Working in an Immaterial World: Intangible Assets and the Supply and Demand for Skilled Labour

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Abstract

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Abstract

This study explores the relationship between technology and the graduate wage premium in a world characterised by the increasing importance of intangible assets. Using the EUKLEMS-INTANProd database for the US, the UK and 6 European countries over the 1995-2019 period, we find that the graduate wage premium has declined in most countries and industries, a trend that precedes the 2007 financial crisis. This decline is mainly explained by the increasing supply of workers educated at the tertiary level. Technology is still skill biased but with heterogeneous effects across industries and different technology indicators. Using a dynamic model specification reveals that both ICT and intangible assets complement skilled labour. However, when differentiating between AI creating and AI using sectors, we find that the relationship between technology and the skill premium is stronger in AI creating industries, and it intensifies after 2005. This indicates that complementarities between the latest wave of technology and skills is particularly concentrated in the most innovative sectors within countries.

1. Introduction

The wage gap between the lowest and the highest paid workers increased during the 1980s and 1990s in several western countries (OECD, 2015), exacerbating trends in global inequality. At the root of this trend was the wave of information and communication technologies which raised the demand for highly educated labour faster than its supply, a phenomenon labelled skill biased technical change (Katz and Murphy 1992, Krueger 1993, Acemoglu 1998, 2002, Goldin and Katz 1998, O'Mahony et al. 2008, Violante 2018). In general, the extent to which the demand effect dominates the supply effect will determine whether the wage premium for the high skilled continues to grow. This underpins the *canonical model* capturing the race between education and technology presented by Acemoglu and Autor (2011) and Autor et al (2020), which builds on the seminal work of Tinbergen (1975) in modelling skill biased technological change.

However, since the global financial crisis in 2007, the trend in the skill wage premium has reversed, despite technological advancement continuing apace with a new wave of digital technologies. In the US, the flattening of the wage premium is discussed in Beaudry et al. (2016) and in Valletta (2018). In Europe there is evidence to suggest a decline in the wage premium, attributed to a more rapid increase in the supply of high skilled labour relative to its demand (Green and Henseke 2021). There are also indications that labour market institutions and globalisation matter (Crivellaro 2016, Gravina and McGregor 2024), but the evidence so far is scant. A greater understanding of the evolution of the skilled wage premium in Europe is therefore warranted, particularly in the face of modest European productivity growth.

In addition to the development of digital technologies, there has been increasing recognition of the importance of intangible assets in the production of goods and services (Corrado, Hulten and Sichel 2009, Haskel and Westlake 2018). While intangible assets are not new to industrial organisations (Veblen, 1908), they are now considered an integral part of knowledge capital, complementing investments in new technologies. Intangible assets may be defined as investments in knowledge creation, 'human capital in the form of education and training, public and private investment in research, and business expenditures for product research and development, market development and organizational and management efficiency' (Corrado et al, 2012, p2). Hence, intangibles include elements of innovative activities like R&D, which have been typically related to skill upgrading (Gera et al. 2001, Machin and Van Reenen 1998) and organizational changes. The latter can also affect skills demand and the skill premium as they complement new digital technologies (Bresnahan, Brynjolfsson and Hitt 2002, Piva et al. 2005); in addition, the move from a centralised Tayloristic organizational structure towards higher decentralization and more flexible work arrangements, have been found to favour high skilled labour in what has been defined as skill biased organizational change (Blundell et al. 2022). This highlights the importance of accounting for the role of both digital technologies next to other innovative activities and organizational changes in the study of the skill wage premium.

The measurement and importance of intangible capital services to the growth and performance of industries and countries has been the subject of discussions for the past decade (Corrado et al, 2021). While studies agree on the positive association between intangibles intensity and productivity, more nuanced findings highlight the increased dispersion of productivity across sectors. Thus, industrial structure matters, and it is becoming even more relevant with the rapid growth in Artificial Intelligence (AI), which combines tangible assets (hardware) with intangible assets (software and databases) (Corrado et al. 2021). While the use of AI has grown rapidly across many sectors in recent years, its innovation is concentrated in a handful of industries (Calvino et al. 2024) and therefore the demand for relevant skills may vary substantially across industrial sectors. Thus, accounting for industry heterogeneity is crucial to our understanding of the changes in the skill wage premium.

