of older labour inputs relative to young low-educated aged 15-29 has a positive impact on labour productivity. Looking at the estimated coefficients for the share of high-educated middle age and older workers respectively it can be inferred that while there is no significant difference in the labour productivity between younger and older high-educated workers the labour productivity of high-educated middle age workers is significantly larger than younger high-educated workers productivity.

Regression results based on the model presented in Equation 3, with the interactions between the logarithm of the share of ICT and shares of low- and high-educated workers by age group, can be found in column 6. The estimated coefficient of the interaction term between the share of low-educated labour inputs aged 50 or above and the ICT capital is negative and statistically significant at .01 level. Coefficient for the interaction term between the share of high-educated older workers and the ICT capital is insignificant. Relative to the share of younger workers, an increase in the share of low-educated older workers has a positive[8] impact on labour productivity at the mean value of the logarithm of the share of the ICT capital. Therefore, a one-standard-error increase of 3.46 percentage points in the share of low-educated older workers produces a 6.2% increase in labour productivity at the mean value of the logarithm of the share of the ICT capital.

The estimated coefficients on the logarithm of the share of the ICT capital and its interaction terms with the labour share by age group and education level indicate that the logarithm of the share of the ICT capital has a positive[9] effect on labour productivity at the mean of the interaction terms. It should be noted that the effect of ICT capital share on labour productivity becomes negative when the average share of low-or high-educated middle aged or low-educated older workers increases.

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[8] $\varphi^*_{lold} + \varphi^*_{loldICT} \times \overline{\ln{(K_{ICT})}} = 0.029 + (-0.022) \times 0.80 = 0.018$

[9] $\varphi^*_{ICT} + \varphi^*_{ICTlmid} \times \overline{Sh_{lmid}} + \varphi^*_{ICTlold} \times \overline{Sh_{lold}} + \varphi^*_{ICThmid} \times \overline{Sh_{hmid}} + \varphi^*_{ICThold} \times \overline{Sh_{hold}} = 1.279 + (-0.004) \times 49.54 + (-0.022) \times 29.44 + (-0.008) \times 57.57 + (0.003) \times 25.59 = 0.04937$

3.3. Robustness checks

It is clear from Table 3 that the lagged natural logarithms of the share of low-educated labour in total labour input ($ln(L_l/L)$) and the share of high-educated labour in total labour input ($ln(L_h/L)$) are rarely statistically significant even on .1 level. Variance inflation factor (VIF) as expected from the correlation plot in Figure 5 has values greater than 5 for both before-mentioned independent variables, meaning that the coefficient estimates and p-values could be unreliable as high correlation between independent variables can make fitting and interpreting the regression model problematic.

To account for this potential problem and check the sensitivity of the results displayed in Table 3, all the models are estimated without the natural logarithm of the share of low-educated labour in total labour input ($ln(L_l/L)$). The results which are available in more detail in Appendix 11 are overall very similar with those in Table 3. The biggest difference can be found in column 3 where the lagged share of hours worked by workers aged 50 or above (Sh_{old}) is statistically significant on .1 level for the model without the lagged natural logarithm of the share of low-educated labour in total labour input ($ln(L_l/L)$).

Another important aspect of the panel data is the stationarity of the variables. As the time dimension of the panel data used in this work $T = 9$ is very short, the application of time series methods and tests is implausible leading to potentially ambiguous results. According to Hecht and Zitzmann (2021), there should be at least 50 different cross-sectional units at 9 available time points to achieve good overall performance of the continuous-time model estimation. Therefore, for this work the cross-sectional depth of $N = 21$ does not compensate for the short time dimension, and the performance of continuous-time model would be fair at best.

Testing for unit root in the variables used in the analysis with Maddala and Wu (1999) first generation test gives tentative evidence for non-stationarity for the dependent variable as well as some independent variables. Potential for unit root is also hidden in the sample time period which spans from the depth of economic crisis to recovery. Hence, the models are estimated with first differences of all the variables in terms of sensitivity analysis. The results for first difference estimation without fixed effects are available for perusal in Appendix 12. Once again, the results are quite similar with the ones from the static fixed effects model without time effects displayed in Table 3. Coefficients for variables are smaller in the case of first differences model, first differences estimation also does not support the finding of a negative relationship between the share of high-educated labour and investment into ICT capital from the fixed effects model.

As mentioned in the last subchapter of the second part about descriptive statistics some countries from the sample of 21 countries noticeably differ from others. To make sure that the results in Table 3 are not driven by data from the outliers, three countries (Ireland, Luxembourg, and Sweden) marked in Figure 1 with yellow are excluded from the sample. Ireland is left out from the restricted sample due to extreme growth in gross value added per hour worked during the sample period while Luxembourg and Sweden stand out with significant growth in the share of ICT capital in the total capital input. The restricted sample therefore consists of 18 countries covering the period from 2008 to 2016.

Appendix 13 describes the results of the fixed effects estimation results based on the restricted sample in more detail. Comparison of results shows that while several variables have lost their statistical significance in the case of restricted sample estimation the coefficients of interest display the same patterns as for the results displayed in Table 3.

Robustness of the results is also checked with dynamic models by including the first lag of the dependent variable on the right-hand side of the models. Selection process between the difference and system generalized method of moments (GMM) designed for small panels with heteroscedasticity and within group autocorrelation follows the rules of thumb suggested by Bond *et al.* (2001) by first estimating the dynamic model with pooled OLS and the least square dummy variable approach and then finding the corresponding FE estimates. The pooled OLS estimate for the lagged dependent variable coefficient is considered an upper-bound estimate as dynamic OLS estimators are biased upward due to correlation between the lagged dependent variable and the individual specific effects while the same coefficient for FE is the lower bound estimate. The downward bias in dynamic fixed effects model also known as Nickell (1981) bias is the most problematic in the case of relatively deep cross section and a rather short time dimension ($N > T$).

The selection process is continued by estimating the lagged dependent variable coefficient for the difference GMM and comparing it to the dynamic FE estimate. If the difference GMM estimate is close or below the fixed effects estimate, system GMM should be preferred for estimation. In this work twosteps model is used for both difference and system GMM due to the presence of heteroscedasticity with Windmeijer adjusted standard errors correcting for small sample bias.

Lagged dependent variable coefficients in dynamic pooled OLS, dynamic FE and system GMM are shown in Table 4. Difference GMM coefficients for the lagged dependent variable are not included in the table as they are out of scale with negative value. This may be due to the small sample which is even further reduced by the first differencing of the difference GMM. Therefore, system GMM is preferred for all six estimations. System GMM coefficients stay within the corridor made up from pooled OLS and dynamic FE coefficients.

Table 4. Lagged dependent variable coefficients in dynamic pooled OLS, dynamic FE, and system GMM

Model	Dynamic pooled OLS	Dynamic FE	System GMM
(1)	0.851	0.606	0.823
(2)	0.856	0.527	0.663
(3)	0.836	0.567	0.652
(4)	0.840	0.522	0.647
(5)	0.821	0.566	0.604
(6)	0.823	0.483	0.553

Source: Author's calculations based on data obtained from EU KLEMS 2019 release

System GMM estimation results are displayed in full in Appendix 14. The results from system GMM do not support the results for the variables of interest from static fixed effects model in Table 3. One reason could again be the smallness ($N = 21, T = 9$) of the panel.

3.4. Discussion of interaction effects and overall results

Figure 6 depicts the marginal effects of interaction between age group shares and the share of ICT capital in total capital input. Graphs in the upper row in the figure illustrate the average marginal effects of the share of hours worked by workers aged 30-49 or 50+ on labour productivity at different values of the share of ICT capital in total capital input. Lower row shows the average marginal effect of the share of ICT capital when the share of hours worked by older workers and mid age workers respectively is held constant at the mean value.

