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Economic Calamity or the Future of Labor? Exploring the Effects of Artificial Intelligence on Job Polarization.

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Abstract

The phenomenon of job polarization has gained significant relevance as Information and Communication Technologies (ICTs) and Artificial Intelligence (AI) have become increasingly integrated in the markets. This has fueled the discussion on whether these technologies can present a risk of job displacement, particularly among the middle and low skilled workers, increasing labor market polarization. To test this hypothesis, the present research builds upon the seminal work of Michaels et al. (2014), which analyzed the effects of ICTs on job polarization, updating the model to reflect the role of AI. The dataset used in the regression model covers 20 countries from the European Union in the period between 2014 and 2020. The study finds evidence of job polarization driven by ICTs and AI, with an increase in the wage share of high skilled workers, and a decrease for both middle and low skilled workers. The analysis suggests that while technological advancements offer growth potential, they also pose significant challenges for labor markets and require targeted actions.

SECTION 1:

Introduction to the Topic

Introduction

In recent years, Artificial Intelligence (AI) has become an essential tool for technological advancement, revolutionizing industries and redefining the human experience. With its roots tracing back to the mid-20th century, AI has evolved from a conceptual curiosity to a driving force behind innovation across very different fields, from healthcare and finance to transportation and entertainment. In recent years especially, AI surpassed its initial limitations, showcasing capabilities once limited only to the realm of science fiction. Today, AI systems power virtual assistants, autonomously navigate vehicles, diagnose diseases, recommend personalized content, and optimize countless processes with unprecedented efficiency and accuracy.

As AI's capabilities continue to increase, so does its adoption. According to data collected by a McKinsey survey over the years (McKinsey & Company, 2022), AI integration has been quickly spreading in different sectors. In 2017, only 20 percent of respondents reported adopting AI in at least one business area. Today, that number has increased to 50 percent. Another substantial change lays in the amount of AI capabilities that the organizations responding in the survey have used in at least one business function or unit. In fact, the average number has increased from 1.9 in 2018 to 3.8 in 2022 (McKinsey & Company, 2022). Accordingly, the number of organizations investing in AI has also risen and is expected to continue on an upward trend in the coming years. All these are signs of a revolution in the way businesses and other organizations operate. However, this has sparked other kinds of fears across workers. Particularly after generative AI entered the scene, the public has been more worried about business disruptions, workforce cuts and reskilling changes linked to the shifting in talent needs.

While the emergence of AI as a source of these fears may be relatively recent, the underlying worries themselves are far from new and have already been the subject of extensive academic discussions. In particular, this tension is a 21st century renewal of the centuries-old topic of job polarization. Some notable examples include the industrial revolution – that transitioned many agrarian economies into industrialized ones – or the advent of automation in manufacturing – that made traditional craftsmanship and skilled laborers question their place in the job market. With globalization gaining momentum, the expansion of supply chains and new sources of labor also started stirring apprehension. In more recent years, before AI became the focal point, similar anxieties also revolved around information and communication technologies (ICTs), and specifically how the introduction of these novel technologies into the market could automate tasks and displace certain jobs, hence generating the phenomenon of job polarization. In their seminal work discussing this issue, Guy Michaels, Ashwini Natraj, and John Van Reenen are among the first to have looked specifically at the effects of ICTs on the labor market (Michaels et al., 2014).

Although the 2014 model from Michaels et al. has been a great source for job polarization discussions, it only covers an analysis of the market until 2004. The technological advancements occurred in the last 20 years – and particularly the emergence of AI – have completely revolutionized the bases that this discussion lays on. Because of this, it becomes useful to expand on this work, complementing it with newer data and taking into account the emergence of AI.

Building and expanding on the work by Michaels et al (2014), this research will aim at exploring the relationship between digital technologies and labor market polarization, explicitly accounting for the emergence of AI technologies. In particular, it will test the correlation between AI and the labor market, corroborating the idea that Artificial Intelligence is contributing to the phenomenon of job polarization. Section 1 will cover the literature review and define the main concepts behind the analysis, Section 2 will focus on the econometric approach, reviewing the descriptive statistics and the regression model, and finally Section 3 will cover ethical considerations, advisable actions to be taken, and final conclusions.

Literature Review

The issue of technologically driven job polarization has inspired many studies surrounding employment dynamics and societal disparities. The research has ranged from focusing on models testing the job polarization theory, to more open discussions regarding the future impacts on society.

As Artificial Intelligence penetrates the markets and changes the status quo, it can have significant implications on income distribution and socio-economic stratification. Authors like Taniguchi and Yamada (2022) focus on examining how job polarization exacerbates existing disparities and increases the levels of inequality. In their research, they mention “capital–skill complementarity”, a phenomenon for which capital and skill levels reinforce each other. The analysis shows how an increase in the demand for skilled workers compared to unskilled workers is linked to a decrease in the rental price of ICT equipment. As ICT equipment has become cheaper, the demand for skilled labor has gone up, while the demand for unskilled labor has lowered (although this latter effect has a lesser intensity compared to the first one on skilled labor). The scenario described by Tamaguchi and Yamada (2022) exemplifies a situation of skill biased technical change, where a shift in the production technologies favors the work of skilled labor over the unskilled one. These findings highlight how different jobs can be augmented or replaced by ICT, depending on the level of skills needed.

The literature has also sparked a discussion of routine biased technical change, where technological shifts favor workers with non-routine tasks over the rest. To fully understand this concept, we must first differentiate between “routine” and “non-routine” tasks, and between “abstract”, and “manual” tasks (Autor, 2015). The first distinction refers to whether an activity follows a pattern repetitive enough to be programmed into a computer, and consequently if it can be automated. The second distinction, instead, characterizes “non-routine” tasks that require problem-solving, intuition, creativity and persuasion as “abstract”, and “non-routine” tasks that require situational adaptability and in-person interaction as “manual”. Autor argues that the “non-routine” tasks are often found at the opposite ends of the occupational skill spectrum, and therefore in high skilled and low skilled jobs. On the other hand, “routine” tasks can be found in middle skilled occupations, which thus become more at risk of being automated.

To further consolidate his argument, Autor brings up Polanyi’s Paradox, according to which “we know more than we can tell”, and as humans we often understand intuitively how to perform a task but cannot put into words its rules or procedures. It follows, then, that “non-routine” tasks (falling under Polanyi’s Paradox) become impossible to program and automate. However, the technological advancements occurred in the most recent years have significantly reduced these limitations, making it increasingly possible to program and automate many tasks once considered not automatable. In fact, Machine Learning (ML) and Artificial Intelligence have improved to such a degree that they are now able to emulate human actions and reactions to “non-routine” tasks. Because of this, sooner rather than later any type of task could potentially be automated (Autor, 2015).

Autor opens an important discussion on the difference between jobs complemented and jobs substituted by technology. This theoretical analysis has been further expanded in the following years, with the addition of Machine Learning and Artificial Intelligence (Agrawal et al., 2019). In particular, this discussion focuses on four main effects of AI on employment: creation of new decision tasks, replacement of prediction tasks, replacement of decision tasks, and augmentation of decision tasks. The argument defended by Agrawal et al. (2019) is that the outcome of AI on the labor market is going to largely depend on what job – and what role – AI is being implemented in. A very positive scenario involves the creation of new jobs thanks to the rise of ML and AI. As these technologies improve and we better understand what are the ways in which they can be implemented, we will witness not only the creation of new jobs, but also of new knowledge and new industries. On the opposite end of the spectrum, in tasks involving prediction – i.e. the forecast of information using existing data – these new technologies can perform a much better job than humans, and so we are more likely to witness a substitution of labor, instead of an augmentation. Finally, Agrawal et al. (2019) argue that jobs involving decision making could have a double outcome from the emergence of AI: they could increase productivity and reduce risks for the workers, but they could also reduce the value of human labor, making it replaceable.

The literature has also identified other possible issues that could emerge with the diffusion of AI. Understanding the full impact of a technology on the market can take time, making it difficult for businesses and workers to accurately prepare. Because of how versatile AI is, the same system could be applied in many diverse fields and evolve in ways difficult to predict (Klinger et al., 2018). This can create coordination failures, where potential adopters of the technology decide to implement a "wait-and-see" strategy while the technology evolves. As a result, workers who could provide complementary skills are not able to react as quickly as necessary. An even bigger issue is generated for those strictly linked to an industry for which the new technology is "competence-destroying" and eliminates the previous sources of comparative advantage. This can create several challenges, not just on the individual level, but also for entire geographic areas where an industry is concentrated. In fact, since industries tend to cluster in specific areas to benefit from dense talent pools, reduce transaction costs and exploit the natural resources, the same technology can generate drastically different outcomes in different geographic areas (Klinger et al., 2018). Therefore, the locations where AI is competence-enhancing will see great economic opportunities arise, while the areas where it is competence-destroying will experience sudden drops in employment rates and gradual well-being decline.

The inequality ramifications of ICTs and AI are not just limited to sectors, but also expand across entire countries. Separate sections of the same population can be affected very differently by the advent of a new technology, depending on whether the technology is competence enhancing or destroying for them. A crucial question arises: is the expansion of ICTs contributing to a positive or negative shift in income inequality within a country? In fact, these technologies could have the potential to increase economic growth and development across the entire social board, but they could also concentrate the benefits to those in the more skilled sectors, who already receive a higher income (Richmond and Triplett, 2018). In answering this question, Richmond and Triplett (2018) stress that the impact on income inequality depends on the type of ICT, such that fixed broadband subscriptions tend to increase inequality, while mobile subscriptions tend to decrease it. This difference may be due to variations in cost structures and access to these technologies: the fixed broadband technologies are much less affordable and would therefore create more of a divide between those who are able to access them and those who cannot. Instead, mobile subscriptions provide opportunities for broader segments of the population, including those in lower-income brackets, to benefit from technological advancements. However, in the lowest-income countries, the research found that ICT may not yet have a significant impact on income inequality due to limited usage and access. This nuanced understanding stresses the importance of considering the specific characteristics of ICTs and their socio-economic context when evaluating their effects on income distribution and on the phenomenon of job polarization. In light of this, the present research aims to focus on AI in particular, due to its strong potential and the many characteristics that set it apart from the ICTs developed so far.

Whether we are dealing with different definitions of skills and tasks or with the economic and social impact of job polarization, this topic has clearly been subject of interest for many scholars. As the research continue to evolve, it becomes increasingly evident that addressing the challenges posed by job polarization is something that needs to be tackled from multiple perspectives, not limiting the discussion to a specific field or a specific issue. The research done so far has touched on multiple aspects, but as new technologies enter and reshape the market, we can expect an evolution of the phenomenon of job polarization. The advancements in the already existing ICTs, as well as the introduction of Artificial Intelligence, have the potential to further impact the labor market. To understand these changes, we complement the existing work by introducing novel data, together with insights specifically related to AI.

Defining the Concepts

1. New Technologies: Advantages and Disadvantages

Before delving into the model and the effects of AI in job polarization, it is important to analyze more in detail some of the key subjects of this research.

The first foundation for this discussion is Artificial Intelligence, a branch of computer science focused on creating smart machines capable of carrying out activities that would typically require human intelligence. In recent years, the capabilities and access points of AI have advanced significantly, leading to a widespread integration of these technologies across vastly different sectors. Artificial Intelligence has now reached such wide-ranging applicability that it can prove itself useful in countless scenarios, a characteristic which it shares with General Purpose Technologies (GPTs). Although the classification as a GPT is a topic still being debated (Vannuccini and Prytkova, 2021), it is also true that AI has the potential to completely revolutionize economies, countries, and societies. As Artificial Intelligence continues to evolve, its versatile applications not only promise revolutionary changes in the world, but also bring both benefits and challenges, as explored in the following paragraphs.

On the one hand, the computational systems and algorithms that AI runs on can reach levels of accuracy and speed that would be virtually impossible for humans. This can have many benefits: lower risks and mistakes, less bias, lower costs, and in general better efficiency and productivity in a faster timeframe. Particularly in areas like science and medicine, these aspects of AI offer significant advantages for research that ultimately benefits everyone. One of the many examples of this is CheXNet, a project developed by Stanford University to accurately detect pneumonia from chest X-rays through a convolutional neural network (Pranav et al., 2017). This model's efficiency and performance have already been proven to be surpassing human capabilities, as on average the algorithm's detections are more accurate than those of the radiologists tested during this project.

Similarly, several kinds of businesses have found ways to leverage AI to their advantage and were able to gain substantial profits. Marketing recommendations, warehouse organizations, and customer service automation are all examples of smart uses of AI that allow corporations to operate at peak efficiency. Even when considering the individual experience, Artificial Intelligence is reshaping society and bringing consistent quality of life improvements, thanks to virtual assistants, responsive chatbots, and much more (Talati, 2024).

More broadly, Information and Communications Technologies (ICTs) have also played an important role in reshaping the nature of work. ICTs – a term which refers to technologies that manage and process information electronically – have enabled the digitalization of various aspects of work, often leading to increased efficiency and productivity in several industries. The many benefits brought by these technologies, as well as their higher flexibility and lower costs, make them often preferable to human labor. Particularly in jobs revolving around prediction or routine tasks, which are easily codifiable and accomplishable by a machine, substituting human workers with robots or AI models is increasingly becoming the more logical economic choice. The price of computing power falling and the accessibility of these technologies rising have led many businesses over the years to prefer this form or capital over labor. ICTs can perform tasks with greater accuracy and speed, operating without regard to human working hours or holidays, and they do not require salaries. In a competitive market governed by standard economic principles, it becomes essential for businesses to prioritize this labor substitution, even if it comes at the expense of displacing human workers. It is by following this reasoning that it becomes clearer why jobs like bank tellers are being replaced by automated teller machines (ATMs), or cashiers at retail stores by self-checkout processes.