The aim of this study is to provide new evidence on the relationship between technology, skill supply and the skilled wage premium for the US, the UK and six EU countries (Germany, Spain, Finland, France, Italy, and the Netherlands), using the EUKLEMS-INTANProd industry database (Bontadini et al. 2023). Our main objective is to understand whether supply or demand factors are at the root of the decreasing wage inequality between highly skilled and low skilled workers. Following Bowlus et al. (2023) we model skill biased technical change (SBTC) as a function of direct measures of technology indicators. The main novelty of our work is to account for heterogenous technologies, focusing on digital technologies and intangible assets. Given the importance of accurately measuring the contribution of intangible capital to the knowledge economy, its relationship with labour is fundamental to the interplay with technology in the production function. We also extend our analysis to the incorporation of a recently developed AI-based industry taxonomy, based on the share of AI patents by industry (Calvino et al. 2024), to offer further insights into the relationship between technology, intangibles and skilled labour. Although our sample period (1995 – 2019) predates the advent of generative AI such as ChatGPT, our study period covers earlier AI innovations. In addition, important investments in research and development and in skills were taking place in the years leading up to the launch of ChatGPT in 2022. As discussed in Minniti et al. (2025) the number of AI patents per million workers increased steadily in Europe from 2000 to 2017 and this may have affected the skill premium.

The longitudinal structure of our dataset enables us to estimate a fully dynamic specification of the canonical model, while controlling for unobserved industry-level heterogeneity. This is a further innovative feature of our work as existing studies have mainly relied on a static model. This is particularly important in the analysis of the labour market implications of information and communication technologies that, like previous general-purpose technologies, are characterised by lagged effects as they require investments in complementary assets such as human capital and organizational changes (Bresnahan et al. 2002, Brynjolffson et al. 2021). Our approach also helps to mitigate issues related to non-stationarity in panel data and offers a potential means of mitigating endogeneity concerns. Furthermore, we include in our model controls for cross-sectional dependence, by incorporating cross-sectional averages of the dependent and independent variables (Pesaran 2006). As discussed in Eberhardt et al. (2013) and Eberhardt and Teal (2020) cross-sectional dependence may be caused by common shocks or spillover effects, whose omission can lead to biased coefficient estimates. Given the time period covered in our analysis, which includes a major financial crisis with worldwide consequences, controlling for cross-sectional dependence is particularly important. In addition, the inclusion of cross-sectional averages may also control for workers' decision to move across industries in response to wage differentials, another potential source of endogeneity.

Our findings reveal that the decline in the skill wage premium predates the financial crisis in all countries and in most industries in our sample. Our data shows that the decline begins in the early 2000s, with an acceleration after 2005. Both demand and supply factors are associated with this decline, although with differences over time and industrial sectors. On the supply side, we find that the increasing number of workers educated at the tertiary level is creating downward pressure on the wage of highly skilled workers, relative to the lower skilled, a result that is robust to different estimation methods, time periods, and industries. On the demand side, we find heterogeneous effects, depending on the technology indicator, industry type and time period. Digital technologies, proxied by ICT, are always characterised by a positive association with the skill premium, indicating skill complementarity, consistent with earlier findings (O'Mahony et al. 2008). For intangible capital, we can only identify a significant role when using the dynamic model, and our results suggest the presence of skill biased organizational change. However, when we distinguish between AI-creating and AI-using sectors, we find differences by type of intangibles. Innovative property intangibles (associated with R&D and design) have a positive and significant correlation with the skilled wage premium in the former, while economic competencies (associated with organisational capital) are relevant mainly among the AI-using sectors. This effect remains robust across different country compositions in our sample, suggesting no major differences between technology leader and follower countries. When focusing on the post 2005 period, we find evidence of stronger complementarities between digital technology and innovative properties in the AI-creating industries, which is partly offset by the negative impact of economic competencies. In the AI-using sectors complementarity exists between skills, digital technologies and organizational changes, with no role for innovative properties.