According to Pepinsky (2017) researchers follow most commonly either the "crosses zero" or "compare extremes" heuristic for interpreting marginal effects plots. The "crosses zero" heuristic assigns significance to the part of the interaction term where the confidence interval does not capture zero while the "compare extremes" heuristic looks for an overlap across the whole range of the confidence band. Both approaches are shown to be less effective than looking at the coefficient and p-value of the interaction term. To conclude, marginal effects plots do not test for significance of the interaction term and should therefore be used for illustrative purposes.

Relationships represented in Figure 6 further clarify the results briefly discussed in the subchapter about the static fixed effects regression results. An increase in the share of ICT capital in total capital input brings about a decrease in the labour productivity related to ageing workforce. Therefore, based on the data used in this work, workforce ageing has a negative effect on labour productivity in countries where the share of investments into ICT is large.

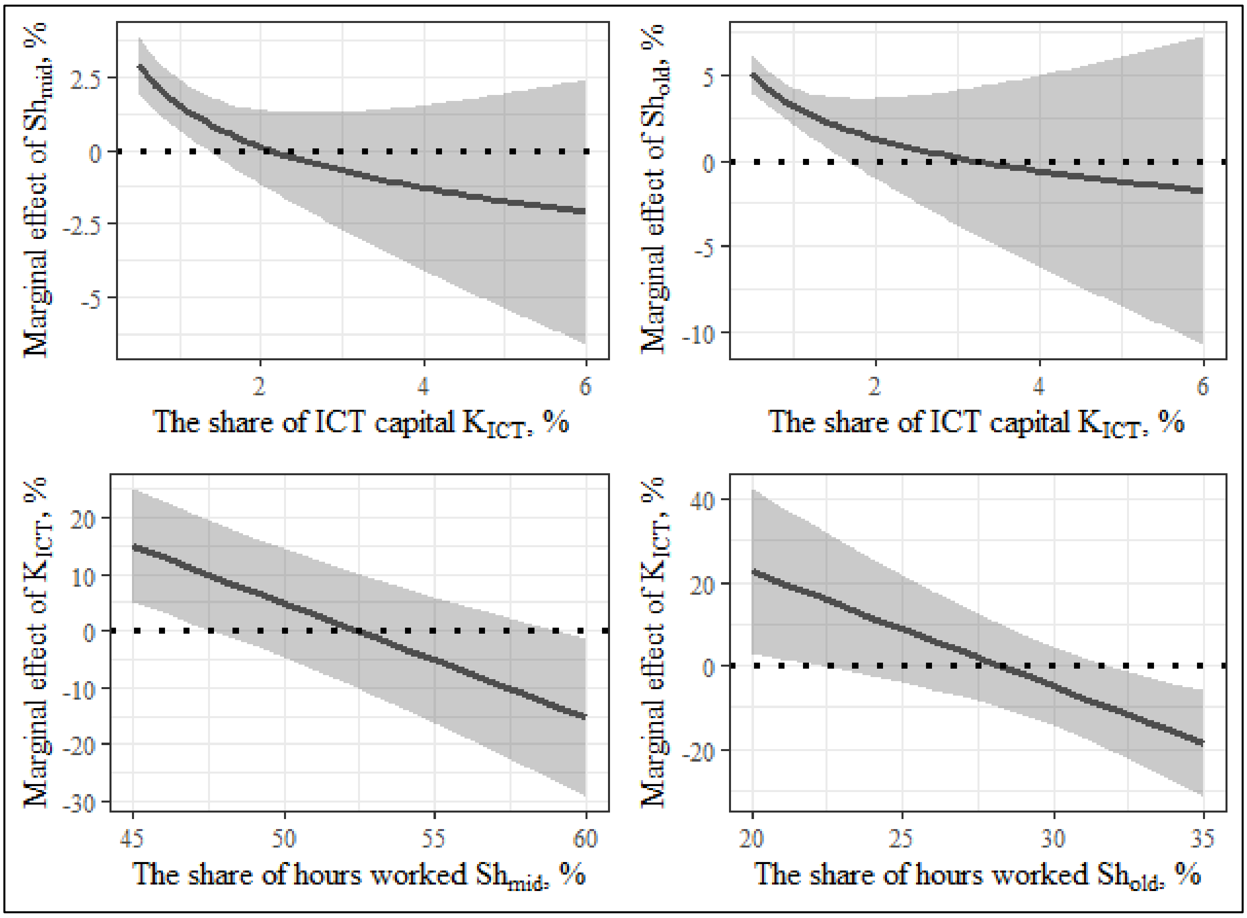

Figure 6. Marginal effects of interaction between age group shares and the share of ICT capital in total capital
Source: Created by author in R based on data from the EU KLEMS 2019 release

Marginal effects of interaction between the share of hours worked by high-educated labour in total hours worked and the share of ICT capital in total capital input from column 3 in Table 3 are shown on Figure 7. The labour productivity effect of high-educated workers decreases when the share of ICT capital in total capital inputs increases. This non-complementary relationship may be caused by the relatively larger share of older workers in the high-educated who might adapt to ICT slower than their younger counterparts, especially as this interaction effects loses its significance in the column 4 in Table 3 where interaction terms between shares of older workers and the share of ICT capital are included in the model.

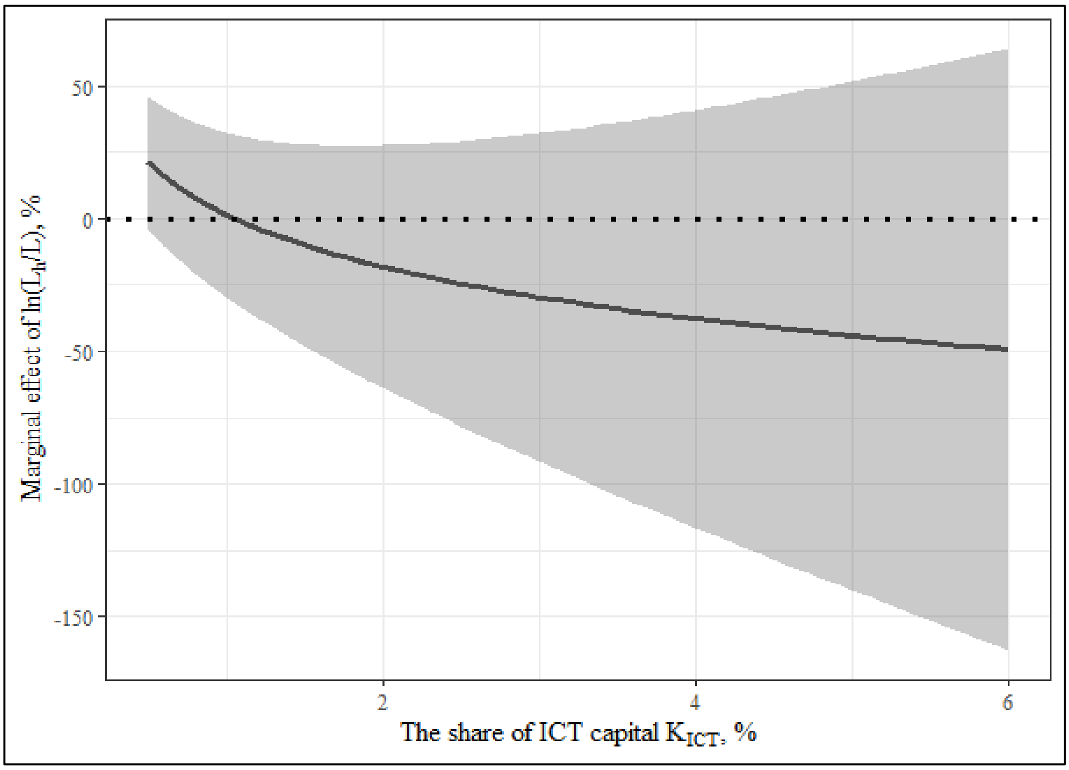

Figure 7. Marginal effects of interaction between the share of high-educated labour and the share of ICT capital in total capital
Source: Created by author in R based on data from the EU KLEMS 2019 release

Figure 8 illustrates the marginal effects of interaction between the shares of low-educated older workers and the share of ICT capital in total capital input. The labour productivity effect of the share of low-educated labour aged 50 or above in low-educated is shown at different shares of ICT capital in total capital inputs. The curve in the graph is downward sloping meaning that when the share of ICT capital increases the labour productivity of the low-educated labour aged 50 or above decreases compared to the low-educated aged 15-29. This leads to conclusion that there is no complementary productivity effect between older workers and the share of ICT capital.