However, the same benefits that AI and ICTs bring for the economy and for society have the potential to cause negative repercussions, beyond the purely economic sphere. For instance, the replacement of humans with machines can lead to a decline in human interactions. While in certain scenarios it might be more convenient to interact directly with a machine, the constant dependence on machines can lead over time to a sense of alienation (Umeh G. and Umeh A., 2024). The same technologies developed to make life easier can lead to a loss of essential human experiences and interactions, leaving individuals to feel isolated and undervalued.

Another relevant issue is the level of trust that can be given to AI. In fact, despite how well the models can be trained, there is always the potential for error. A very famous example of the dangers that could originate from AI comes from *Mata v. Avianca* (S.D.N.Y., 2023). This case originated from an attorney blindly trusting information provided by the popular chatbot ChatGPT, which later turned out to be nonexistent and just a "hallucination" of the machine. In addition to these kinds of issues, Artificial Intelligence can also be affected by bias. When training algorithms with data from the real world, human bias can easily be amplified, transferred to the models, and have severe repercussions, whether this is in a public, business or private scenario. In general, blindly trusting AI and giving it too much authority can result in many risks and unintended consequences.

In all these instances, the nature of work changing significantly brought many concerns to the working population, although in reality the situation was never as catastrophic as it seemed (Joel et al., 2015). At its core, this outcome stems from the distinction between labor substitution and complementarity. However, as Artificial Intelligence continues to improve, the type and the number of jobs that machines have the ability to replace are expanding. Even workers that before had no reason to fear substitution are now being faced with a more concrete danger.

2. Complementarity, Substitution and Structural Unemployment

In the previous section we explored how historical changes in the nature of work, driven by innovations like automation and digitalization, have raised concerns among the working population. With the rate at which these technologies have been deployed, one would expect that by now the entire labor market would be dominated by machines, but this is clearly not the case. The reason for this is that, in most cases, the technology implemented has been complementary to the job (Autor, 2015). To further our discussion, we can define complementarity as the scenario where technology enhances and augments human labor, resulting in increased productivity and efficiency. In this environment, machines and human workers use their skills to work together and achieve outcomes that neither could achieve alone. On the other hand, substitution occurs when automation and technologies replace human labor, leading to job loss and changes in the structure of the labor market. When a machine can accomplish a task at a lower cost, and potentially with better results than a human, then that task is going to be substituted by the machine.

In general, however, many of the tasks that cannot be substituted by automation (and in our case AI) can be augmented by it. For instance, tasks requiring complex predictions can be augmented by AI systems that provide data-driven insights (Agrawal, 2019). Additionally, Artificial Intelligence can be very beneficial in tasks involving large-scale data analysis, allowing human workers to focus on the interpretation of the results and the decision-making process that follows. Complementarity also allows for the creation of new tasks where machines have substituted labor, or where in the past there was no job position at all. The emergence of AI, in fact, has created a whole new market looking for workers able to use these new technologies as a tool. Therefore, although many older jobs are at risk of being replaced by machines, many new opportunities have the potential to positively offset the employment rate numbers.

Therefore, as new technological advancements come into the picture and consumer behaviors change, the demand for labor shifts accordingly. Economies around the world are being driven by very different fields compared to previous centuries, or even previous decades. It should be reasonable, then, to expect skill shifts and observe more demand for workers able to supply what is needed at the moment. In other words, “focusing only on what is lost misses a central economic mechanism by which automation affects the demand for labor: raising the value of the tasks that workers uniquely supply" (Autor, 2015, p. 5). However, while the newfound complementarity can lead to the creation of new job opportunities, it is not easy for the market to immediately adapt to it. Technologies can take time to evolve and find their place in the market, while the adopters of such technologies decide to wait for this evolution before investing in it (Klinger et al., 2018). Furthermore, this skill shift comes at the expense of those who do not have the expertise and/or education levels that are being demanded at the time. This situation is known as "structural unemployment": a mismatch between the skills that workers have and the skills that employers need. To cite an example typical of our discussion, a machinery worker being replaced by a robot would need to learn how to operate and manage that same robot. Those who do not learn will either need to be retrained for another job, look for a lower- or un-skilled position, or face long-term unemployment. Moreover, if a worker stays unemployed for too long, their skills will become outdated, and it will be even more difficult in the future to re-enter the labor force.

This idea of structural unemployment is something that goes beyond the advent of Artificial Intelligence, and that is quite complex to deal with. Although in theory it may seem straightforward to address this issue by retraining workers and promoting job transitions, the reality is far more intricate. In order to effectively tackle structural unemployment, there needs to be a significant effort in policy adjustments, and investments in education and workforce development. Because the root of the problem lies in the qualifications of the workforce itself, it is not enough to provide short-term economic stimuli in an attempt to decrease the unemployment rate. Instead, long-term strategies need to be established to ensure that the working population is prepared for the shift, training not just the future generations, but also the ones currently experiencing the shock.

3. The Concept of Job Polarization

As Artificial Intelligence continues to influence markets through complementarity and substitution dynamics, and as structural unemployment becomes a pressing concern, the phenomenon of job polarization becomes increasingly relevant. While briefly mentioned in the earlier chapters, it now requires a more detailed examination and definition within this discussion.

Job polarization refers to the phenomenon of increasing concentration of employment in the highest and lowest skilled occupations, with a simultaneous decline in middle skilled jobs. As a consequence, the labor market gets split between high wage and low wage sectors, while the middle wage ones slowly disappear. Job polarization has gained more prominence lately with the advent of automation and AI. In fact, the effect of new technologies on the labor market tends to be significant, as these advancements usually complement high skilled tasks while substituting for routine middle skilled roles.

To better understand job polarization, it's essential to distinguish between high skill, low skill, and middle skill jobs. High skill jobs typically require advanced education, specialized training, and cognitive abilities. These roles often involve complex problem-solving capabilities, intuition, decision-making, and creativity. In the context of AI, high skill jobs include data scientists, software developers, and research analysts, occupations that demand a high level of expertise in leveraging technology and interpreting data. On the other hand, low skill jobs are characterized by tasks that involve minimal training or formal education. These roles are mostly manual, and revolve around situational adaptability, visual and language recognition, and service-oriented tasks that are less susceptible to automation. In these occupations physical dexterity and interpersonal skills are more valued than specialized knowledge. Examples of these professions are janitor staff, housekeepers, or security guards. Finally, we focus our attention on middle skill jobs. These occupations require a moderate level of education and training, and are very often linked to routine tasks, whether in cognitive or manual activities. Examples of middle skill careers include administrative assistants, paralegals, and typists. These roles often require following pre-determined instructions and procedures that become a "routine" and that, by nature, are very easy to code. Although in the past – particularly in the second half of the 20^{th} century – these occupations were seen as the preferable option for the vast majority of the working class, since they were less physically demanding and dangerous than many of the alternatives, today the landscape has been completely altered. Because these jobs involve tasks so easy for computers to replicate and automate, there has been a significant fall in demand for these services, leading to a surge in unemployment for the middle skilled sectors.

The data backing this phenomenon has been quite consistent. *Figure 1*, a visualization of the data reported in the 2014 paper from Goos et al., clearly shows how job polarization has had a real effect on the labor markets of many Western countries. The graph shows the percentage point change in employment share for different occupation groups (high wage, middle wage, and low wage) in each country in the period between 1993 and 2010. The high paying occupations coincide with the ones we have described as high skilled, such as corporate managers, physical, mathematical, and engineering professionals, managers and professors. On the other hand, the middle paying jobs include office and customer service clerks, drivers and mobile operators – in essence, careers falling under the middle skill spectrum. Finally, low paying occupations are the same requiring a low skill set: laborers in mining, construction, manufacturing and transport, personal and protective service workers, etc. In the figure there is a clear distinction between the high paying jobs – all experiencing growth in the period selected – and the middle paying ones – all on a negative trend.

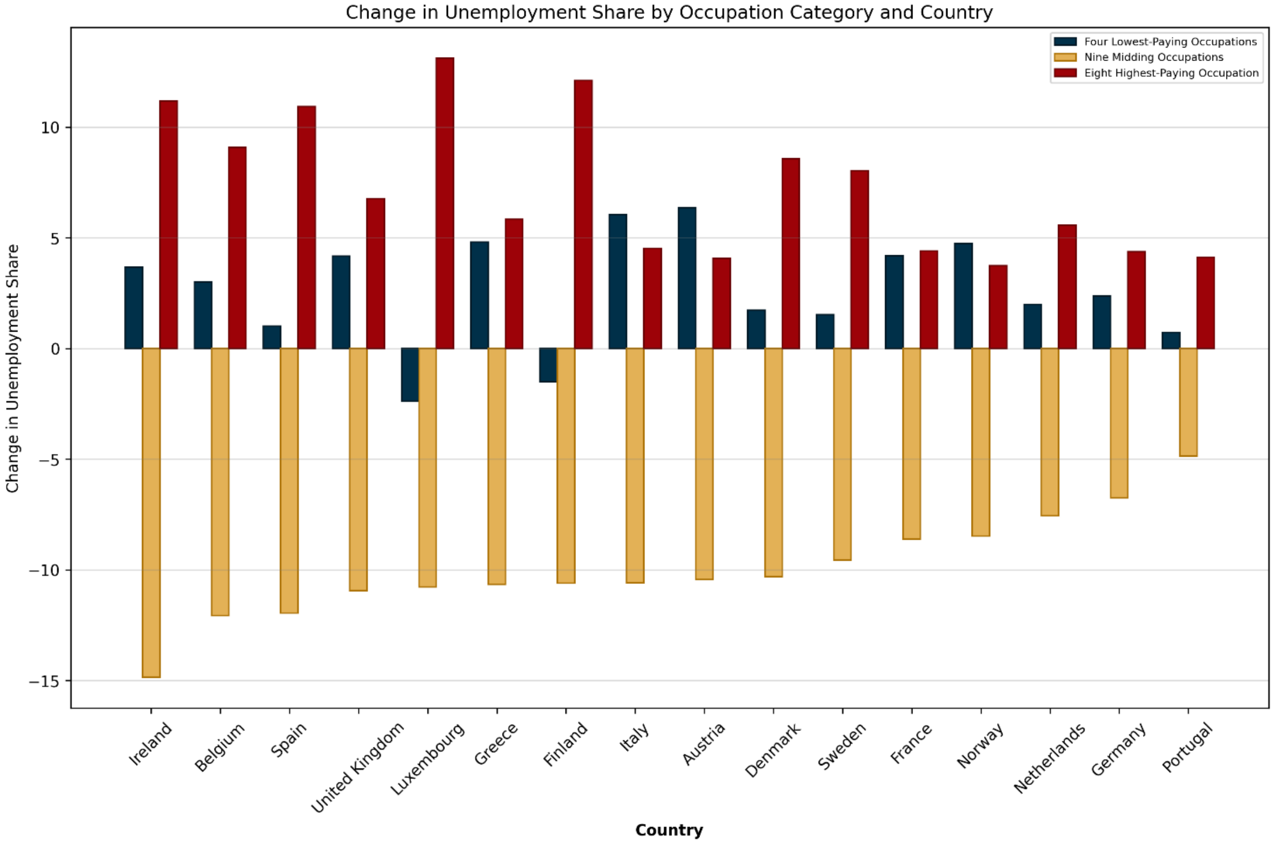

Figure 1: Percentage Change in Occupational Employment Shares by Country and Occupational Wage, 1993-2010. *High-paying occupations:* corporate managers; physical, mathematical, and engineering professionals; life science and health professionals; other professionals; managers of small enterprises; physical, mathematical, and engineering associate professionals; other associate professionals; life science and health associate professionals. *Middle-paying occupations:* stationary plant and related operators; metal, machinery, and related trade work; drivers and mobile plant operators; office clerks; precision, handicraft, craft printing, and related trade workers; extraction and building trades workers; customer service clerks; machine operators and assemblers; and other craft and related trade workers. *Low-paying occupations:* laborers in mining, construction, manufacturing, and transport; personal and protective service workers; models, salespersons, and demonstrators; and sales and service elementary occupations.

Data source: Goos, et al. (2014, Table 2).

SECTION 2:

Econometric Approach

Descriptive Statistics

To provide a comprehensive overview of the analysis, the following section explores the descriptive statistics of the main concepts of our study, such as digitalization and job polarization. To do so, we will use the same dataset that is implemented in the regression model, which includes information on ICT and Non-ICT capital services, the level of value added, AI penetration in the market, and wage share for high, middle, and low skilled workers. The dataset covers the period going from 2014 to 2020 for the following European countries: Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Slovakia, Slovenia, Spain, and Sweden. The data will be described more in detail in the "Methodology and Data" section.

1. Digitalization

The first topic to investigate is the phenomenon of digitalization, a process of integration of digital technologies in the market. Calvino et al. (2018) highlight the multifaceted nature of this phenomenon and identify five key indicators: investment in ICT equipment and software, purchases of ICT intermediates, increases in robot stock and use, increase in ICT specialists as measure of digital-related human capital, and increase in online sales. Building on this and recognizing the challenges in using a unique indicator to capture digitalization, we opt to rely on capital stocks in current prices for ICT and Non-ICT, normalized on the number of hours worked.[1] This choice is in line with the indicators provided by Calvino et al. (2018), who point to the importance of investment in ICT assets. We choose to use stocks rather than investment for two reasons: firstly, this is consistent with the reference work of Michaels et al. (2014) which compares the wage and the remuneration of

[1] Similar line plots were also generated using ICT and Non-ICT capital services, the same variables that are applied to the regression models. They can be found in the Appendix.

capital, and secondly, stocks take into account the accumulated technological change that has taken place over time.