Our work contributes to four branches of the literature. First, we extend the analysis of skill biased technical change, particularly by contributing to recent studies that document a decline in the skill wage premium, as referenced above. Consistent with earlier research, our results largely support the presence of a complementary relationship between skills and technology (O'Mahony et al. 2008); however, this complementarity no longer offsets the negative impact of the increasing supply of skilled workers on their wages, leading to a decline in the wage premium for graduates. We build on the existing work by providing industry-level evidence for a group of European countries and the US, and by adopting a methodology that controls for country and industry heterogeneity, and for the dynamic impact of technology and skills' supply on the wage premium. This framework helps in identifying the role of different types of technologies, most notably, intangible assets.

Second, we contribute to the literature on the effect of intangible assets on the labour market, complementing recent work by O'Mahony et al. (2021). With the growing importance of intangibles in the economy, understanding whether these technologies complement or substitute different types of labour is relevant for policy development. The research of Gravina and Foster-McGregor (2025) is relevant to our analysis, particularly their inclusion of intangible assets in the estimation of the skill wage premium, although our work uses a different theoretical and analytical framework and extends the time frame of the analysis. In line with their findings, our results show that high-skilled workers typically benefit from technological progress. We also find that intangibles have heterogenous effects across different industries.

Third, our analysis includes different types of intangibles - innovative properties and economic competencies - which allows us to distinguish between skill biased and organizational-biased technical changes, complementing the work of Blundell et al. (2022). In contrast to their finding, we show that the role of organizational changes, as captured by economic competencies, on the skill premium is significant but not as relevant as the role of innovative properties and ICT. In addition, in more recent years, organizational changes are positively related to the skill premium only among AI-users.

Finally, our work contributes to the rapidly growing literature on the impact of AI on the labour market, particularly on the outcomes of high-skilled workers. Since AI can substitute for tasks that are associated with high-skilled occupations - such as entry level work performed by lawyers and doctors -it may contribute to the decline of the skill wage premium and reduce wage inequalities (Bloom et al. 2025). Consistent with this view, Webb's (2020) analysis shows that high-skill occupations are most exposed to AI. Our results do not support this negative prediction as they show that the impact of ICT and innovative properties is positive and significant in AI creating industries. Until 2019, the main factor driving the decline in the skill wage premium is the increasing relative supply of college educated workers.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on the interconnections between skills, technology, and intangible assets. Section 3 documents trends in the skill wage premium, the technological indicators employed in the empirical analysis and the supply of skills. Section 4 outlines the theoretical framework and sets out the hypotheses to be tested. Section 5 presents the empirical results and provides a detailed discussion. Section 6 concludes by drawing out policy implications and suggesting directions for future research.

2. Technology, skills and intangibles: existing evidence

The interaction between skills and technology as two key inputs into the production process has led to an abundance of empirical findings documenting an increasing wage gap between high skilled college educated workers and those without tertiary qualification. In the 1980s and 1990s this wage premium has been related to the emergence of digital technologies and their complementary organizational changes (Krueger 1993; Autor, Katz, and Krueger 1998; Goldin and Katz, 1998; Chun, 2003; Autor, Levy, and Murnane 2003; O'Mahony et al. 2008). In recent years, however, scholars have documented a decline in the skill wage premium, with a focus on the US economy, raising doubts about the inherently skill biased nature of technology.