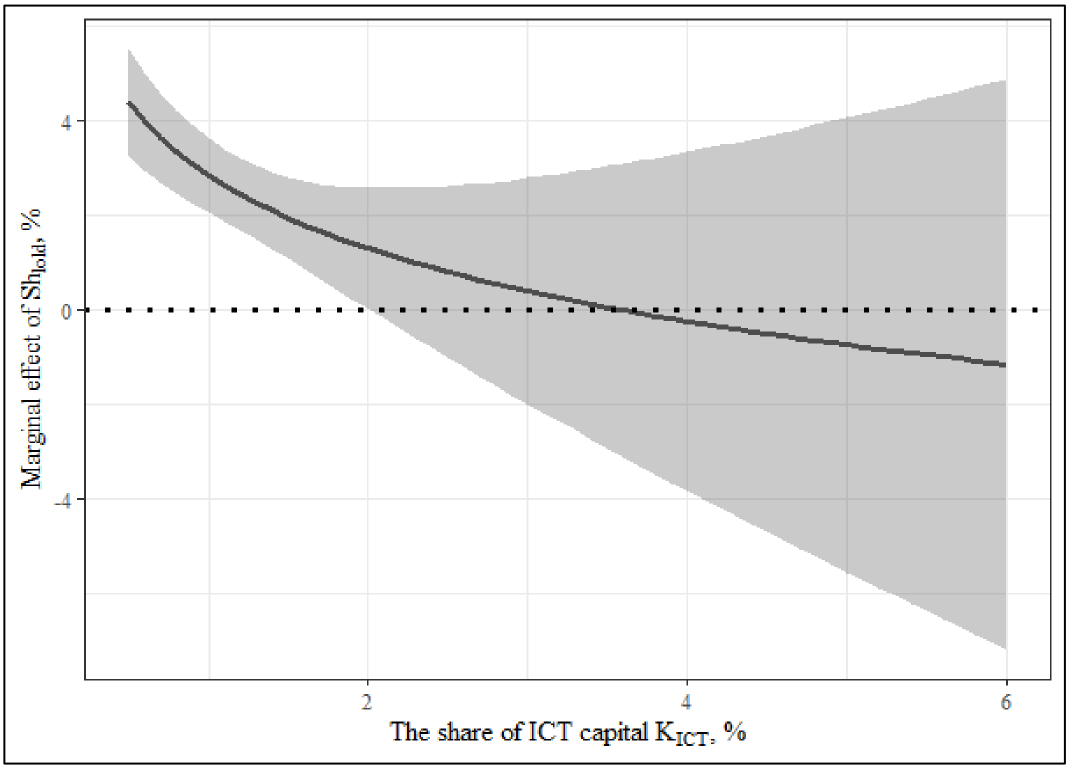

Figure 8. Marginal effects of interaction between the share of low-educated older workers and the share of ICT capital in total capital
Source: Created by author in R based on data from the EU KLEMS 2019 release

Based on the results of the static fixed effects regression, all the established hypotheses were refuted. The main research question how investments into ICT affect the labour productivity of older workers was answered by incorporating interactions between the shares of hours worked by age groups and the share of ICT capital in the total capital inputs into the analysis and the adverse effect of the investments into ICT for the labour productivity of older workers can be seen in the upper row of Figure 6.

CONCLUSION

The aim of this thesis was to investigate the relationship between workforce ageing and productivity in selected EU countries, as well as how the education level of ageing workers affects their adaption to new technology in the workplace. It is important to support and facilitate employment amongst the older people in the context of the ongoing population ageing for most developed countries as it puts increasingly higher pressure on working-age populace through the rising social expenditure.

The main handled research question in this work was how investments into ICT affect the labour productivity of older workers. To fulfil the aim of the thesis and answer the main research question, the author worked through the relevant previous literature about labour force ageing, digitalization and productivity, and based on the knowledge aquired used static fixed effects model to examine the validity of the three proposed hypothesis. The small panel data sample from the EU KLEMS 2019 release used for the empirical analysis covered 21 European Union countries for 9 time periods from 2008 to 2016.

The first hypothesis that workforce ageing has a negative effect on labour productivity in the selected sample of EU countries was refuted. A baseline empirical analysis of the logarithmic form of the production function, with the gross value added per hour worked as the dependent variable, indicated a positive relationship between workforce ageing and labour productivity. According to this model a one percentage point increase in the share of hours worked by workers aged 50 or above brings about 1.4 percent increase in the gross value added per hour worked compared to the reference group of labour inputs aged 15-29.

The main research question was answered and the validity of the second hypothesis refuted by incorporating interactions between the shares of hours worked by age groups and the share of ICT capital in the total capital inputs into the analysis. The results uncovered that an increase in the ICT capital share does not improve the older workers' productivity relative to younger workers. This means that investments into ICT which rise the ICT capital share in total capital inputs worsen the labour productivity of older workers compared to that of their younger (aged 15-29) counterparts and therefore ageing has a negative impact on labour productivity in countries where the share of investments into ICT is large.

Regarding effects between ICT capital and education it was found that an EU country with a high-share of high-educated labour lessens the labour productivity by investing in more ICT capital therefore refuting complementarity between ICT capital and high-educated labour for EU countries. This adverse relationship was not robust after controlling for the non-complementarity between ICT capital and both mid age and older workers who form roughly over 80% of the high-educated.

An increase in the share of low-educated labour aged 50 or above relative to young low-educated aged 15-29 has a positive impact on labour productivity while there is no significant difference in the labour productivity between younger and older high-educated workers. However, the labour productivity of high-educated middle age workers is significantly larger than younger high-educated workers productivity.

The analysis of the third and final hypothesis that there is a complementary effect between older workers and ICT capital for both low- and high-educated workers led to following results. An increase in the ICT capital share does not improve the low-educated older workers' productivity relative to low-educated younger workers, while there is no impact for high-educated older worker's productivity compared to the productivity of high-educated younger workers. Therefore, there is a non-complementary effect between low-educated older workers and ICT capital.

The robustness of the results from the static fixed effects regression were checked in four ways. In order to account for potential multicollinearity, a model without the lagged natural logarithm of the share of low-educated labour in total labour input was estimated. Potential non-stationarity of variables was mitigated with first-differencing all the variables. The static fixed effects model was estimated using restricted country sample from which three outlier countries were removed. Finally, the sensitivity of results was checked with a dynamic system GMM model. The first three checks yielded relatively similar results to the static fixed effects model. The dynamic system GMM model results however did not support the results for the variables of interest.

The results desribed in current work are in no way final. The models described could be estimated for each country separately as well as on data from the previous or future releases. A separate view on manufacturing and services could be created by utilizing the industry level dimension of the EU KLEMS datasets. One other interesting branch of future research would be to estimate how investments into ICT affect the labour productivity of older workers on individual worker level.

KOKKUVÕTE

VANANEV TÖÖJÕUD DIGIAJASTUL: VANEMAEALISED TÖÖTAJAD, DIGITALISEERIMINE NING TOOTLIKKUS EUROOPA LIIDU RIIKIDES

Miina Hõbenael

Käesoleva lõputöö eesmärgiks oli hinnata seost tööjõu vananemise ja tootlikkuse vahel valitud Euroopa Liidu riikides. Lisaks vaadeldi, kuidas mõjutab vananevate töötajate haridustase nende suhet uute tehnoloogiatega. Arenenud riikide elanikkonna vananemise kontekstis on oluline toetada eakate tööhõivet, kuna see aitab vähendada ühiskonna vananemisega kaasnevate sotsiaalkulude survet tööealisele elanikkonnale.