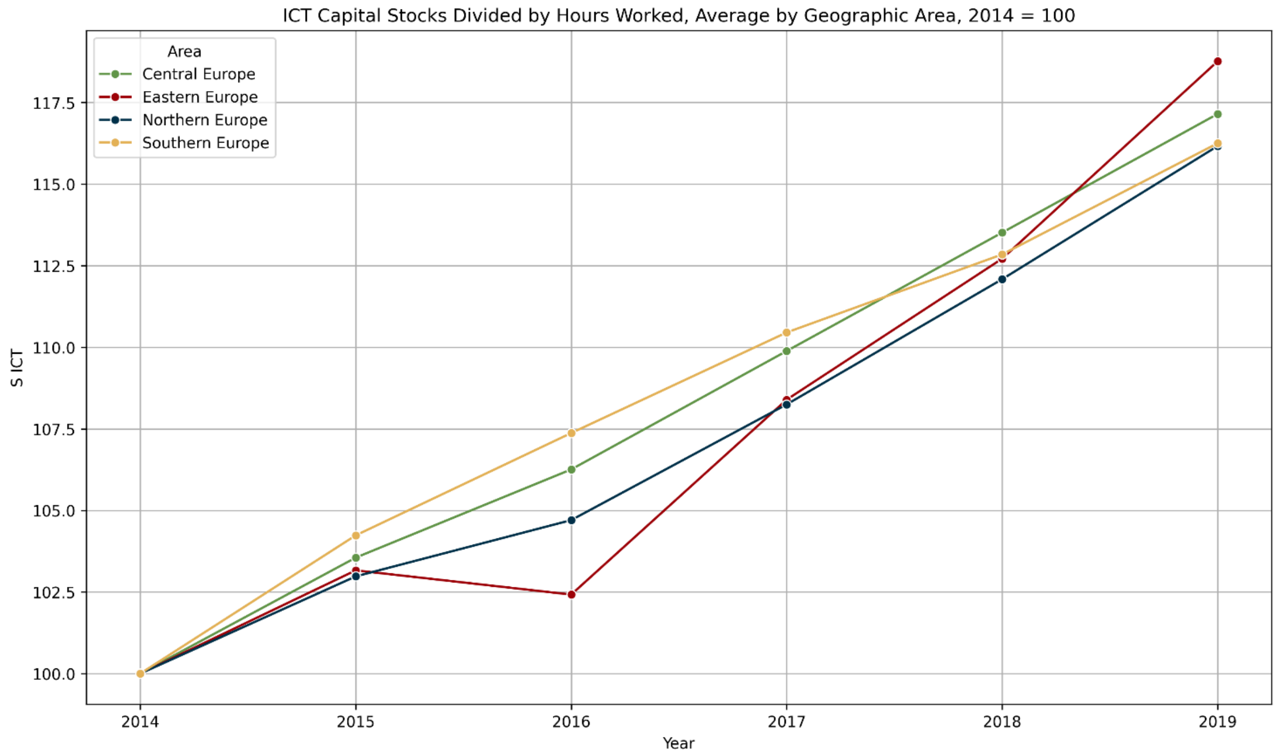

Figure 2: Time series (2014 to 2019) of ICT capital stocks over number of hours worked, 2014 = 100. The data is taken from the EUKLEMS & INTANProd dataset and is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

Figure 2 focuses on the trend of ICTs in the market, showing a clear growth over the years all across Europe. The Figure, along with all other graphs reported below, does not include 2020, to eliminate the noise caused by the sudden drop in hours worked due to Covid-19 restrictions. *Figure 2* shows an ongoing digitalization in the market, where ICT investments have steadily grown over the years, outpacing the growth in hours worked. *Figure 3*, which reports the Non-ICT capital stocks, is also showing an overall growth over the years, although not nearly with the same intensity as for ICT capital stocks. Northern Europe experiences a larger jump in 2020 for both graphs, due to a simultaneous increase of ICT and Non-ICT investments, and larger decrease in hours worked compared to the other regions. Instead, Southern Europe is the only region with a declining trend for

Non-ICT capital stocks. This is due to a larger increase in hours worked compared to a steadier movement in Non-ICT investments.

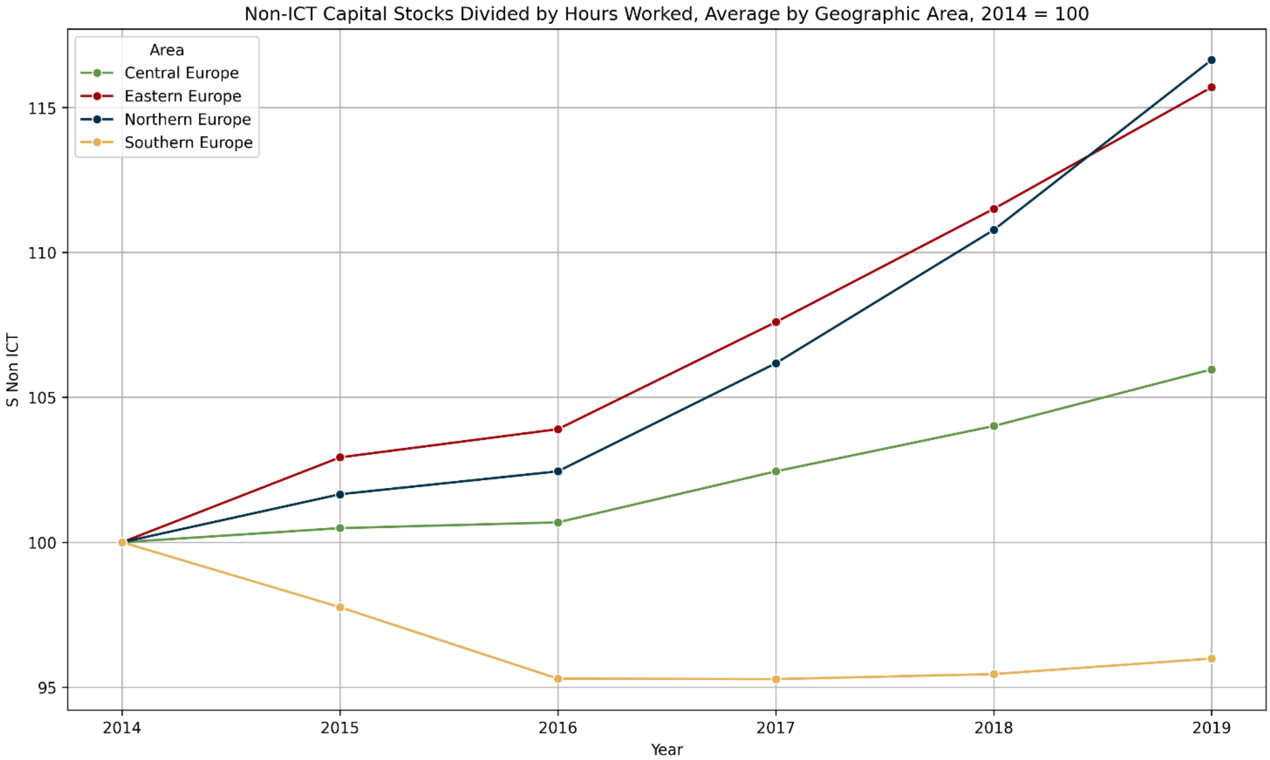

Figure 3: Time series (2014 to 2019) of Non-ICT capital stocks over number of hours worked, 2014 = 100. The data is taken from the EUKLEMS & INTANProd dataset and is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

These graphs are in line with the previous discussion on the changes in the markets. As the markets become more digital, ICTs play more of a role in the economic activities of Europe, while the role of Non-ICTs becomes less significant. This is also evident from the movements of AI Penetration (*Figure 4*).

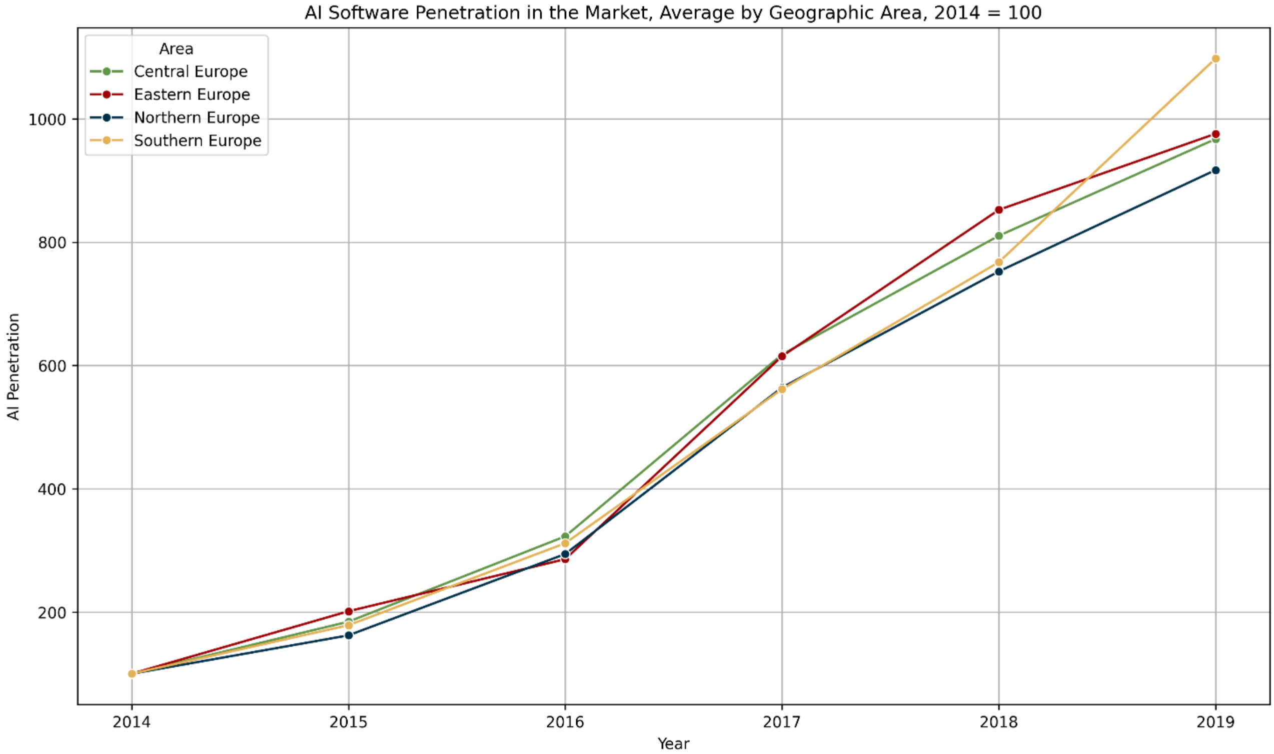

Figure 4: Time series (2014 to 2019) of AI Penetration in the market, measured through software development (number of GitHub projects related to AI), 2014 = 100. The data is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: OECD AI Policy Observatory (2024).

The data once again reveals a clear and consistent upward trend across all regions, marked by two significant accelerations in AI development. The first acceleration in 2016 coincides with some of the initial breakthroughs in the world of AI, such as AlphaGo's victory against the top Go player Lee Sedol ("AlphaGo"). A few years later, in 2019, we witness a second acceleration, as AI systems started becoming more accessible to the public. For instance, in 2019 Microsoft launched the Turing Natural Language Generation generative language model, which introduced AI in the daily lives of many users (Rosset, 2020). These achievements, together with many more simultaneous developments in the world of AI, sparked increasing interest both from users and developers, and fueling a surge of innovation.

2. Job Polarization

Together with digitalization, it is important to understand the effects of the changing markets for the different skill segments of the labor force. In particular, using the share of wage attributed to high, medium, or low skilled workers, we can gain more insights on the phenomenon of job polarization.

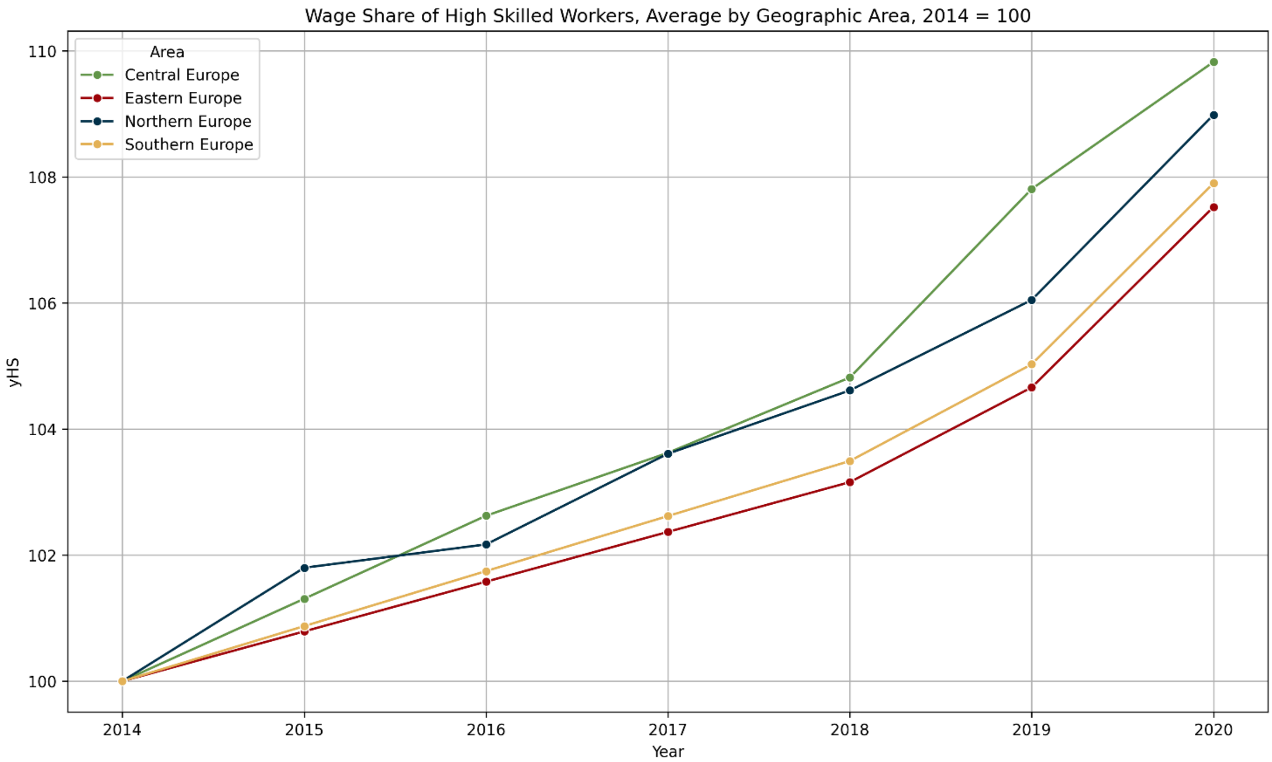

Figure 5: Time series (2014 to 2020) of wage share for high skilled workers, 2014 = 100. The data divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

Specifically, for high skilled workers (*Figure 5*) the wage share is increasing across all regions in Europe, highlighting how this portion of the workforce is securing more compensation as the years pass, and suggesting that they are becoming increasingly valuable in the labor market. For what concerns middle (*Figure* 6) and low (*Figure* 7) skilled workers, instead, we witness a very different trend.