Acemoglu and Autor (2011) provide an extensive historical description of the labour market outcomes of college graduates in the US, both in terms of employment numbers and wage growth. Their study shows a period of rapid growth in the skilled wage premium from the early 1980s to the early 2000s, a trend particularly driven by technology, supporting the skill-biased technical change (SBTC) hypothesis. However, the trend changes in the late 1990s. Beaudry et al. (2016) find that technological bias has fallen since 2000, and more sharply since 2008. In addition, since the 2000s, the highly educated have competed with the less educated for lower-level jobs. Their model assumes that SBTC can cause a boom and bust in the demand for cognitive skills that are highly correlated with workers educated at the tertiary level. Hence, both demand (technological) and supply factors have contributed to the decline of the college wage premium.

Valletta (2018) focuses on two related explanations for the observed decline of the skill wage premium in the US. First, the presence of labour market polarization, which emphasizes a shift away from medium-skilled occupations, where several tasks have been replaced by automation or outsourcing. As these occupations mainly provided graduate jobs, graduate employment has shifted towards lower pay, lower skilled jobs, contributing to the overall decline of the skill wage premium. The second explanation relates to skill downgrading, due to the weaker relationship between digital technologies and high-level skills and a slowdown in information technology (IT) investments. In fact, as technology reaches maturity, it becomes more accessible and codified and it relies less heavily on cognitive skills, an argument also discussed in Chun (2003) and O'Mahony et al. (2008). The weaker demand for advanced cognitive skills cascades down the skill distribution as highly skilled workers compete with and replace the lower skilled in less cognitively demanding occupations.

The effect of technology on the demand for skills also depends on investments in different types of capital assets that complement technological changes. The work on measuring intangibles, pioneered by Corrado at al. (2005), has led to the distinction of three main asset types: digitized information, innovative property and economic competences. These have been identified as playing a significant role in unlocking productivity gains and explaining trends in the labour share. O'Mahony et al. (2021) report a decline in the labour share of value added evident in the 1980s and 1990s, which was offset by investments in intangible assets, demonstrating their importance to the knowledge economy. Moreover, this highlights the role they play in the movement of the skill wage premium over time. Indeed, Beaudry et al. (2016) find that the decline in the skill wage premium is associated with the decreasing trend in investments in IT and software since 2000 and intensified after the financial crisis. As intangible assets (such as software, R&D and organizational changes), are complementary to high skills, their decline reduces the demand for skilled labour and the wage premium. This conclusion finds support in the analysis by Haskel and Westlake (2020), who also document the decline in investment in intangible assets in the UK as one of the causes of the productivity slowdown after the great recession, which may have played a role in the decline of the skill wage premium.

Rapid developments in AI, however, seem to contradict these arguments. Both AI innovations and use have spread at an increasing pace since 2013 (Wipo 2019, Baruffaldi et al. 2020). This suggests that both tangible (hardware) and intangible assets (software development, patenting activities and related organizational changes) are likely to have grown. These developments have led to a rise in optimism in relation to a positive impact on productivity, while at the same time creating concerns about the labour market consequences. The effects on the demand for different skills and hence the skill premium are still uncertain. The literature points to an industrial polarization, where AI innovations, measured by patenting activity, is concentrated in a handful of industries (Media, IT Services, Telecommunications, Computers and Electronics, Transportation and Storage, Legal and Accounting, Finance and Insurance, and Scientific R&D) (Calvino et al. 2024). These AI-creating sectors are likely to behave differently from the rest of the economy in terms of skill demand, hence accounting for industry heterogeneity is particularly important to understand the AI effects on the labour market.

From the supply side, most industrialized countries have experienced an increasing supply of workers educated at the tertiary level. This increasing number of graduates do not always find employment in graduate-level jobs, hence they have to accept positions that typically do not require a degree. This phenomenon of overqualification (or overeducation) leads to a wage penalty, which means that overqualified graduates earn significantly less than those who find a job match (Vecchi and Robinson 2024). These penalties range between 21% (Finland) and 43% (France) (Flisi et al. 2014). Hence, the phenomenon of overeducation is likely to have contributed to a decline in the average graduates' wage premium over time. Studies have discussed the possibility that the increase in university education has led to a higher heterogeneity in graduate skills, suggesting that a significant number of graduates do not develop the necessary skills to move into graduate jobs (Chevalier 2003, Chevalier and Lindley 2009, Corneiro and Lee 2011, Vecchi et al. 2021). The lower wage premium would then reflect the lower *quality* of graduates.