Peamiseks uurimisküsimuseks oli, kuidas mõjutavad investeeringud info- ja kommunikatsioonitehnoloogiasse (IKT) vanemate töötajate tööjõu produktiivsust. Töös püstitati kolm hüpoteesi:

1. Tööjõu vananemine mõjutab tööjõu produktiivsust valitud Euroopa Liidu riikides negatiivselt.
2. Vananemisel on positiivne mõju tööjõu tootlikkusele riikides, mida iseloomustab suur IKT-sse tehtavate investeeringute osakaal.
3. Vanemad töötajad ja IKT kapital täiendavad üksteist olenemata töötajate haridustasemest.

Lõputöö eesmärgi täitmiseks kasutati 2019. aastal välja antud EU KLEMS tasakaalustatud paneelandmete regressioonanalüüsi staatilise fikseeritud efektidega mudeliga. Kasutatud valim hõlmas 21 perioodil 2008-2016 Euroopa Liitu kuulunud riiki: Austria, Belgia, Tšehhi, Taani, Eesti, Soome, Prantsusmaa, Saksamaa, Kreeka, Iirimaa, Itaalia, Läti, Leedu, Luksemburg, Holland, Protugal, Slovakkia, Sloveenia, Hispaania, Rootsi, Ühendkuningriik. Kogumajanduse koondandmed võeti EU KLEMS statistikaandmebaasi kõigist neljast jaotisest.

Esimene töös püstitatud hüpotees, et tööjõu vananemine mõjutab tööjõu produktiivsust valitud Euroopa Liidu riikides negatiivselt, ei leidnud kinnitust. Tootmisfunktsiooni logaritmilise vormi empiiriline analüüs, kus sõltuvaks muutujaks oli brutolisandväärtus töötunni kohta, näitas tööjõu vananemise ning tootlikkuse vahel positiivset seost. Mudeli tulemuste kohaselt kaasneb 50-aastaste ja vanemate töötajate töötundide osakaalu suurenemisega ühe protsendipunkti võrra võrreldes 15-29 aastastega tootlikkuse 1,4-protsendiline kasv.

Peamisele uurimisküsimusele vastati ja teise hüpoteesi paikapidavus lükati ümber, kaasates mudelisse interaktsioonid vanuserühmade töötundide osakaalude ning IKT kapitali osakaalu vahel. Tulemused näitasid, et IKT kapitaliosa suurenemine ei parada vanemate töötajate tootlikkust võrreldes nooremate töötajatega. See tähendab, et investeeringud IKT-sse, mis suurendavad IKT kapitali osakaalu kogukapitalis, halvendavad vanemate töötajate produktiivsust, mistõttu on vananemisel negatiivne mõju tööjõu tootlikkusele riikides, mida iseloomustab suur IKT-sse tehtavate investeeringute osakaal.

Kolmas ja viimane töös püstitatud hüpotees, et vanemad töötajad ja IKT kapital täiendavad üksteist olenemata töötajate haridustasemest, lükati samuti ümber. IKT kapitaliosa suurendamine ei paranda madala haridustasemega vanemaealiste töötajate tootlikkust võrreldes madala haridustasemega nooremate töötajatega. Samas ei avalda IKT kapitali osakaalu suurenemine mõju kõrge haridusega vanemaealiste töötajate tootlikkusele võrreldes kõrge haridusega nooremate töötajate tootlikkusega. Seetõttu võib väita vaid seda, et madala haridustasemega vanemaealiste töötajate osakaal ja IKT kapital ei täienda tööjõu produktiivsuse kontekstis üksteist.

Staatiliste fikseeritud efektide regressiooni tulemuste püsivust kontrolliti neljal viisil. Võimaliku multikollineaarsuse arvestamiseks hinnati mudelit, millest oli välja jäetud madala haridustasemega tööjõu osatähtsuse naturaallogaritm. Muutujate võimalikku mittestatsionaarsust leevendati kõigi muutujate esimest järku diferentsimisega. Staatilise fikseeritud mõjude mudeli hindamisel kasutati valimit, millest olid riikide lõikes eemaldatud erindid. Viimaks kontrolliti tulemuste tundlikkust dünaamilise süsteemi GMM-mudeliga. Esimesed kolm kontrollhindamist andsid suhteliselt sarnased tulemused staatilise fikseeritud efektide mudeliga. Dünaamilise süsteemi GMM-mudeli tulemused seevastu ei toetanud fikseeritud efektidega mudeli tulemusi.

Töös kirjeldatud tulemused ei ole lõplikud. Kirjeldatud mudeleid saab hinnata nii iga riigi kohta eraldi kui ka kasutades EU KLEMS-i eelmiste või tulevaste väljaannete andmeid. Tootmise ja teenuste kohta on võimalik luua eraldi vaade, kasutades EL KLEMS andmete tööstustasandi mõõdet. Veel üks potentsiaalne käesoleva töö laiendamise võimalus oleks hinnata IKT mõju vanemaealiste töötajate produktiivsusele mikrotasandil.

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APPENDICES

Appendix 1. Data availability and abbreviations for different EU countries in 2019 release

Country	Abbreviation	Labour productivity	Capital-to-labour ratio	Labour shares	Share of ICT capital
Austria	AT	1995-2017	1995-2017	2008-2017	1995-2017
Belgium	BE	1999-2017	1999-2017	1999-2017	1995-2017
Bulgaria	BG	1995-2017	2008-2017	2008-2017	NA
Croatia	HR	2008-2016	NA	2008-2017	NA
Cyprus	CY	2008-2017	NA	2008-2017	NA
Czech Republic	CZ	1995-2017	1995-2017	2008-2017	1995-2017
Denmark	DK	1995-2017	1995-2017	2008-2017	1995-2017
Estonia*	EE	2000-2017	2008-2016	2008-2017	2000-2016
Finland	FI	1995-2017	1995-2017	2008-2017	1995-2017
France	FR	1995-2017	1995-2017	2008-2017	1995-2017
Germany	DE	1995-2017	1995-2017	2008-2017	1995-2017
Greece*	EL	1995-2017	2008-2016	2008-2017	1995-2016
Hungary	HU	2010-2017	2010-2016	2008-2017	NA
Ireland*	IE	1995-2017	2008-2016	2008-2017	1995-2016
Italy	IT	1995-2017	1995-2017	2008-2017	1995-2017
Latvia*	LV	1999-2017	2008-2016	2008-2017	1995-2016
Lithuania*	LT	1995-2017	2008-2016	2008-2017	1995-2016
Luxembourg	LU	1995-2017	2008-2017	2008-2017	1995-2017
Malta	MT	NA	NA	2009-2017	NA
Netherlands	NL	1995-2017	1995-2017	2008-2017	1995-2017
Poland	PL	2008-2017	NA	2008-2017	NA
Portugal*	PT	2000-2017	2008-2016	2008-2017	2000-2016
Romania	RO	1995-2017	2008-2016	2008-2017	NA
Slovakia	SK	1995-2017	2000-2017	2008-2017	2000-2017
Slovenia	SI	2000-2017	2008-2017	2008-2017	2000-2017
Spain*	ES	1995-2017	1995-2016	2008-2017	1995-2016
Sweden*	SE	1995-2017	1995-2016	2008-2017	1995-2016
United Kingdom	UK	1995-2017	1995-2017	2008-2017	1995-2017

Source: Compiled by the author based on the data availability in EU KLEMS 2019 release

Notes:

1. Countries marked with light grey not included in the sample.
2. Countries with a "*" restrict the sample end year to 2016.
3. "NA"- data for calculating not available in the dataset
4. Data availability in the context of having continuous panel data.