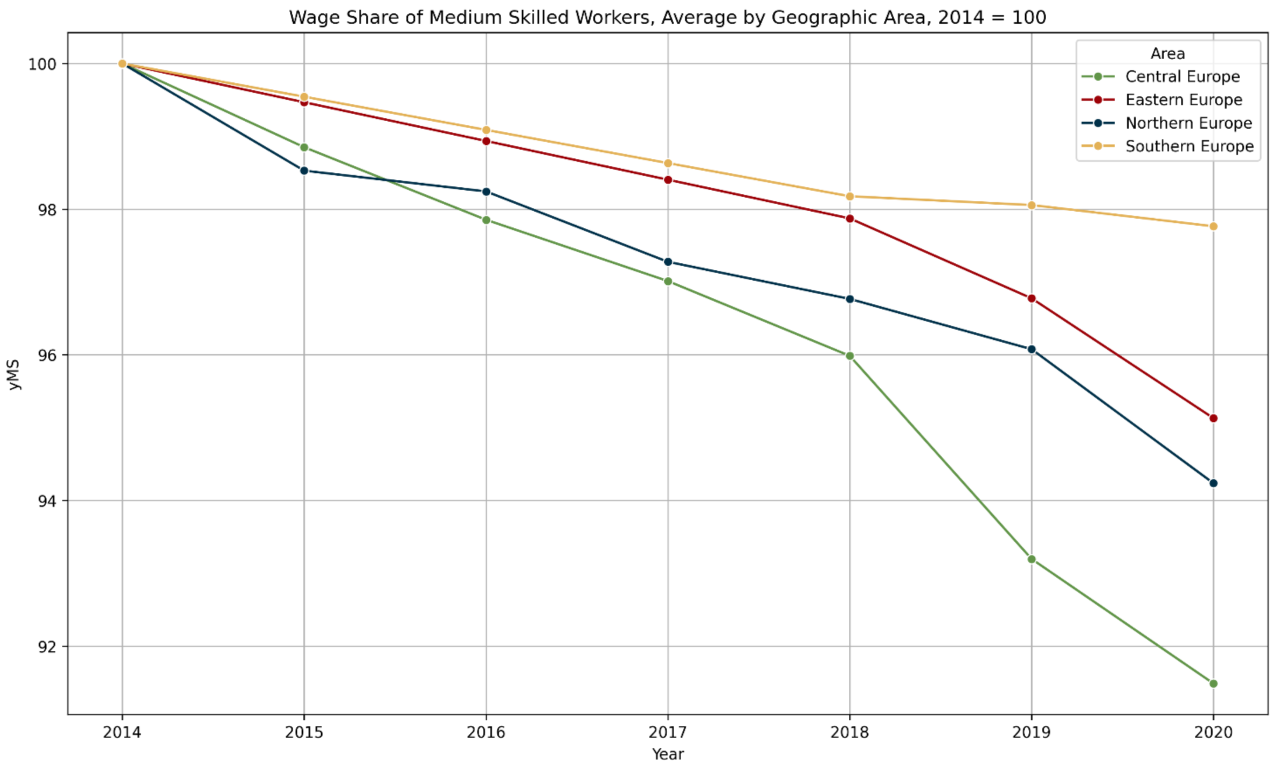

Figure 6: Time series (2014 to 2020) of wage share for middle skilled workers, 2014 = 100. The is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

Both of these segments are experiencing a decline in wage share over the same period. This trend is also in line with what is expected from the overall changes in the markets, with the many middle and low skilled tasks becoming automated and replaced by machines. The downward movements for middle skilled wage share are consistent with the previous literature, which associates many replaceable tasks with the ones performed by middle skilled workers. On the contrary, the clear decrease in low skilled workers wage brings new insights to the discussion, as previous research was not always able to identify significant changes for this segment of the population.

As middle and low skilled workers receive a decreasing portion of the total compensation, the phenomenon of job polarization becomes increasingly rooted in the market. The data plotted clearly illustrates how this trend is manifesting in real markets, showing a growing disparity in wage distribution. Over the years, the wage shares for high skilled workers are increasing, while the ones for middle and low skilled workers are diminishing. When considering the gains of one section of the workforce over the other (*Figures 11 to 13* in Appendix) we clearly notice the uptick of high skilled workers compared to the other two counterparts.

The plotted data overlooking the phenomena of digitalization and job polarization gives us a starting point to understand how these forces are shaping the labor market. While we observe that digitalization and polarization occur simultaneously, it is possible that other factors are also at play, and that one is not what is really causing the other. To understand if the two phenomena are directly correlated, we use an econometric approach to test whether digitalization is contributing to job polarization, updating the regression model from the 2014 research from Michaels et al. The model is expanded to include not only a more recent set of years, but also to focus on the present of Artificial Intelligence in the markets.

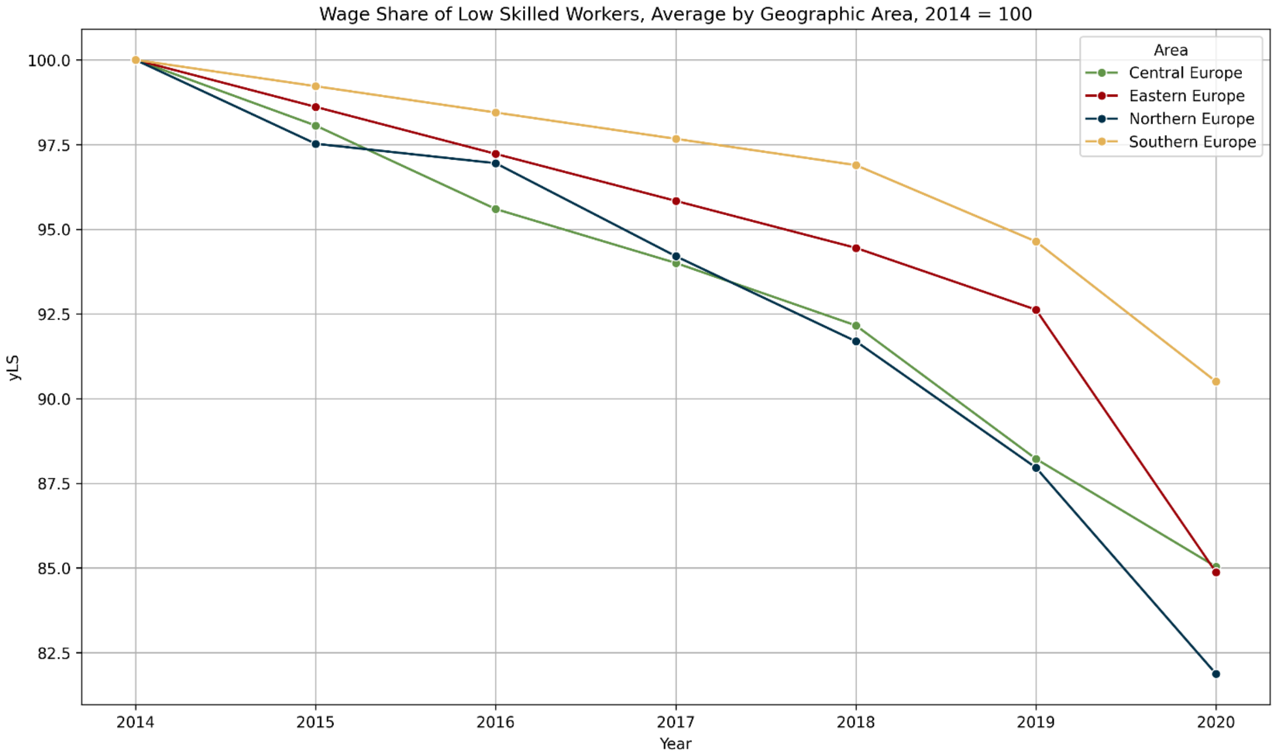

Figure 7: Time series (2014 to 2020) of wage share for low skilled workers, 2014 = 100. The data is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

Regression Model

To further the academic discussion on job polarization, this research developed a regression model to examine the impact of Artificial Intelligence on the labor market. This section explores the construction and application of the econometric approach, going over a brief analysis of the reference model, an overview of the methodology and data used in the analysis, the regression model itself, and the results and considerations deriving from it.

1. Reference Model

As mentioned previously, part of this research will be focused on updating the regression model from Michaels et al. (2014). The analysis is thoroughly described in a paper published on The Review of Economics and Statistics¸ titled “Has ICT Polarized Skill Demand? Evidence From Eleven Countries Over Twenty-Five Years”.

The 2014 model tests the hypothesis that ICT polarized the labor market by increasing the demand for the highly educated, while decreasing it for the middle educated and remaining stable for the low educated workers. The authors base their analysis on the EUKLEMS dataset including information on most OECD countries. They focus on the data of eleven countries: Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, the United Kingdom, and the United States. This choice was dictated by availability of the information their model required: data on skill composition, ICT and non-ICT capital, and value added between 1980 and 2004. Additionally, they assume the following distinction between types of tasks and skill levels: cognitive nonroutine tasks are mostly performed by educated workers, manual nonroutine tasks are performed by less educated workers, and routine tasks by middle educated workers.

The model aims at predicting the share of wage that each skill level receives, differentiating between country, year, and industry. Moreover, to smooth out measurement error and have a better look at historical trends, their estimations are in long differences of twenty-five years. The regression equations obtained are the following:

$$\Delta SHARE_{ijt}^{S} = \beta_{0j}^{S} + \beta_1^S \Delta(C/Q)_{ijt} + \beta_2^S \Delta(K/Q)_{ijt} + \beta_3^S ln\, Q_{ijt} + \beta_4^S \Delta AI_{ijt} + \beta_4^S \Delta(C/Q * AI)_{ijt} + u_{ijt}^S$$

Where C = ICT capital services, K = non-ICT capital services, Q = value added, S = skill level, i = industry, j = country, and t = year.

The model's results are supportive of the job polarization hypothesis: it is the industries experiencing the fastest growth in ICT services that also present the fastest growth in demand for the highly educated workers, and the fastest fall in demand for workers with an intermediate level of education. Instead, for low-skilled workers the changes in technology are insignificant.

This study is an important foundation for the research on job polarization. It provides solid evidence of the shifts of the labor market in the last few decades linked to the rise of ICTs. However, the data presented in the model may no longer reflect the current landscape, given the amount of progress made in technology fields since 2004. Because of this, it would be useful to create and run an updated model that takes into account a timeframe closer to the present, and that focuses its attention on one of the most significant innovations in the current markets: Artificial Intelligence.

2. Methodology and Data

In order to run an updated model to analyze job polarization from a more modern perspective, it is necessary to revise some of the aspects of the dataset in the reference model. Similarly to the model of Michaels et al, the data is mostly deriving from EUKLEMS & INTANProd (Bontadini et al., 2023), the only exception being the data on Artificial Intelligence, which is taken from the OECD AI Policy Observatory (OECD.AI, 2024).

The panel dataset used in the regression model is composed of 140 observations throughout seven years (2014 to 2020), deriving from twenty different countries of the European Union (EU):

Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Slovakia, Slovenia, Spain, and Sweden.

The remaining eight Member States not included are missing either due to a lack of sufficient data on their accounts, or due to a presence of outliers. Moreover, the model was restricted to focus only on Member States of the EU, which are countries within a close geographical area, with common laws and relatively similar cultures. These similarities help mitigating errors and confounders stemming from external factors.

Regarding the time restrictions, the dataset could not extend past the year 2020 since the EUKLEMS dataset has not yet released data beyond that year. Instead, the years before 2014 were excluded due to three reasons. Firstly, wage shares as computed in EUKLEMS & INTANProd rely on the Structure of Earning Survey (SES) which is compiled every four years – 2010, 2014 and 2018 – with the years in between being interpolated. Consequently, we start our analysis from 2014, the first benchmark year in the wage shares data from EUKLEMS & INTANProd (Bontadini et al., 2023). Secondly, workers' skills are identified in terms of educational attainment through the ISCED classification (Eurostat, 2023), which has been updated in 2011 and reflected in the data starting in 2014. In doing so, we minimize possible noise in our estimates due to changes in the skill classification system. Thirdly, before 2014, AI was still in the early stages of its evolution, and therefore its influence in the markets was limited compared to the one seen in the subsequent years.