Studies that focus on Europe in the recent skill wage premium literature are scarcer. Crivellaro (2013) provides direct evidence of the negative relationship between the wage premium and the supply of graduates across 12 EU countries, between 1994 and 2009. While technological progress, captured through proxies such as time trends and R&D intensity, continues to complement skilled labour and is positively associated with the wage premium, its effect is outweighed by the growing pool of graduates entering the labour market. Institutional factors such as minimum wage regulations and union membership further compress wage differentials, although their effect is minor. Together, these dynamics contribute to a narrowing of the wage gap between skilled and unskilled labour Europe. In a similar vein, Gravina and McGregor (2024) find that EU Employment Protection Legislation (EPL) reduce wage inequalities, while openness to trade, investments in robotics and R&D contribute to increase the premium for highly skilled workers.

Blundell et al. (2022) argue that the way technology interacts with factors supply can lead to different wage outcomes in different countries, depending on whether they are leaders or followers in the development and adoption of new technologies. They estimate the canonical model for the UK, over the 1993-2016 period, including controls for age and regions. Their results appear different to expectations as they reveal a positive relation between the relative supply of skilled labour and the wage premium, and a mostly negative technology impact. In most cases, these coefficient estimates are not statistically significant (see Table 1, page 158). This is consistent with the rather flat college wage premium observed in the UK, despite the increase in the supply of graduates. Their conclusion is that a model of endogenous technological choice, whereby firms choose among different technology depending on their leader/follower status, fits the UK economy better than the canonical model. In this country, the increasing proportion of educated labour has promoted the adoption of decentralised and more flexible organizational structure, i.e. skill biased organizational change rather than skill biased technical change is behind the observed movement in the wage premium.

Labour supply decisions are also influenced by the economic cycle. The work of Oreopoulos et al. (2012) for Canada and Schwandt and von Wachter (2019) for the US, show that graduating during times of recession leads to negative labour market outcomes and a long-term decline in earnings, particularly among disadvantaged graduates (for example graduates from less prestigious universities). Part of the wage losses associated with graduating during a recession can be explained by poorer matching between graduates' skills and the skill required in the industries of their main employment (Liu et al. 2016). Thus, the 2008 financial crisis could have contributed to the observed decline in the skill wage premium. In contrast, evidence for the UK shows that graduating during a recession can improve labour market outcomes because of increased effort (Bičáková et al. 2021). Hence, the labour market effects of major shocks are uncertain.

Overall, we find contrasting views of the relationship between technology and the supply of skills and how this affects the wage premium in different countries. The evidence so far has mainly focused on the US, where the canonical model appears to have lost predictive power in recent years, suggesting a changing relation between technology and the demand for skills, which intensified after the financial crisis. In Europe, the increase in the supply of graduates seems to be the main driver of the decline in the college premium. Despite the increasing importance of intangible assets, there has been no attempt so far in expanding the definition of technology to include their role, nor have we found analyses of how AI may be contributing to the declining wage premium. We explore these issues in the remainder of the paper.