Appendix 2. Data compiling from EU KLEMS 2008, 2012 and 2019 releases

Country	2008 Release	2012 Release	2019 Release
AT	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
BE	1995-1998 labour productivity, capital-to-labour ratio, labour shares	Included, data for bridging gaps not needed	1999-2017 labour productivity, capital-to-labour ratio, labour shares 1995-2017 share of ICT capital
CZ*	1995-2005 labour shares	Not included	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
DK*	1995-2005 labour shares	Not included	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
FI	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
DE	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
IT	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
NL	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital
SI*	1995-1999 labour productivity, share of ICT capital 1995-2005 capital-to-labour ratio, labour shares	Not included	2008-2017 capital-to-labour ratio, labour shares 2000-2017 labour productivity, share of ICT capital
ES	1995-2005 labour shares *No capital input files*	2006-2007 labour shares	2008-2017 labour shares 1995-2016 capital-to-labour ratio, share of ICT capital 1995-2017 labour productivity
UK	1995-2005 labour shares	2006-2007 labour shares	2008-2017 labour shares 1995-2017 labour productivity, capital-to-labour ratio, share of ICT capital

Source: Compiled by the author based on EU KLEMS 2008, 2012 and 2019 releases
Notes:

1. Meanings of the country abbreviations used can be found in Appendix 1.
2. Countries for which application of interpolation techniques is necessary marked with “*”.

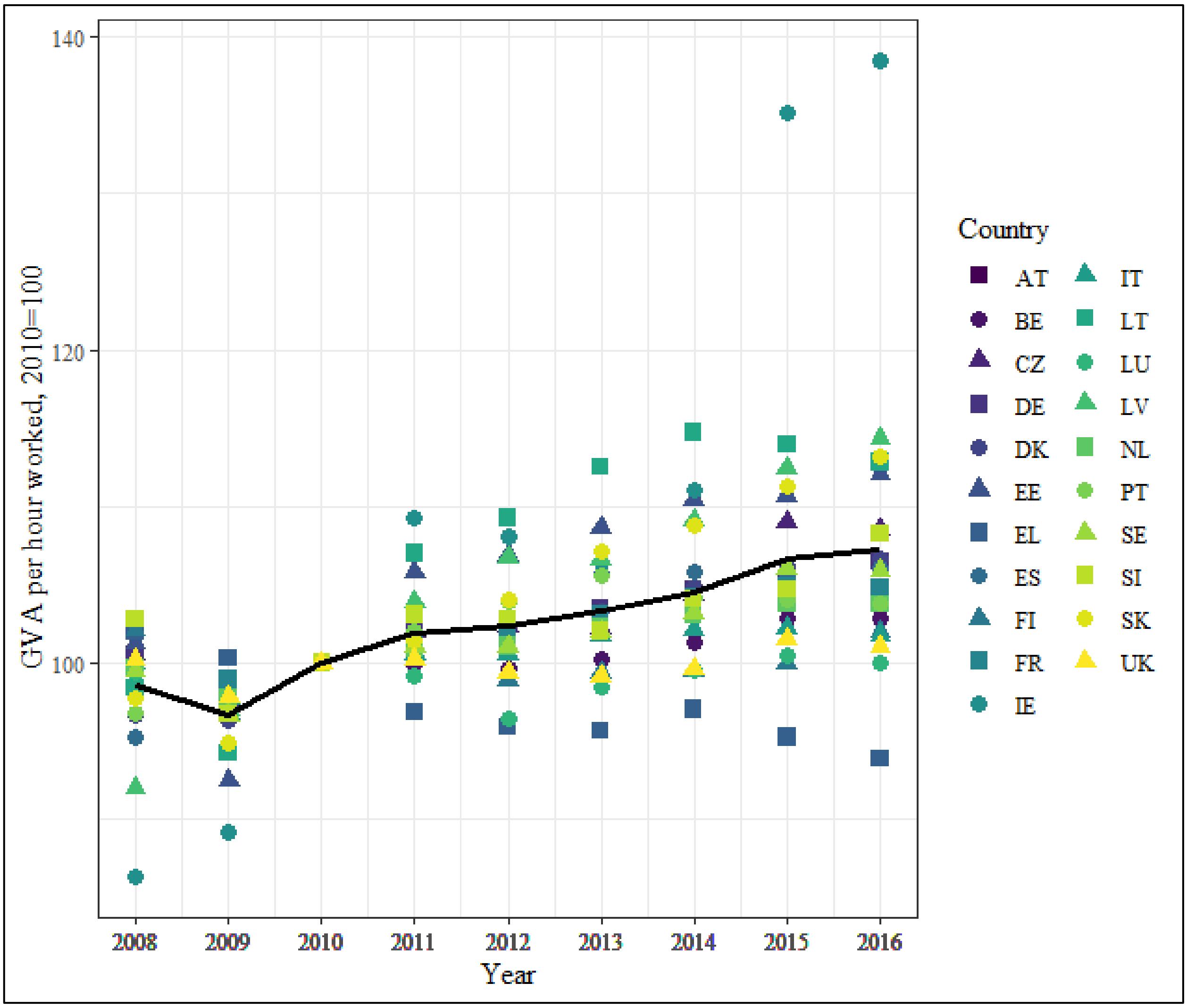
Appendix 3. Descriptive statistics of logarithmic variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Natural logarithm of GVA per hour worked, volume 2010=100, $\ln(Y/L)$	4.63	0.05	4.46	4.93
Natural logarithm of capital-to-labour ratio, $\ln(K/L)$	4.60	0.05	4.37	4.72
Natural logarithm of the share of low-educated labour in total labour input, $\ln(L_l/L)$	4.21	0.12	3.93	4.44
Natural logarithm of the share of high-educated labour in total labour input, $\ln(L_h/L)$	3.43	0.28	2.70	3.90
Natural logarithm of the share of ICT capital in the total capital input, $\ln(K_{ICT})$	0.80	0.35	-0.06	1.73

Source: Author's calculations based on data obtained from EU KLEMS 2019 release
Notes:

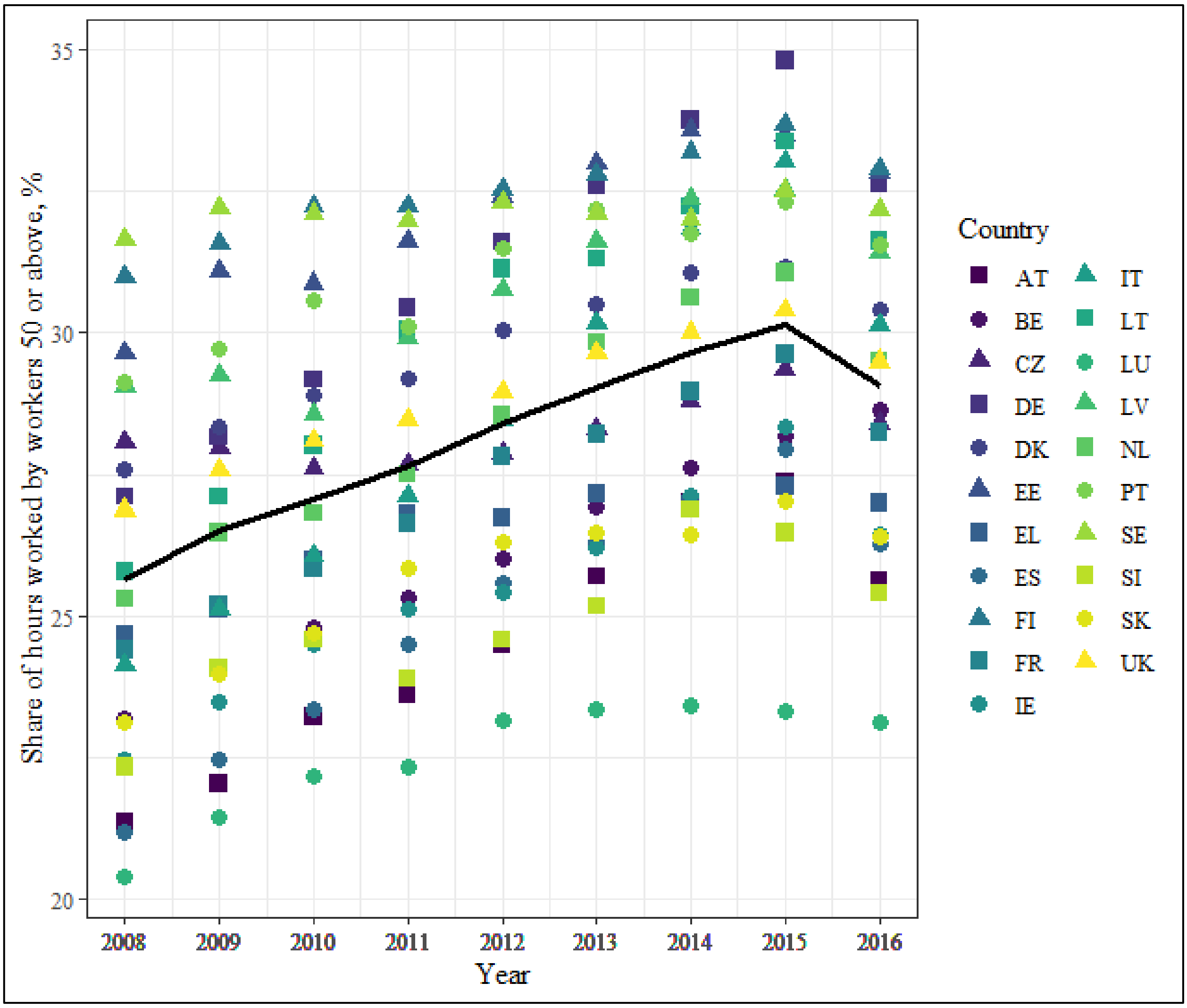
1. Sample covers 189 observations from 21 EU countries for period 2008-2016.
2. "GVA"- gross value added

Appendix 4. Time heterogeneity of the variable gross value added per hour worked



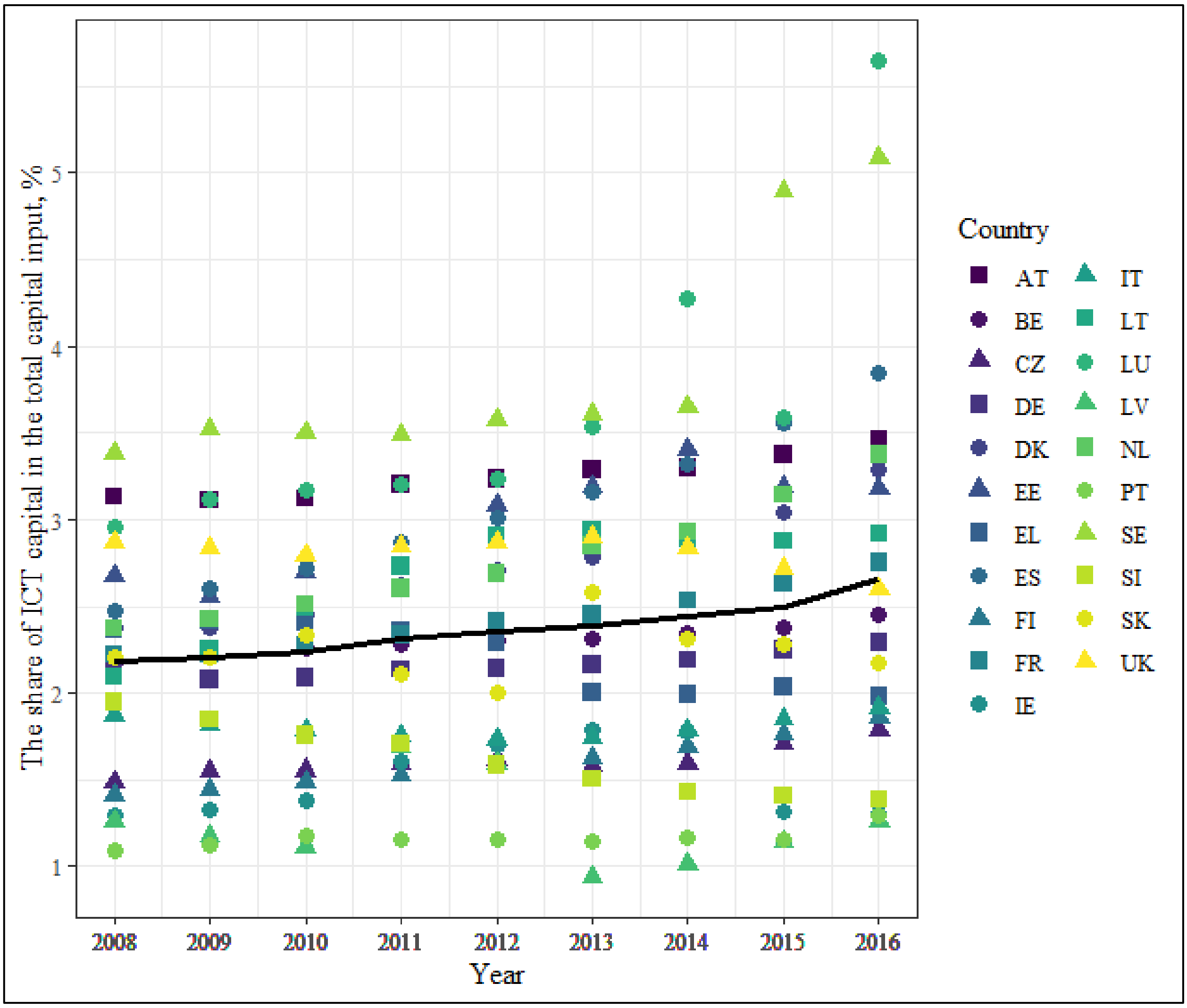
Source: Created by author in R based on data from the EU KLEMS 2019 release

Appendix 5. Time heterogeneity of the share of hours worked by workers aged 50 or above



Source: Created by author in R based on data from the EU KLEMS 2019 release

Appendix 6. Time heterogeneity of the share of ICT capital in the total capital input



Source: Created by author in R based on data from the EU KLEMS 2019 release

Appendix 7. Results for statistical tests for the regressions based on the main sample

Test	(1)	(2)	(3)	(4)	(5)	(6)
			Pooled OLS better than FE?			
F-test for individual effects	H1*** FE better	H1*** FE better	H1*** FE better	H1*** FE better	H1*** FE better	H1*** FE better
			Pooled OLS better than RE?			
Breusch-Pagan Lagrange multiplier (LM) test	H1*** RE better	H1*** RE better	H1*** RE better	H1*** RE better	H1*** RE better	H1*** RE better
			RE better than FE?			
Hausman test	H1** FE better	H1*** FE better	H1* FE better	H0 RE better	H1*** FE better	H0 RE better
			Time fixed effects?			
F-test for twoways effects	H0 No time fixed effects	H0 No time fixed effects	H0 No time fixed effects	H0 No time fixed effects	H0 No time fixed effects	H0 No time fixed effects

Notes: Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.