Another difference with the reference model lies in the absence of industry specific data. This choice was dictated by the lack of such data for Artificial Intelligence, a field that is relatively new and for which such detailed information has still not been published.

The independent variables that the dataset is composed of are the following:

C: ICT capital services, measuring the contribution of these new technologies to the economic growth of each country;

K: Non-ICT capital services, measuring the contribution of traditional physical capital assets to the economic growth and productivity of each country;

Q: Value added, represents the total level of goods and services in an economy after deducting their cost. This variable helps stabilize the model by absorbing the economic factors that are external to the model (such as the different sizes or growth rates of the countries);

AI Penetration: Artificial Intelligence penetration in the markets of each country. Because of how recent the topic of AI is, the data available is very limited. Therefore, the proxy used in this instance is “Artificial Intelligence Software Development”. The data is taken from the OECD AI Policy Observatory, which – in collaboration with GitHub – identifies public projects (or “repositories”) containing AI code. A project is then assigned to one or more countries using fractional counts[2], which are based on the location of the contributions to the project (also called “commits”).

It is also important to note that the independent variables taken from the EUKLEMS dataset are measured in local currencies. Therefore, before proceeding with the model, the values that were not already expressed in Euros were transformed by using the conversion rates provided by Eurostat (Eurostat, 2024).

Some additional calculations were then applied to the dataset to obtain some of the variables needed for the regression model:

ICT: natural logarithm of ICT capital services divided by value added (ln C/Q), to measure the use of new technologies;

NonICT: natural logarithm of Non-ICT capital services divided by value added (ln K/Q), to measure the use of traditional capital;

VA: natural logarithm of value added (ln Q);

[2] For instance, if one project receives a commit from Italy and one from Germany, the value for that project will be 0.5 in each of the two countries. Further information on https://oecd.ai/en/github.

AI: natural logarithm of *AI Penetration* (ln AI);

*ICT * AI*: interaction term (ln C/Q * ln AI), to analyze the joint effect of the two variables.

The depended variables considered are linked to the share of each worker type (high, middle, and low skilled) in labor compensation. In particular, these variables measure how much of the total annual earnings in a country are distributed among workers with a high level of education ($Share^H$), with a middle level ($Share^M$), and with a low level ($Share^L$).

3. Updated Model

To test the effects of Artificial Intelligence on the different labor groups, a panel regression model was developed (*Table 1*), based on the following equation:

$$SHARE_{jt}^{S} = \beta_0^S + \beta_1^S \ln(C/Q)_{jt} + \beta_2^S \ln(K/Q)_{jt} + \beta_3^S\, ln(AI)_{jt} + \beta_4^S(\ln(C/Q) * \ln(AI))_{jt} + u_{jt}^S$$

where S = (H, M, L), j = country, and t = year.

The model includes country fixed effects. This approach accounts for unobserved heterogeneity by controlling for time-invariant characteristics within each country that could influence the dependent variable. This helps mitigate bias that could arise from omitted variables and unobservable country-specific factors, making the analysis more reliable and robust. As a robustness check, the same model was also tested by including time fixed effects (*Table 2*). The results are consistent with the hypothesis tested, however there is a loss of significance among the coefficients. This decrease in significance suggests that controlling for time fixed effects might be obscuring some of the relationships we are interested in. In the context of quickly advancing technologies the passage of time can have a substantial impact on the results of the analysis, and subsequently a model that does not smooth-out these differences can perform better.

To ensure the validity of the regression models, it was also necessary to run a heteroskedasticity test to check for the presence of non-constant variance in the residuals. In particular, the Breusch-Pagan test was employed to obtain the Lagrange Multiplier (LM) statistic and the F-statistic. Their respective p-values were above the significance level threshold of 0.01 – therefore finding no evidence of heteroskedasticity – in all regressions run except for the one listed in Column 3 of *Table 1*. To take care of this, the model's the standard errors were transformed into robust ones. This led to the loss of significance for a limited set of variables, but ultimately did not affect the results excessively. The model run before using robust standard errors is summarized in *Table 3*.

Finally, the variables used in the model do not exhibit multicollinearity. When running a correlation matrix, no correlation coefficient reaches or exceeds the absolute value of 0.8, with the exception of the interaction term. However, given the nature of interaction terms, it is natural to have higher values in their correlation coefficient.

4. Regression Results

4.1 $SHARE^H$ Regressions

The first set of results (Panel A of *Table 1*) derives from the panel regressions run on the wage share for the high skilled workers ($SHARE^H$).

Column 1 reports the summary of the first regression, which includes only *ln C/Q* as independent variable. The coefficient is significant and positive, in line with the findings from the reference model: a 1% increase in the use of ICT leads on average and over the years to 0.00095 percentage points (p.p.) increase of the wage share for skilled workers. Because these are shares, which do not fluctuate much over time, it is normal to have very small changes in percentage points. Additionally, while the effect on the country level is rather small, it is likely to change significantly across industries, with some being affected to such a degree to affect the country-level average effects. On the other hand, Column 2 shows the results of the regression involving also *ln K/Q* and *ln Q*. Here, the coefficient is significant and positive for *ln C/Q* and *ln Q*, but insignificant and negative for *ln*

K/Q. This suggests that there is no sign of capital-skill complementarity for Non-ICT capital services and high skilled workers.

Column 3 and 4 of the table, instead, introduce the effects of AI penetration. The coefficients are positive and statistically significant, suggesting AI penetration itself has a substantial impact on increasing the wage share for skilled workers, independently of ICT use. This indicates that AI technologies are directly related to the growth for high-skilled labor. On average, we expect a 1% increase in the use of AI to lead to 0.006 p.p. increase of the wage share for skilled workers over the years. In addition, the positive interaction term in Column 5 suggests that the effect of ICT use on the wage share for skilled workers is amplified by the presence of AI. In other words, not only does AI penetration directly benefit skilled labor, but it also enhances the already positive impact of ICT use.

4.2 $SHARE^M$ Regressions

The second set of results (Panel B of *Table 1*) derives from the panel regressions run on the wage share for the middle skilled workers ($SHARE^M$). The estimates reported follow the same specifications as Panel A.

Column 1 reports the result of the regression involving *ln C/Q* as the only independent variable. The coefficient is significant but negative, proving that a 1% increase in the use of ICT capital services leads on average and over the years to a decrease in the wage share for middle skilled workers by 0.00055 percentage points. Column 2 presents the regression results adding *ln K/Q* as the second independent variable. In this case, the coefficient of ICT capital services is still negative and significant, while for Non-ICT capital services it is positive and significant. As Non-ICT capital services are often used by middle skilled workers, the positive relationship found in this regression is consistent with the expected results of the research.

The coefficients for *ln AI* in Column 3 and Column 4 are negative and significant, strengthening the hypothesis that AI Penetration reduces the wage share for middle-skilled workers. In particular, the third regression finds that a 1% increase in the use of AI leads on average and over the years to a decrease in the wage share for middle skilled workers by 0.00003 percentage points. Finally, the regression in Column 5 includes all independent variables. *Ln K/Q* is again positive and significant, in line with the regressions of Panel B. Together with the interaction term, value added and AI penetration are also negative and significant. These findings reinforce the notion that AI, much like ICT, is contributing to the decline of middle skilled jobs. This phenomenon is caused not just by Artificial Intelligence on its own, but also by its additive effect to ICT services.

Overall, the results obtained from $SHARE^M$ align with the job polarization theory, which sees middle skilled jobs are more susceptible to automation and technological displacement.

4.3 $SHARE^L$ Regressions

Finally, the third set of results (Panel C) reports the findings from the panel regressions run on the wage share for the low skilled workers ($SHARE^L$).

Column 1 reports the result of the regression involving *ln C/Q* as independent variable. The coefficient being negative and significant indicates that a 1% increase in the use of ICT is associated on average with a 0.00055 p.p. decrease in the wage share for low skilled workers. This coefficient remains significant also for the regression in Column 2, which introduces *ln K/Q* as the second independent variable. For this second estimate, the value is negative but insignificant, suggesting that Non-ICT capital services would have the potential to replaced low skilled professions.

Columns 3, 4, and 5 see the introduction of *ln AI* and *ln C/Q * ln AI*. In all cases, these independent variables are significant and negative. This implies that AI penetration leads to a reduction in the wage share for low-skilled workers, both when taken as a stand-alone and when combined with the effect of ICT use. Instead, the signs and significance of ICT and Non-ICT capital services remains in line with the results of the previous regressions.

Interestingly, the coefficients related to AI for $SHARE^L$ are all lower than the respective counterparts in Panel B. This hints at different rates with which job polarization is affecting the labor market. Although low skilled workers are experiencing a negative change, this is not happening to the same degree as for the middle skilled workers.

5. Considerations on the Model

The results of these three sets of panel regressions provided us with important insights to analyze the impact of Artificial Intelligence on job polarization.

To begin with, the analysis is in line with the previous research on job polarization for what concerns the impact of the spread of ICT and Non-ICT capital services in various countries over the years. The literature on this topic has consistently found a strong positive effect for high skilled workers, and a negative one with middle skilled workers. The research conducted by the updated models has confirmed these hypotheses, obtaining significant coefficients with the expected signs. This indicates that, even with more recent data, the findings on job polarization from previous research remain valid and applicable. The persistent positive impact of ICT on the wage share of skilled workers confirms that technological advancements continue to favor high skilled labor, while the negative effect of ICT on middle skilled workers highlights how employment is still on a risky trajectory for occupations easy to automate. This is part of the process that ultimately contributes to job polarization.

Our model was also successful in studying the effects of Artificial Intelligence on the issue, adding a new layer of information to the research. As was hypothesized, AI penetration has been complementary to high skilled occupations, leading over time to an average increase of their wage share. The interaction term between ICT and AI further amplifies this effect, suggesting that the presence of AI enhances the positive impact of ICT on high skilled wages. This is consistent with the complementarity theory, where high skilled workers are able to leverage these technologies to increase productivity and earnings.

Additionally, the model confirmed the hypothesized negative effect of Artificial Intelligence on middle skilled jobs. AI Penetration has a significant negative effect on wage shares for the middle skilled, contributing to the shrinking phenomenon of this labor sector. As these new technologies enter the market and employers prefer them to human labor, the process of erosion of middle skilled jobs continues. While this effect was already present due to ICT investments, it is now amplified by AI penetration in the markets. This once more supports the job polarization theory, where middle skilled jobs are most vulnerable to technological advancements.

Furthermore, this analysis has brought up new insights for the low skilled occupations. In previous research, it was argued that the technological improvements deriving from ICTs had an insignificant impact on low skilled workers. This point was reiterated in the reference model by Michaels et al. Instead, the updated model developed on more recent data has found a significant effect not just from ICTs but also from AI penetration. This effect highlights a negative relation between these technological advancements and the wage share at the lowest end of the skill spectrum. This newly found significance suggests that the substantial improvements undergone by ICT and AI could now be affecting a broader range of occupations than was previously observed, including non-routine tasks that low skilled workers often perform. These results imply a potential new challenge for this part of the workforce, which might face increased risks of job displacement and wage reductions due to the advancing capabilities of technologies.

Table 1: Panel OLS Regression Results for the Updated Model, robust standard errors. Fixed effects present on country level. Significance codes: 0.001: '***'; 0.05: '**' 0.1: '*'.

	(1)	(2)	(3)	(4)	(5)
		A. Dependent variable: High Skilled Wage Bill Share			
const	0.819***	-0.059	0.336*	-0.013	0.063
	(0.051)	(0.166)	(0.182)	(0.223)	(0.211)
ln ICT	0.095***	0.064***	0.056***		0.019
	(0.014)	(0.014)	(0.012)		(0.016)
ln Non-ICT		-0.038	-0.035		-0.035
		(0.024)	(0.022)		(0.021)
ln Q		0.060***	0.023	0.038**	0.035**
		(0.012)	(0.014)	(0.019)	(0.016)
ln AI			0.006***	0.007***	0.033***
			(0.002)	(0.002)	(0.01)
ln ICT * ln AI					0.008***
					(0.003)
Observations	147	147	147	147	147
R^2	0.309	0.46	0.536	0.409	0.577
Adj R^2		0.449	0.523	0.401	0.562
		B. Dependent variable: Middle Skilled Wage Bill Share			
const	0.230***	0.916***	0.694***	0.849***	0.846***
	(0.034)	(0.108)	(0.123)	(0.151)	(0.14)
ln ICT	-0.055***	-0.027***	-0.022**		-0.002
	(0.01)	(0.01)	(0.009)		(0.013)
ln Non-ICT		0.046***	0.045***		0.045***
		(0.014)	(0.013)		(0.013)
ln Q		-0.044***	-0.024**	-0.034***	-0.030***
		(0.007)	(0.01)	(0.013)	(0.01)
ln AI			-0.003***	-0.004***	-0.018**
			(0.001)	(0.001)	(0.007)
ln ICT * ln AI					-0.004**
					(0.002)
Observations	147	147	147	147	147
R^2	0.237	0.485	0.541	0.418	0.571
Adj R^2		0.474	0.528	0.410	0.555
		C. Dependent variable: Low Skilled Wage Bill Share			
const	-0.049**	0.143	-0.03	0.164	0.091
	(0.024)	(0.087)	(0.094)	(0.101)	(0.109)
ln ICT	-0.041***	-0.037***	-0.033***		-0.017**
	(0.007)	(0.007)	(0.006)		(0.008)
ln Non-ICT		-0.009	-0.01		-0.01
		(0.014)	(0.013)		(0.013)
ln Q		-0.016**	0.001	-0.005	-0.005
		(0.007)	(0.008)	(0.009)	(0.008)
ln AI			-0.002***	-0.003***	-0.015***
			(0.001)	(0.001)	(0.005)
ln ICT * ln AI					-0.004***
					(0.001)
Observations	147	147	147	147	147
R^2	0.261	0.298	0.365	0.229	0.402
Adj R^2		0.283	0.347	0.169	0.381

SECTION 3:

Final Considerations

Ethical Considerations

As extensively discussed in the past literature on job polarization, and as proved by the model described in the previous chapter, the deployment of Artificial Intelligence is fundamentally reshaping the labor market. This shift comes with many benefits, such as increased productivity and efficiency, but also with many ethical challenges, particularly concerning job displacement and its socio-economic impacts. This section explores such ethical considerations, going over the complexities and risks associated with AI-driven job automation.