3. Skill premium, technology and skill supply: evidence from the EUKLEMS & INTANProd database, 1995-2019

3.1 Declining skill wage premium in Europe and in the US

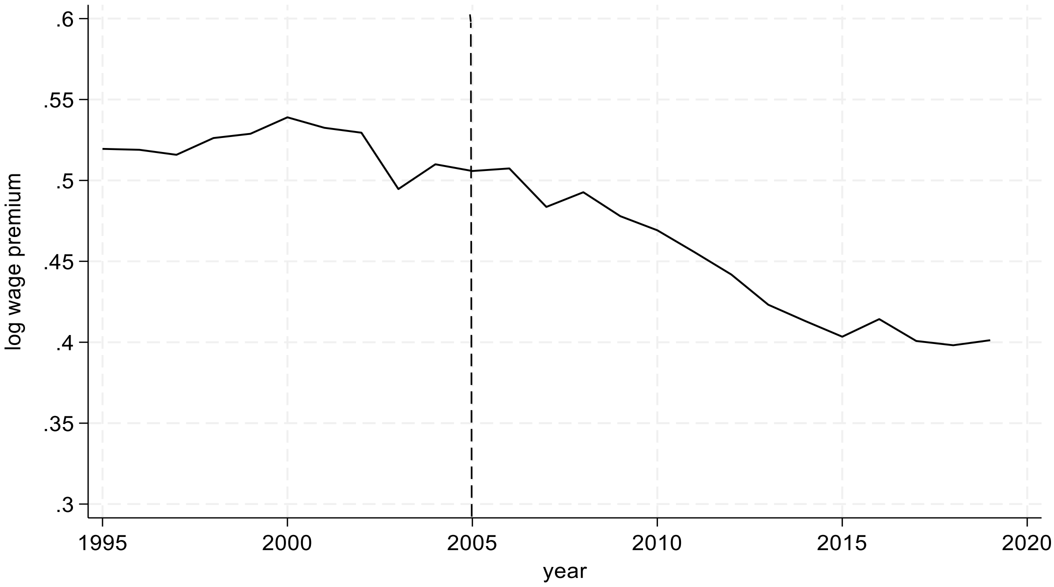
The analysis in this study makes use of the EUKLEMS data set. This is a harmonised set of country and industry national accounts developed initially by a number of European Institutes led by the Groningen Growth and Development Centre (GGDC) and the National Institute of Economic and Social Research (NIESR). The database has subsequently been extended and developed (see O'Mahony and Timmer 2009). The latest vintage has been produced by a consortium of research institutes led by LUISS (Bontadini et al. 2003) who have updated the database as well as incorporating intangible capital, following the methodology established in the EU-funded INTAN project. The methodology for the data construction is available from the EUKLEMS & INTANProd website[1]. Currently, this database covers the period 1995 to 2019.

Our analysis focusses on six EU countries for which full data are available (Germany, Finland, France, Italy, Spain, the Netherlands), plus the UK, and the US. For these countries, EUKLEMS & INTANProd contains complete data on intangible assets, capitalised at the sectoral level (17 sectors) for the period 1995 to 2019. In addition, data on labour markets is provided by a skills breakdown of high, intermediate and low skilled workers employment and wage shares, enabling the calculation of wage premia. Note that these data only include divisions of labour input by type from 2008 so earlier releases of EUKLEMS were used to backdate to 1995.

Figure 1 presents the log of graduates/non graduates annual wage premium from 1995-2019, constructed as an average of the wage premium for our sample.

[1] https://euklems-intanprod-llee.luiss.it/

Figure 1: Mean wage premium of high skilled workers, 1995-2019



Source: EUKLEMS & INTANProd and authors' calculations.

As expected, the wage premium overall has declined over the period of analysis, starting from 2000, with the negative trend becoming more prominent after 2005/2006. Hence, and consistent with Beaudry et al. (2016), the change in trend predates the financial crisis. While in the year 2000 graduates were enjoying a premium of 54 log points, this falls to 40 log points by 2019, indicating that at the peak of the cycle, a graduate worker was earning 72% (=exp(0.54) -1) more than a non-graduates and this differential declines to 50% by 2019. Naturally these aggregate trends mask differences across countries and industries. Table 1 reports country averages for the pooled sample and for two subperiods, 1995-2005 and 2006-2019. This clearly shows that, when we focus on individual countries, we find a similar pattern: except for the US, the average skill wage premium is lower after 2005.