Appendix 8. Pooled ordinary least squares regression results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.562***	0.528***	0.520***	0.486***	0.532***	0.535***
	(0.177)	(0.163)	(0.147)	(0.144)	(0.151)	(0.129)
$\ln(L_l/L)$	-0.304	-0.377	-0.466	-0.542*	-0.226	-0.214
	(0.317)	(0.307)	(0.340)	(0.300)	(0.305)	(0.311)
$\ln(L_h/L)$	-0.079	-0.091	-0.062	-0.075	-0.059	-0.027
	(0.121)	(0.112)	(0.105)	(0.098)	(0.128)	(0.123)
Sh_{mid}	-0.001	0.006	0.000	0.007	–	–
	(0.002)	(0.007)	(0.002)	(0.007)		
Sh_{old}	0.002	0.005	0.005	0.007	–	–
	(0.002)	(0.005)	(0.003)	(0.006)		
$\ln(K_{ICT})$	-0.044	0.549	0.393	0.953*	-0.032	0.491
	(0.028)	(0.555)	(0.285)	(0.574)	(0.026)	(0.479)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.009	–	-0.009	–	–
		(0.008)		(0.007)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.005	–	-0.004	–	–
		(0.007)		(0.006)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.125	-0.126*	–	–
			(0.088)	(0.076)		
Sh_{lmid}	–	–	–	–	0.000	0.006
					(0.002)	(0.005)
Sh_{lold}	–	–	–	–	0.005**	0.013**
					(0.002)	(0.006)
Sh_{hmid}	–	–	–	–	-0.003	-0.004
					(0.002)	(0.005)
Sh_{hold}	–	–	–	–	-0.001	-0.003
					(0.002)	(0.004)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	-0.007
						(0.006)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.011
						(0.007)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	0.002
						(0.006)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	0.002
						(0.005)
Observations	168	168	168	168	168	168
R^2	0.396	0.419	0.433	0.457	0.454	0.494
Adjusted R^2	0.373	0.389	0.409	0.426	0.427	0.455

Source: Author's calculations based on data obtained from EU KLEMS 2019 release

Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 9. Random effects regression results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.483***	0.474***	0.482***	0.467***	0.456***	0.448***
	(0.116)	(0.106)	(0.099)	(0.100)	(0.106)	(0.088)
$\ln(L_l/L)$	-0.236	-0.357	-0.553*	-0.585**	-0.107	-0.263
	(0.324)	(0.292)	(0.333)	(0.291)	(0.267)	(0.276)
$\ln(L_h/L)$	-0.048	-0.077	-0.027	-0.063	-0.034	-0.077
	(0.119)	(0.098)	(0.088)	(0.083)	(0.107)	(0.106)
Sh_{mid}	0.002	0.012**	0.002	0.011**	–	–
	(0.003)	(0.005)	(0.003)	(0.005)		
Sh_{old}	0.009***	0.019***	0.011***	0.016***	–	–
	(0.003)	(0.005)	(0.003)	(0.004)		
$\ln(K_{ICT})$	-0.027	1.253***	0.739***	1.507***	-0.019	1.092***
	(0.031)	(0.327)	(0.286)	(0.367)	(0.031)	(0.302)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.015***	–	-0.013***	–	–
		(0.005)		(0.005)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.018***	–	-0.011**	–	–
		(0.006)		(0.005)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.220**	-0.164**	–	–
			(0.086)	(0.068)		
Sh_{lmid}	–	–	–	–	0.000	0.004
					(0.003)	(0.006)
Sh_{lold}	–	–	–	–	0.009***	0.021***
					(0.003)	(0.007)
Sh_{hmid}	–	–	–	–	0.002	0.002
					(0.003)	(0.006)
Sh_{hold}	–	–	–	–	0.000	0.000
					(0.002)	(0.004)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	-0.005
						(0.005)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.017**
						(0.007)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	-0.005
						(0.006)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	-0.002
						(0.005)
Observations	168	168	168	168	168	168
R^2	0.557	0.592	0.618	0.620	0.599	0.642
Adjusted R^2	0.540	0.571	0.601	0.598	0.578	0.614

Source: Author’s calculations based on data obtained from EU KLEMS 2019 release
Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 10. Fixed effects with time effects regression results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.445***	0.471***	0.501***	0.481***	0.450***	0.413***
	(0.116)	(0.101)	(0.112)	(0.097)	(0.137)	(0.087)
$\ln(L_l/L)$	0.022	-0.018	-0.451	-0.183	0.083	-0.229
	(0.252)	(0.256)	(0.337)	(0.435)	(0.296)	(0.324)
$\ln(L_h/L)$	-0.082	-0.086	-0.002	-0.064	-0.096	-0.226*
	(0.120)	(0.097)	(0.111)	(0.090)	(0.126)	(0.136)
Sh_{mid}	0.006	0.014**	0.002	0.013**	–	–
	(0.007)	(0.006)	(0.007)	(0.006)		
Sh_{old}	0.009	0.028***	0.009	0.025**	–	–
	(0.008)	(0.010)	(0.007)	(0.011)		
$\ln(K_{ICT})$	-0.016	1.680***	0.894**	1.783***	-0.030	1.267***
	(0.054)	(0.377)	(0.408)	(0.455)	(0.049)	(0.290)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.018***	–	-0.016***	–	–
		(0.004)		(0.004)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.027***	–	-0.022*	–	–
		(0.009)		(0.011)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.259**	-0.086	–	–
			(0.112)	(0.121)		
Sh_{lmid}	–	–	–	–	0.000	-0.002
					(0.006)	(0.008)
Sh_{lold}	–	–	–	–	0.011*	0.020*
					(0.006)	(0.011)
Sh_{hmid}	–	–	–	–	0.006*	0.012*
					(0.003)	(0.007)
Sh_{hold}	–	–	–	–	-0.002	-0.001
					(0.003)	(0.005)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	0.002
						(0.008)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.016*
						(0.008)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	-0.013*
						(0.008)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	-0.005
						(0.006)
Observations	168	168	168	168	168	168
R^2	0.307	0.444	0.378	0.449	0.377	0.513
Adjusted R^2	0.136	0.297	0.220	0.297	0.212	0.365

Source: Author's calculations based on data obtained from EU KLEMS 2019 release
Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 11. Fixed effects regression results without the share of low-educated labour

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.443***	0.468***	0.491***	0.475***	0.438***	0.433***
	(0.095)	(0.082)	(0.090)	(0.083)	(0.115)	(0.082)
$\ln(L_h/L)$	-0.004	-0.023	0.135*	0.004	-0.071	-0.067
	(0.073)	(0.051)	(0.074)	(0.063)	(0.076)	(0.056)
Sh_{mid}	0.005	0.015**	0.002	0.014**	_	_
	(0.007)	(0.006)	(0.007)	(0.006)		
Sh_{old}	0.014*	0.033***	0.013*	0.031***	_	_
	(0.008)	(0.009)	(0.007)	(0.009)		
$\ln(K_{ICT})$	-0.007	1.829***	0.646***	1.858***	-0.031	1.263***
	(0.047)	(0.364)	(0.248)	(0.394)	(0.045)	(0.327)
$\ln(K_{ICT}) \times Sh_{mid}$	_	-0.020***	_	-0.019***	_	_
		(0.005)		(0.005)		
$\ln(K_{ICT}) \times Sh_{old}$	_	-0.028***	_	-0.026***	_	_
		(0.009)		(0.009)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	_	_	-0.182***	-0.035	_	_
			(0.068)	(0.050)		
Sh_{lmid}	_	_	_	_	-0.001	0.002
					(0.004)	(0.008)
Sh_{lold}	_	_	_	_	0.013**	0.029***
					(0.006)	(0.009)
Sh_{hmid}	_	_	_	_	0.006**	0.007
					(0.003)	(0.006)
Sh_{hold}	_	_	_	_	-0.001	-0.005
					(0.003)	(0.004)
$\ln(K_{ICT}) \times Sh_{lmid}$	_	_	_	_	_	-0.006
						(0.006)
$\ln(K_{ICT}) \times Sh_{lold}$	_	_	_	_	_	-0.023***
						(0.007)
$\ln(K_{ICT}) \times Sh_{hmid}$	_	_	_	_	_	-0.006
						(0.006)
$\ln(K_{ICT}) \times Sh_{hold}$	_	_	_	_	_	0.003
						(0.004)
Observations	168	168	168	168	168	168
R^2	0.613	0.696	0.641	0.697	0.664	0.734
Adjusted R^2	0.545	0.637	0.575	0.636	0.599	0.673