1. Skill Acquisition

To begin with, we should consider what are the barriers of entry that a person would have to face if they wanted to change their career path and transition from a medium or low skilled job to a high skilled one. This switch is significantly more challenging than the reverse, since high skilled employment often demands substantial investments in education, extensive training, and the acquisition of specialized knowledge and competences. Depending on the field and position that a worker might want to apply for, they will be faced with multiple requirements that they likely do not have, and obtaining them can be a challenging and burdensome task. Acquiring the skills necessary for many high skilled jobs will require a substantial amount of time and effort, and more often than not a large monetary investment.

The financial burden of pursuing higher education and specialized training programs can be overwhelming, particularly for those already working in medium or low skilled jobs, who may not have the financial resources to support such an investment. Additionally, the time commitment required to gain new skills often means that these workers must balance their current job responsibilities with their educational ones. On the other hand, if a middle or low skilled worker is looking to obtain higher skills because they have already lost their job, the scenario becomes even more complex. To begin with, the resources available to spend on education and training will be even more scarce. Furthermore, it is likely that this person will be more incentivized to look for another middle or low skilled job, rather than pause for an undefined period of time and obtain a different set of skills. This would allow them to earn a salary again, however it would not fix the overall issue, and it would likely just delay the inevitable.

In this scenario, it is also important to remember that these are not just numbers or abstract concepts, but real lives. The middle or low skilled worker that is at risk of losing their job is one of the many people that in the near future might be struggling to make ends meet, who might have children or elderly relatives to take care of, medical bills or other debts piling up. In such a situation, it is not feasible to stay out of the workforce for too long while also spending resources on training for higher skills. This is instead a privilege that is often only available to those who are already in an advantageous position, and who can afford to obtain the right qualifications. If there are no measures put in place to lessen these barriers of entry, we risk fueling a winner take all system, where the rich get richer, and the poor remain at the bottom. While stopping progress from taking place is not the solution, neither is placings the burden of technological adaptation on those who are already at a disadvantage.

2. Social Reconstruction

As AI continues to reshape the job market, we will witness a deep reconstruction of society. The model outlined in this research highlights how in the future imbalances in society will increase, particularly at the expenses of middle and low skilled workers. If opportunities are not equally distributed, high-paying jobs will be concentrated among a small, highly skilled workforce, while lower skilled workers will see their job opportunities diminish. The result of this job polarization effect will be a wider gap between the economic classes, and a more restricted social mobility.

As already discussed, the barriers of entry to high skilled employment are not easily obtainable, particularly for someone who has already entered the workforce. However, this issue also pertains to future generations who have yet to start working. While it might be true that in the future more people will be directed towards high skilled jobs from the start, this will not be the case for everyone. Not all young people will have the opportunity to acquire relevant expertise and to be trained specifically for high skilled jobs. This gap can stem from many factors, including the quality and accessibility of education, the resources available, and the support levels present. Additionally, pursuing higher education often requires a significant financial investment, which is not affordable by everyone. As a result, upcoming generations will enter the labor-market disproportionately. On the other end of the spectrum, we also need to consider that not everyone will want to pursue a high education level. As it has been the case both in the past and present day, many people will be more interested in the opportunities and lifestyle associated with middle or low skilled jobs, and for them being forced into high skilled labor is not the preferred choice. For many, the financial and personal investment required for higher education may not align with their career aspirations or economic realities. However, these people will be at a disadvantage as the number of positions to fill diminishes.

As the rise in automation reduces the demand for human labor in certain sectors, we will witness an increase in unemployment rates not just in certain groups of people, but also across entire geographical areas. This is particularly pressing for rural areas, which often rely on industries susceptible to automation, such as agriculture and manufacturing. For instance, rural regions in Southern Italy, which have limited access to advanced education and training opportunities, could see a significant decline in employment prospects as automation takes hold. As the supply of labor shifts, we can expect to see several issues arising: higher poverty rates, migration to different regions or countries, and social unrest. Consequently, this unrest could fuel political instability, creating opportunities for extremist political parties to gain influence. On this matter, a study on the German political behavior found that being unemployed increases the chances of affinity to extremist rightwing parties (Geishecker and Siedler, 2012). This risk is also present if the individual is still employed but concerned about job loss. A more recent study conducted on several European countries, instead, found that increases long-term unemployment rates lead to higher support for radical-left parties (Mádr, 2023). This research indicates that economic insecurity not only impacts the well-being of the population on the individual level, but also has intense social and political consequences, potentially destabilizing democratic institutions and amplifying societal divisions.

3. Psychological Effects

The unemployment rate increasing as a result of job polarization will also have vast psychological effects on the population, as work is not just a means of earning a living but also a source of many essential psychological and social benefits. In fact, regardless of the sector and occupation a person might be involved in, work can be a great medium to create and maintain a time structure, a sense of identity and of purpose, as well as social interactions. When a job is lost, all the non-intrinsic benefits of working are lost as well. This loss can lead to a series of negative consequences, such as decreased self-esteem, anxiety and depression, particularly if the person is unable to find a new job that matches their skills and experience. Social isolation is an additional factor to consider, as the daily routines and interactions that once provided structure and support suddenly vanish.

In addition to the loss of these intrinsic benefits of work, an unemployed person will also be faced with the worries of financial insecurity and job searching. Both of these are large sources of stress, which can compound the emotional strain and make the situation feel even more overwhelming. Furthermore, these individuals will have to deal with the stigma of being unemployed, which can lead to feelings of shame, isolation, and increased risk of substance abuse (Nolte-Troha et al., 2023). Unemployment can also strain personal relationships, by generating conflicts and tension in families, and contributing to the negative emotions felt by the individual. And as this other support erodes, the mental health challenges grow even stronger.

Focusing on this issue, recent research found that "chronic job insecurity was associated with a small increase in neuroticism and small decreases in conscientiousness and agreeableness, indicating its impairing effect on individuals' emotional, motivational, and social stability" (Wu, Chia-Huei et al., 2020, p. 1321). In other words, prolonged periods of unemployment or job insecurity can fundamentally alter an individual's personality traits, making them more prone to negative emotional states, less motivated and potentially less likely to successfully coexist in their community. On a large scale this can have severe consequences for society. As more people experience these psychological shifts, communities may see a rise in social tensions, a decline in collective productivity, and a decrease of social cohesion. Anxiety and distrust become more prevalent, and the challenges of reintegrating the unemployed into meaningful work grow.

In light of this, the trends predicted by the model for the future of the labor market become even more worrying. As job polarization changes the structure of the workforce, millions of people will have to face economic and psychological consequences, negatively affecting their wellbeing and that of their community.

Conclusions

The model presented in this analysis has found evidence of polarization in the labor market and has brought to light new aspects to consider due to the rise of Artificial Intelligence. The spread of ICTs continues to benefit high skilled workers, while it poses a threat to middle and low skilled workers. Although this information was already consolidated, this research was able to expand on the existing knowledge, showing that the phenomenon is still present and has continued to evolve in more recent years. The introduction of new technologies, and particularly of Artificial Intelligence, has further contributed to job polarization, putting at risk not just middle skilled workers, but now also low skilled workers.

The analysis concentrated on the European Union markets, although it is reasonable to believe that similar patterns can be found in other countries of the developed world where there is a strong push for digitalization. Particularly in the United States, research over the past decades has been consistent with job polarization expectations and found that workers with middle or low skill levels have seen their struggles increase over the years. Tüzemen and Willis (2013), for instance, highlight how in the United States the shifts linked to job polarization have pushed more and more Americans to pursue higher educational attainments. In an equivalent manner to the patterns witnessed in Europe, the changes in the markets have favored the high skilled workers while disadvantaging those with middle or low skills. This parallel further stresses how this phenomenon is not restricted to a confined group of countries, but is impacting a significant portion of humanity.

To further develop the analysis, it will be useful to expand the dataset and include more recent years. As AI continues to grow, its effects in the market will be perceived more strongly, making the discussion on job polarization increasingly significant. Additionally, future improvements might require a distinction between industries, to understand more in detail what are the fields that AI is affecting the most. These improvements, which were not possible to implement at present due to the lack of data, will give a more thorough understanding of the shifts in the economy and in the labor market.

To prepare for these changes in the markets, it is important to start implementing targeted actions both in the public and private sphere. To face the challenges of job polarization, governments must adopt a comprehensive approach that goes beyond short-term economic stimuli, and instead aims to fix the core of the issues. This includes not only immediate investments in training programs but also strategic planning for the future workforce. An important area of focus should be education, to provide comprehensive exposure to STEM (Science, Technology, Engineering, Mathematics) subjects, as well as promote updated curricula including new subjects that bridge the gap between traditional and emerging disciplines. Separately, it will be essential to provide financial aid to those who wish to continue with high education but don't have the means to, particularly through scholarships and investments in public universities. For those already in the labor force, instead, on demand online courses or night lectures would be more suitable. Investing in these training opportunities is essential to ensure that they are available for anyone, and to provide a diversified amount that can suit different interests. Moreover, governments should focus their resources on fields where new positions can be created. Investments are also crucial in the geographic areas where the shocks of job polarization might be felt with stronger intensity, to avoid leaving these areas completely behind. Furthermore, the investments should be directed to creating and incentivizing businesses that are resilient to technological advancements and capable of thriving in this new landscape.

Private businesses can also play a part in reducing the shock of job polarization. These target actions revolve around an internal re-training for the positions that are at risk of being eliminated, to redirect the workers into different tasks. While certain occupations will inevitably be replaced, new ones will arise in the business as a consequence. This internal reshuffling of tasks can significantly reduce the shocks of job polarization for both the business and the worker. The worker would benefit from remaining in a familiar position, avoiding also the shocks related to becoming unemployed. The business, on the other hand, could save on the costs of turnover. This approach not only preserves employment but also enhances the workforce's adaptability and skill set. Unfortunately, the direct retraining from a position to another is not always possible. For these situations, businesses should still play an active role in supporting their workers, offering emotional, social, and career assistance.

Having gone over the economic background, as well as the ethical implications and actions to take, we can better answer the core question of this research: whether the rising presence of Artificial Intelligence in the markets represents an economic calamity or just the future of labor. While the findings of the econometric model might lead to assume that the middle and low skilled workers are on track to disappear from the labor market, the situation is not as dire. The challenges are real, but we must not forget all the new opportunities that can arise thanks to the introduction of ICTs and AI. Higher productivity and profitability, the reduction of physical risks for workers, and the introduction of new fields are all positive outcomes that we can expect to witness, and that are going to balance the negative aspects that this progress will bring along. However, in order to ensure that these advances are distributed and benefitting everyone, further actions will be needed to tackle not just the short-term concerns, but also the long-term ones. Halting progress is not an option, but moving forward will require serious determination and concrete actions from all parties to ensure that welfare is maximized for everyone. The greatest mistake we can make at a time like this is allowing fear and distrust to hold us back from embracing progress, "for time and the world do not stand still. Change is the law of life. And those who look only to the past or the present are certain to miss the future." (John F. Kennedy, 1963).

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Appendix

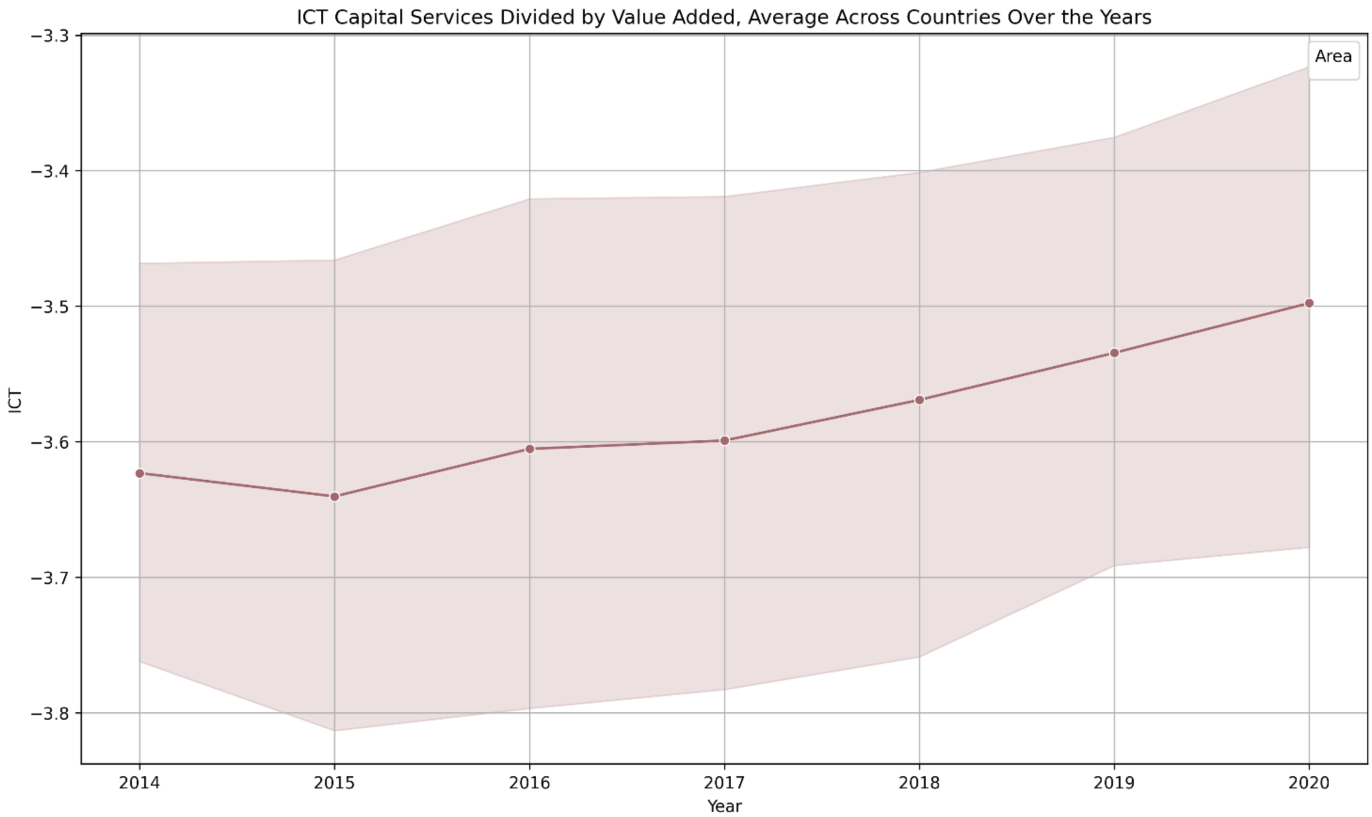

Figure 8: Time series (2014 to 2020) of ICT Capital Services divided by Value Added. The data is expressed in natural logarithm, and is reporting the average of the values across all countries considered (Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Slovakia, Slovenia, Spain, and Sweden).