Table 1: Average wage premium for high skills in each country– country average

	1995 -2019	1995-2005	2006-2019
Germany	0.560	0.559	0.560
Spain	0.402	0.419	0.389
Finland	0.352	0.358	0.347
France	0.405	0.450	0.370
Italy	0.479	0.604	0.381
The Netherlands	0.563	0.700	0.456
UK	0.505	0.530	0.486
US	0.551	0.544	0.556

Source: EU KLEMS &INTANProd and authors' calculations. Observations: 425 per country.

Figure 2 compares trends in the wage premium in the US and in Europe. Country by country figures for all European countries can be found in appendix Figure A.1. Both the United States and Europe have experienced a decline in the wage differential between skilled and unskilled workers; however, the trend appears less pronounced in the U.S. Given the relatively less stringent labour market regulations in the U.S., adjustments may occur more through changes in employment levels rather than through wages.

Figure 2: Mean wage premium of high skilled workers, US and Europe, 1995-2019

Source: EU KLEMS &INTANProd and authors' calculations.

Changes in the wage premium may be driven by industry trends. Beaudry et al. (2016), for example, claim that in the US the 2007-2009 financial crisis destroyed many jobs, which were typically highly paid graduate jobs. This may have contributed to the decline of the wage premium. To understand the relevance of industry variations, Table 2 reports the wage premium across all industries included in our study, presenting the average over the 1995-2019 period and for the two subperiods pre and post 2006.

Table 2: Average wage premium for high skilled workers – industry average

	1995-2019	1995-2005	2006-2019
Mining	0.526	0.571	0.498
Manufacturing	0.590	0.649	0.544
Electricity, gas, steam	0.404	0.446	0.371
Water, sewage	0.411	0.438	0.389
Construction	0.532	0.594	0.482
Wholesale and retail	0.568	0.605	0.589
Transport and storage	0.447	0.519	0.390
Accommodation and food	0.414	0.460	0.377
Information and communication	0.325	0.332	0.320
Finance and insurance	0.415	0.456	0.383
Professional and scientific activity	0.535	0.586	0.495
Administrative and support activities	0.495	0.523	0.474
Public admin and defence	0.376	0.441	0.325
Education	0.471	0.463	0.477
Human health and social work	0.610	0.661	0.570
Arts, entertainment and recreation	0.415	0.492	0.354
Other service activities	0.543	0.583	0.512

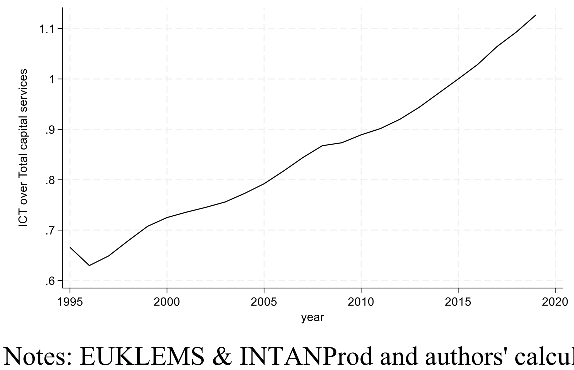
Source: EUKLEMS & INTANProd and authors' calculations. Figures represent unweighted averages across all countries. Observations: 112 per industry.

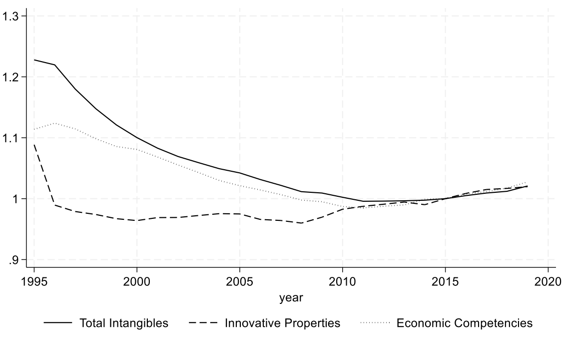
In the period 1995-2005, the wage premium for skilled workers ranged between 40% in the Information and Communication industry and 94% in Human health and social work, with Manufacturing also characterised by a 91% difference in wages between high and lower skilled workers. After 2005, the wage premium for skilled workers declines substantially in all industries. The premium also declines in the Financial and Insurance sector from 58% to 45%. Although substantial, this decrease does not suggest that this industry is a driver of the lower wage premium in the later period, as suggested by Beaudry et al. (2016).