Source: Author's calculations based on data obtained from EU KLEMS 2019 release

Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 12. First differences estimation results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.339***	0.327***	0.333***	0.327***	0.314***	0.303***
	(0.094)	(0.090)	(0.094)	(0.093)	(0.085)	(0.075)
$\ln(L_l/L)$	-0.054	-0.047	-0.153	-0.048	-0.027	0.050
	(0.136)	(0.187)	(0.193)	(0.283)	(0.131)	(0.199)
$\ln(L_h/L)$	-0.003	0.002	0.026	0.002	-0.012	0.020
	(0.059)	(0.042)	(0.045)	(0.037)	(0.055)	(0.049)
Sh_{mid}	0.005	0.012***	0.004	0.012***	–	–
	(0.005)	(0.003)	(0.005)	(0.005)		
Sh_{old}	0.013**	0.025***	0.013**	0.025**	–	–
	(0.006)	(0.008)	(0.006)	(0.010)		
$\ln(K_{ICT})$	-0.012	1.045***	0.246	1.046***	-0.017	0.845***
	(0.010)	(0.282)	(0.202)	(0.260)	(0.015)	(0.317)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.011***	–	-0.011***	–	–
		(0.002)		(0.004)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.016***	–	-0.016*	–	–
		(0.006)		(0.008)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.073	-0.001	–	–
			(0.055)	(0.073)		
Sh_{lmid}	–	–	–	–	0.003	0.011**
					(0.003)	(0.004)
Sh_{lold}	–	–	–	–	0.011*	0.025***
					(0.005)	(0.009)
Sh_{hmid}	–	–	–	–	0.003	-0.001
					(0.002)	(0.003)
Sh_{hold}	–	–	–	–	0.002	-0.001
					(0.002)	(0.004)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	-0.010***
						(0.004)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.017***
						(0.006)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	0.003
						(0.003)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	0.001
						(0.004)
Observations	147	147	147	147	147	147
R^2	0.237	0.263	0.240	0.263	0.255	0.287
Adjusted R^2	0.210	0.226	0.208	0.221	0.217	0.228

Source: Author’s calculations based on data obtained from EU KLEMS 2019 release
Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 13. Fixed effects regression results based on sample without outliers

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(K/L)$	0.369***	0.421***	0.429***	0.428***	0.390***	0.371***
	(0.092)	(0.091)	(0.081)	(0.081)	(0.102)	(0.090)
$\ln(L_l/L)$	-0.037	-0.262	-0.411	-0.411	-0.022	-0.294
	(0.357)	(0.396)	(0.397)	(0.401)	(0.335)	(0.436)
$\ln(L_h/L)$	0.074	-0.009	0.108	0.136	0.034	-0.033
	(0.124)	(0.139)	(0.100)	(0.114)	(0.103)	(0.154)
Sh_{mid}	-0.004	0.001	-0.007*	-0.010	–	–
	(0.005)	(0.009)	(0.004)	(0.008)		
Sh_{old}	0.005	0.019**	0.003	-0.000	–	–
	(0.006)	(0.009)	(0.005)	(0.011)		
$\ln(K_{ICT})$	0.004	1.005**	0.783***	0.591	-0.003	0.116
	(0.047)	(0.492)	(0.241)	(0.407)	(0.039)	(0.544)
$\ln(K_{ICT}) \times Sh_{mid}$	–	-0.008	–	0.003	–	–
		(0.007)		(0.005)		
$\ln(K_{ICT}) \times Sh_{old}$	–	-0.020**	–	0.004	–	–
		(0.008)		(0.012)		
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.226***	-0.254***	–	–
			(0.067)	(0.094)		
Sh_{lmid}	–	–	–	–	-0.006	-0.010
					(0.004)	(0.007)
Sh_{lold}	–	–	–	–	0.005	0.017***
					(0.004)	(0.006)
Sh_{hmid}	–	–	–	–	0.003	0.002
					(0.003)	(0.007)
Sh_{hold}	–	–	–	–	-0.001	-0.010*
					(0.003)	(0.005)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	0.005
						(0.006)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.016***
						(0.005)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	-0.001
						(0.008)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	0.009
						(0.006)
Observations	144	144	144	144	144	144
R^2	0.663	0.697	0.716	0.717	0.688	0.741
Adjusted R^2	0.599	0.632	0.659	0.654	0.622	0.676

Source: Author's calculations based on data obtained from EU KLEMS 2019 release
Notes:

1. Dependent variable is the logarithm of gross value added per hour worked.
2. Robust standard errors clustered by country in parentheses.
3. All explanatory variables inserted into the models with a one-period lag.
4. Significance Level values *, **, *** indicate significance at 10%, 5% and 1% level.
5. All models significant on 1% level.

Appendix 14. System GMM results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(Y/L)$	0.823*** (0.140)	0.663*** (0.179)	0.652*** (0.179)	0.647*** (0.228)	0.604*** (0.161)	0.553*** (0.195)
$\ln(K/L)$	0.273* (0.153)	0.430** (0.185)	0.402** (0.160)	0.413** (0.174)	0.471*** (0.161)	0.495** (0.210)
$\ln(L_l/L)$	-0.058 (0.052)	-0.026 (0.122)	-0.040 (0.065)	-0.028 (0.079)	-0.029 (0.070)	0.011 (0.152)
$\ln(L_h/L)$	0.003 (0.019)	0.017 (0.044)	0.032 (0.043)	0.044 (0.065)	0.006 (0.027)	0.037 (0.056)
Sh_{mid}	-0.002* (0.001)	-0.004 (0.009)	-0.002* (0.001)	-0.003 (0.011)	–	–
Sh_{old}	-0.002 (0.002)	-0.004 (0.006)	-0.001 (0.003)	-0.003 (0.010)	–	–
$\ln(K_{ICT})$	-0.035* (0.016)	-0.223 (0.799)	0.052 (0.210)	-0.085 (1.122)	-0.031** (0.015)	-0.262 (1.589)
$\ln(K_{ICT}) \times Sh_{mid}$	–	0.002 (0.011)	–	0.002 (0.013)	–	–
$\ln(K_{ICT}) \times Sh_{old}$	–	0.003 (0.008)	–	0.003 (0.012)	–	–
$\ln(K_{ICT}) \times \ln(L_h/L)$	–	–	-0.026 (0.063)	-0.038 (0.060)	–	–
Sh_{lmid}	–	–	–	–	-0.001 (0.001)	0.001 (0.009)
Sh_{lold}	–	–	–	–	0.001 (0.001)	0.005 (0.012)
Sh_{hmid}	–	–	–	–	-0.002** (0.001)	-0.007 (0.007)
Sh_{hold}	–	–	–	–	-0.002* (0.001)	-0.006 (0.008)
$\ln(K_{ICT}) \times Sh_{lmid}$	–	–	–	–	–	-0.002 (0.011)
$\ln(K_{ICT}) \times Sh_{lold}$	–	–	–	–	–	-0.005 (0.013)
$\ln(K_{ICT}) \times Sh_{hmid}$	–	–	–	–	–	0.006 (0.009)
$\ln(K_{ICT}) \times Sh_{hold}$	–	–	–	–	–	0.006 (0.010)
Sargan test p-value	0.129	0.558	0.464	0.629	0.668	0.925
Autocorrelation test (1) p-value	0.033	0.230	0.191	0.256	0.342	0.318
Autocorrelation test (2) p-value	0.070	0.128	0.127	0.137	0.188	0.173
Wald test for coefficients p-value	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's calculations based on data obtained from EU KLEMS 2019 release

Notes:

1. GMM instruments: the lags of dependent variable not used as independent variable.

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