Data source: EUKLEMS & INTANProd (2023).

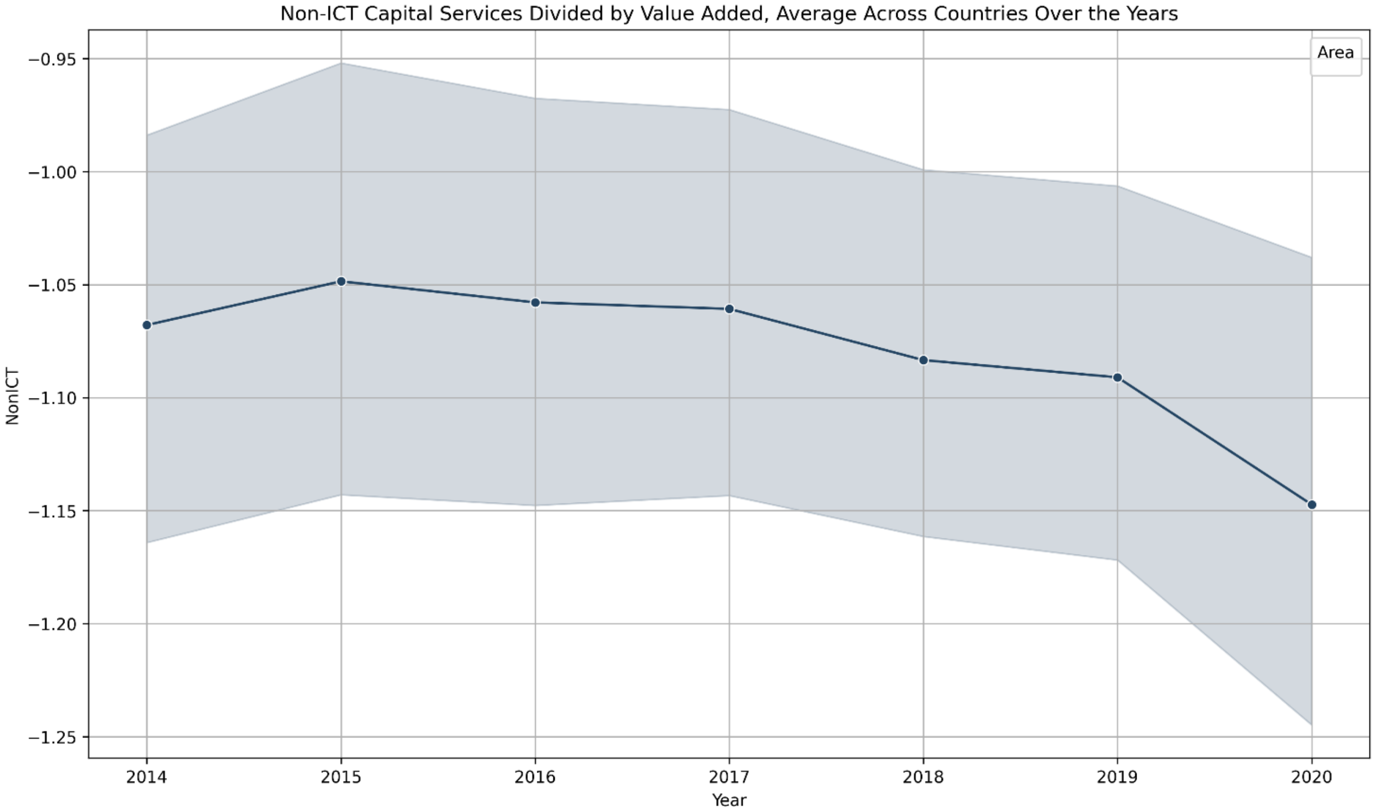

Figure 9: Time series (2014 to 2020) of Non-ICT Capital Services divided by Value Added. The data is expressed in natural logarithm, and is reporting the average of the values across all countries considered (Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Slovakia, Slovenia, Spain, and Sweden).

Data source: EUKLEMS & INTANProd (2023).

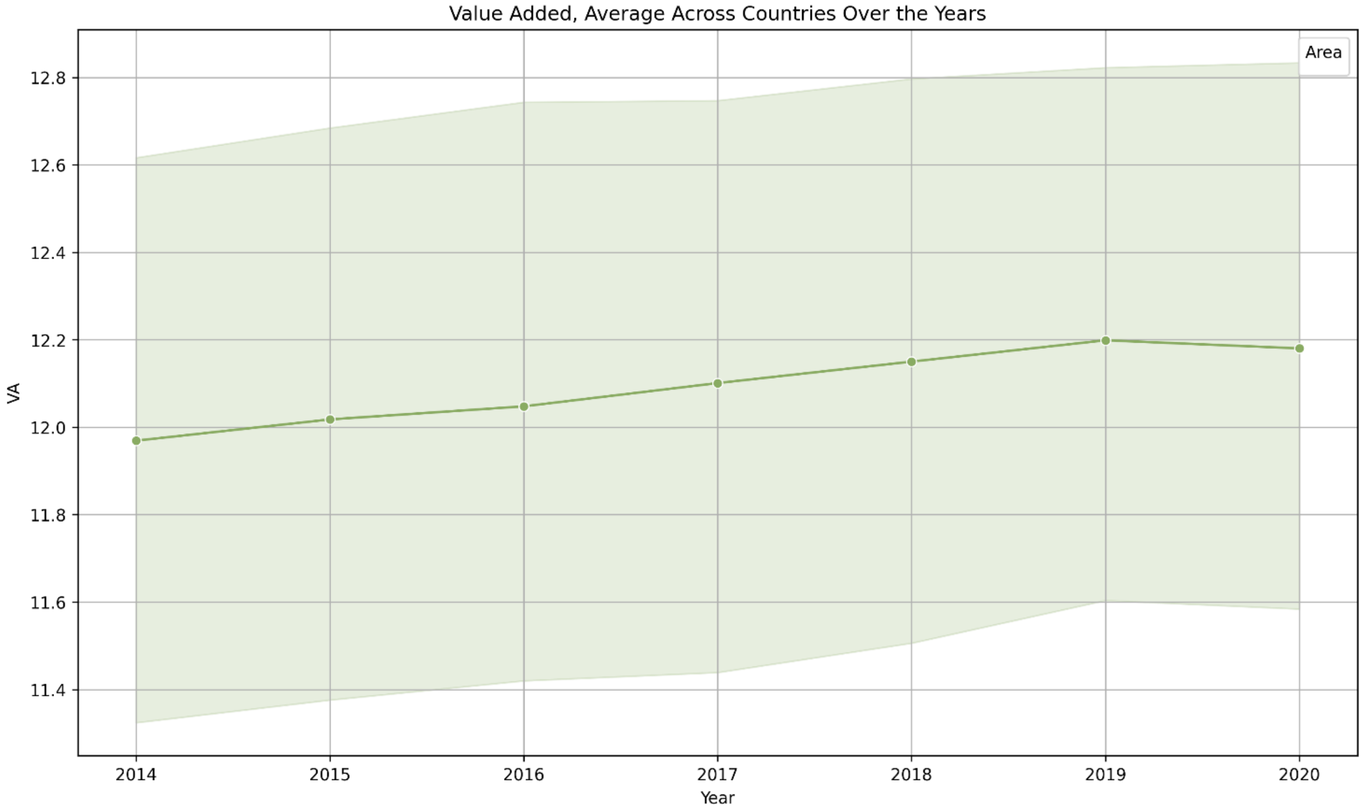

Figure 10: Time series (2014 to 2020) of Value Added. The data is expressed in natural logarithm, and is reporting the average of the values across all countries considered (Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Slovakia, Slovenia, Spain, and Sweden).

Data source: EUKLEMS & INTANProd (2023).

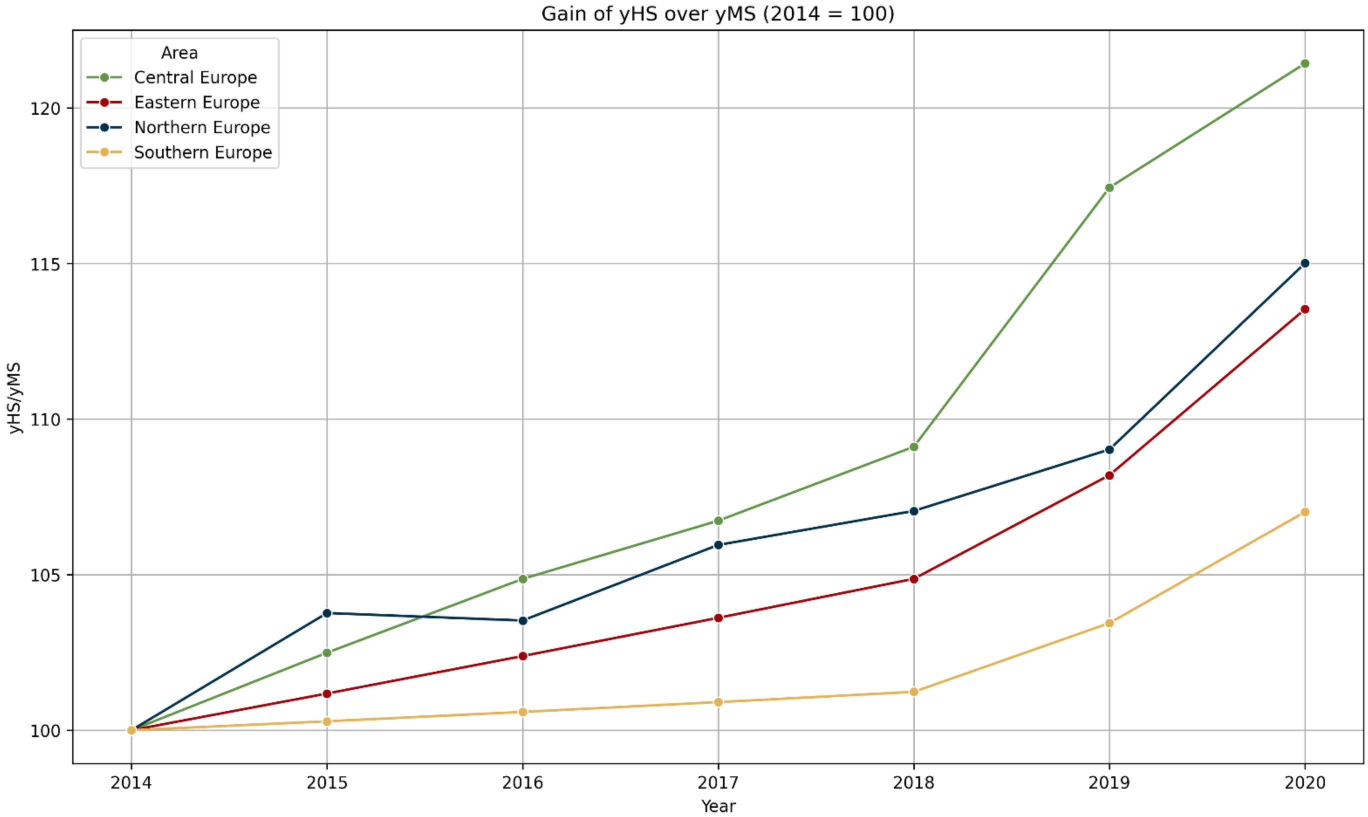

Figure 11: Time series (2014 to 2020) of wage share of High Skilled workers (*yHS*) divided by wage share of Middle Skilled workers (*yMS*), 2014 = 100. The data is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

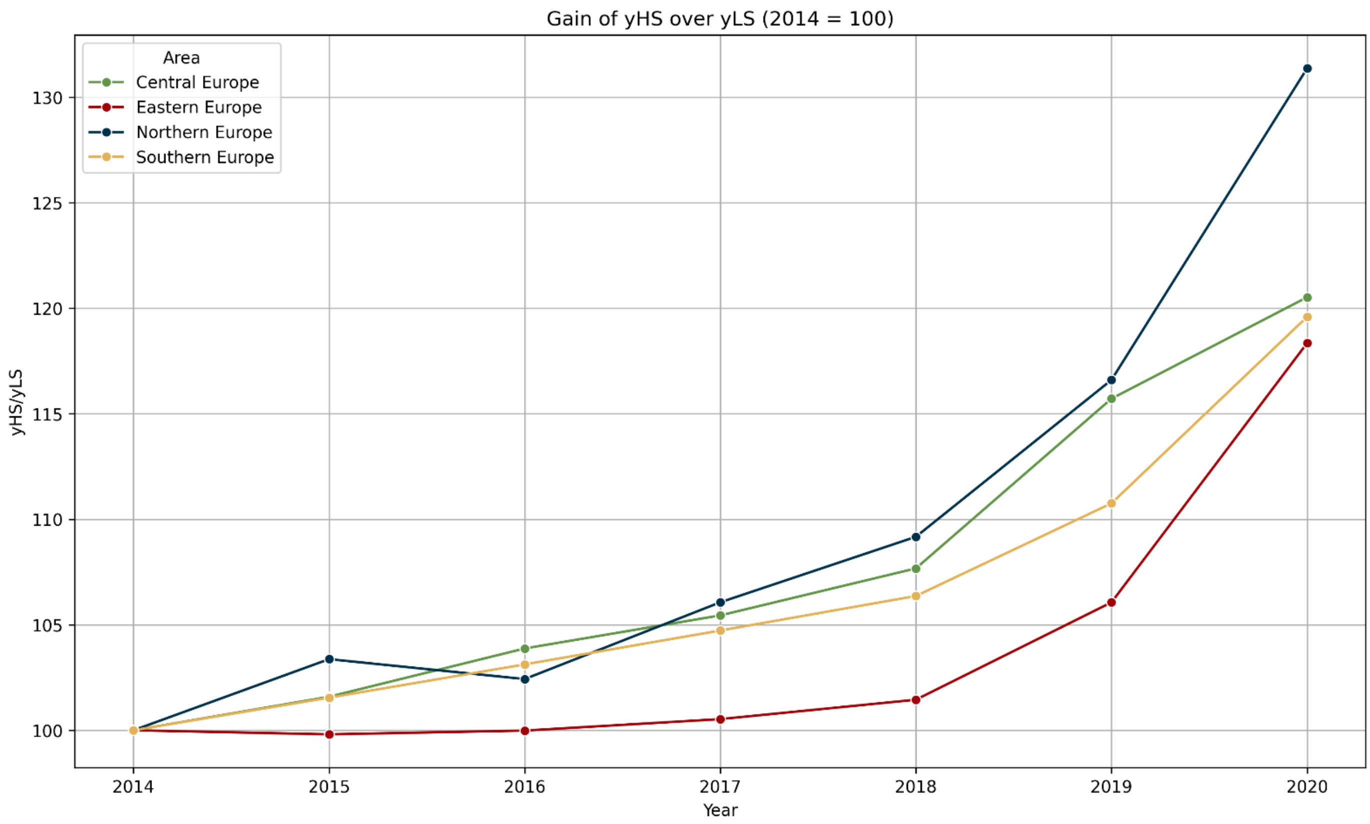

Figure 12: Time series (2014 to 2020) of wage share of High Skilled workers (*yHS*) divided by wage share of Low Skilled workers (*yLS*), 2014 = 100. The data is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

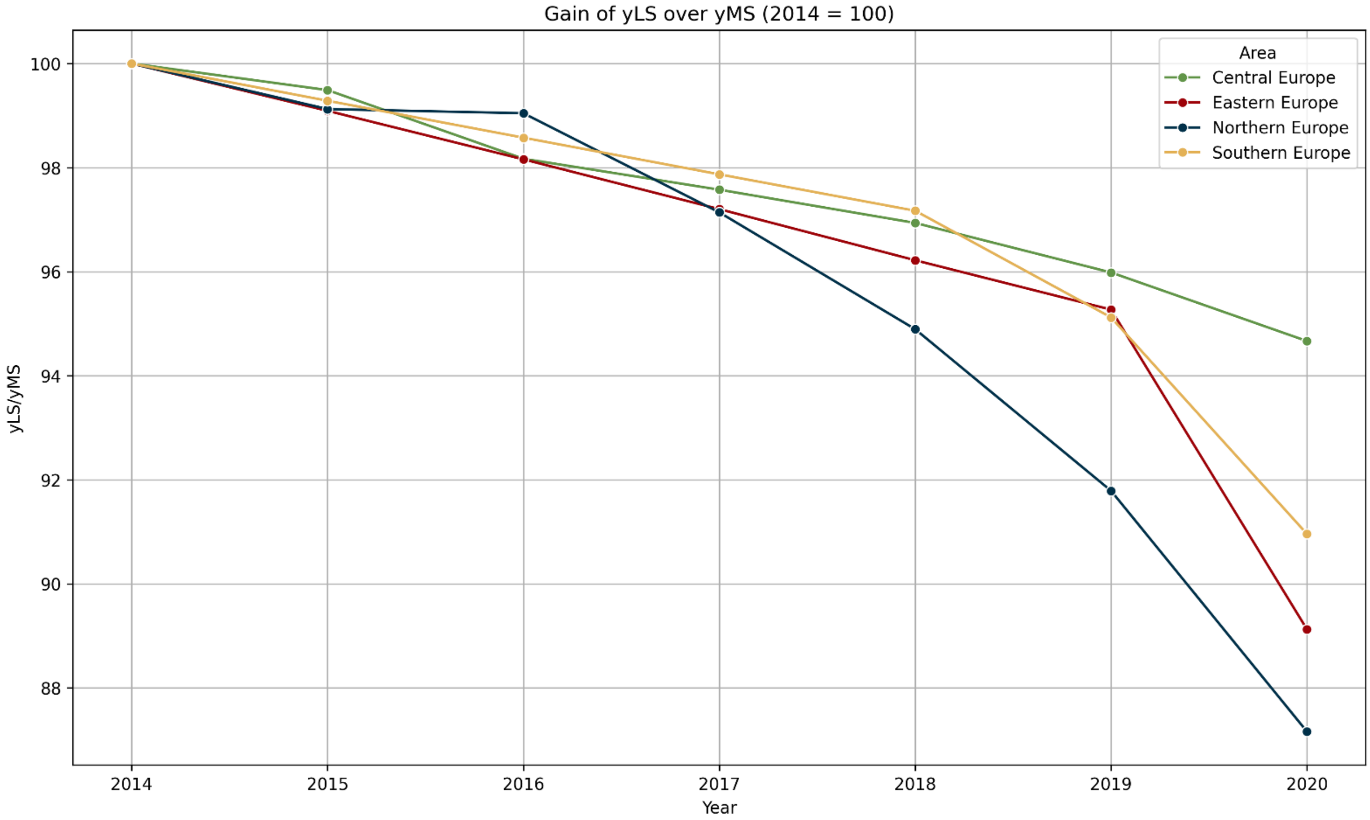

Figure 13: Time series (2014 to 2020) of wage share of Low Skilled workers (*yLS*) divided by wage share of Middle Skilled workers (*yMS*), 2014 = 100. The data is divided by geographic area (where *Central Europe*: Belgium, France, Germany, Luxembourg, and the Netherlands; *Eastern Europe*: Bulgaria, Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Slovakia, and Slovenia; *Northern Europe*: Denmark, Finland, Ireland, and Sweden; *Southern Europe*: Italy and Spain). Each line represents the average of the data in the geographic area.

Data source: EUKLEMS & INTANProd (2023).

Table 2: Panel OLS Regression Results for the Updated Model, robust standard errors. Fixed effects present on country and time level. Significance codes: 0.001: '***'; 0.05: '**' 0.1: '*'.

	(1)	(2)	(3)	(4)	(5)
			A. Dependent variable: High Skilled Wage Bill Share		
const	0.587***	1.495***	1.501***	1.433***	1.226***
	(0.036)	(0.186)	(0.184)	(0.185)	(0.2)
ln ICT	0.030***	0.025***	0.025***		0.002
	(0.01)	(0.009)	(0.009)		(0.012)
ln Non-ICT		0.021	0.02		0.018
		(0.014)	(0.014)		(0.014)
ln Q		-0.075***	-0.076***	-0.080***	-0.060***
		(0.015)	(0.015)	(0.015)	(0.016)
ln AI			0.002	0.002	0.021***
			(0.001)	(0.001)	(0.006)
ln ICT * ln AI					0.005***
					(0.002)
Observations	147	147	147	147	147
R^2	0.071	0.233	0.248	0.195	0.304
Adj R^2		0.217	0.227	0.184	0.279
			B. Dependent variable: Middle Skilled Wage Bill Share		
const	0.031	-0.660***	-0.661***	-0.547***	-0.559***
	(0.022)	(0.102)	(0.102)	(0.112)	(0.113)
ln ICT	-0.018***	-0.017***	-0.017***		-0.008
	(0.006)	(0.005)	(0.005)		(0.007)
ln Non-ICT		-0.040***	-0.040***		-0.039***
		(0.008)	(0.008)		(0.008)
ln Q		0.054***	0.054***	0.053***	0.048***
		(0.008)	(0.008)	(0.009)	(0.009)
ln AI			0	-0.001	-0.007**
			(0.001)	(0.001)	(0.004)
ln ICT * ln AI					-0.002**
					(0.001)
Observations	147	147	147	147	147
R^2	0.023	0.074	0.093	0.053	0.136
Adj R^2		0.054	0.067	0.040	0.105
			C. Dependent variable: Low Skilled Wage Bill Share		
const	0.031	-0.660***	-0.661***	-0.547***	-0.559***
	(0.022)	(0.102)	(0.102)	(0.112)	(0.113)
ln ICT	-0.018***	-0.017***	-0.017***		-0.008
	(0.006)	(0.005)	(0.005)		(0.007)
ln Non-ICT		-0.040***	-0.040***		-0.039***
		(0.008)	(0.008)		(0.008)
ln Q		0.054***	0.054***	0.053***	0.048***
		(0.008)	(0.008)	(0.009)	(0.009)
ln AI			0	-0.001	-0.007**
			(0.001)	(0.001)	(0.004)
ln ICT * ln AI					-0.002**
					(0.001)
Observations	147	147	147	147	147
R^2	0.067	0.387	0.389	0.22	0.409
Adj R^2		0.374	0.371	0.205	0.388

Table 3: Panel OLS Regression Results for the Updated Model, before controlling for Heteroskedasticity. Fixed effects present on country level. Significance codes: 0.001: '***'; 0.05: '**' 0.1: '*'.

	(1)	(2)	(3)	(4)	(5)
		A. Dependent variable: High Skilled Wage Bill Share			
const	0.819^{***}	-0.059	0.336^{*}	-0.013	0.063
	(0.046)	(0.16)	(0.173)	(0.177)	(0.184)
ln ICT	0.095^{***}	0.064^{***}	0.056^{***}		0.019
	(0.013)	(0.013)	(0.012)		(0.016)
ln Non-ICT		-0.038^{**}	-0.035^{**}		-0.035^{**}
		(0.019)	(0.018)		(0.017)
ln Q		0.060^{***}	0.023^{*}	0.038^{**}	0.035^{**}
		(0.012)	(0.014)	(0.015)	(0.014)
ln AI			0.006^{***}	0.007^{***}	0.033^{***}
			(0.001)	(0.001)	(0.008)
ln ICT * ln AI					0.008^{***}
					(0.002)
Observations	147	147	147	147	147
R^2	0.309	0.46	0.536	0.409	0.577
Adj R^2		0.449	0.523	0.401	0.562
		B. Dependent variable: Middle Skilled Wage Bill Share			
const	0.230^{***}	0.916^{***}	0.694^{***}	0.849^{***}	0.846^{***}
	(0.031)	(0.102)	(0.112)	(0.115)	(0.121)
ln ICT	-0.055^{***}	-0.027^{***}	-0.022^{***}		-0.002
	(0.009)	(0.008)	(0.008)		(0.01)
ln Non-ICT		0.046^{***}	0.045^{***}		0.045^{***}
		(0.012)	(0.011)		(0.011)
ln Q		-0.044^{***}	-0.024^{***}	-0.034^{***}	-0.030^{***}
		(0.007)	(0.009)	(0.01)	(0.009)
ln AI			-0.003^{***}	-0.004^{***}	-0.018^{***}
			(0.001)	(0.001)	(0.005)
ln ICT * ln AI					-0.004^{***}
					(0.002)
Observations	147	147	147	147	147
R^2	0.237	0.485	0.541	0.418	0.571
Adj R^2		0.474	0.528	0.410	0.555
		C. Dependent variable: Low Skilled Wage Bill Share			
const	-0.049^{**}	0.143^{*}	-0.03	0.164^{*}	0.091
	(0.022)	(0.085)	(0.094)	(0.094)	(0.102)
ln ICT	-0.041^{***}	-0.037^{***}	-0.033^{***}		-0.017^{*}
	(0.006)	(0.007)	(0.006)		(0.009)
ln Non-ICT		-0.009	-0.01		-0.01
		(0.01)	(0.01)		(0.009)
ln Q		-0.016^{**}	0.001	-0.005	-0.005
		(0.006)	(0.007)	(0.008)	(0.007)
ln AI			-0.002^{***}	-0.003^{***}	-0.015^{***}
			(0.001)	(0.001)	(0.004)
ln ICT * ln AI					-0.004^{***}
					(0.001)
Observations	147	147	147	147	147
R^2	0.261	0.298	0.365	0.229	0.402
Adj R^2		0.283	0.347	0.169	0.381

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