3.2 The demand side:examining changes in the technology indicators.

Our analysis relies on three main indicators of technological changes: digital technologies, as represented by Information and Communication Technologies (ICT) which also includes software, and the two components of intangible assets, innovative properties and economic competencies. Innovative properties constitute a key component of intangible capital, encompassing assets derived from research and development (R&D), technological innovation, and creative activities such as patents, copyrights, trademarks, designs, and proprietary software. To avoid double counting, in our analysis innovative properties are net of computer software. Economic competencies refer to assets that capture the value of firm-specific human and organizational capital, such as employee training, spending on strategic planning, and investment in brand names (Corrado et al. 2009). In our analysis, capital assets are expressed as a proportion of total capital services, averaged across countries and industries. Aggregate trends in digital technologies and intangibles are presented in Figure 3.

Figure 3: Trends in the technology indicators expressed as a ratio of total capital services





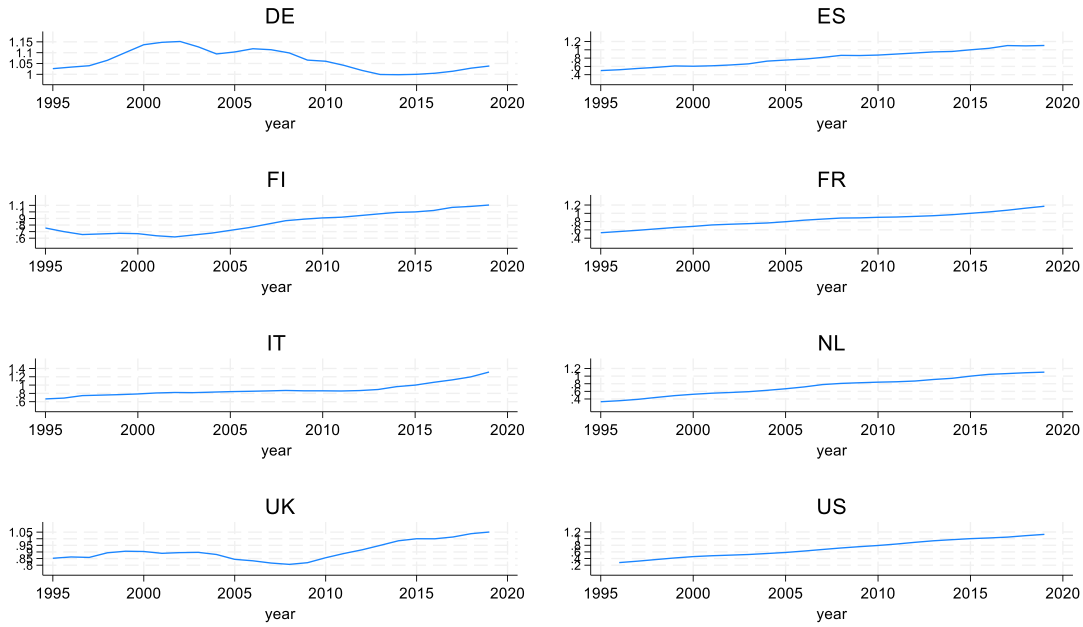
Notes: EUKLEMS & INTANProd and authors' calculations.

ICT displays a consistent upward trend across the entire period, indicating its growing importance over time. A comparable pattern characterises innovative properties, which also show sustained growth, suggesting a broader trend of increasing innovation-related assets. In contrast, economic competencies exhibit a more nuanced evolution: they initially decline but begin to recover and show positive growth starting around 2010. Taken together, these trends suggest that both ICT and other intangible assets have become increasingly prominent in recent years. This seems to contrast with the work by Beaudry et al. (2016) and Haskel and Westlake (2021), who discuss a potential decline in intangible investment.

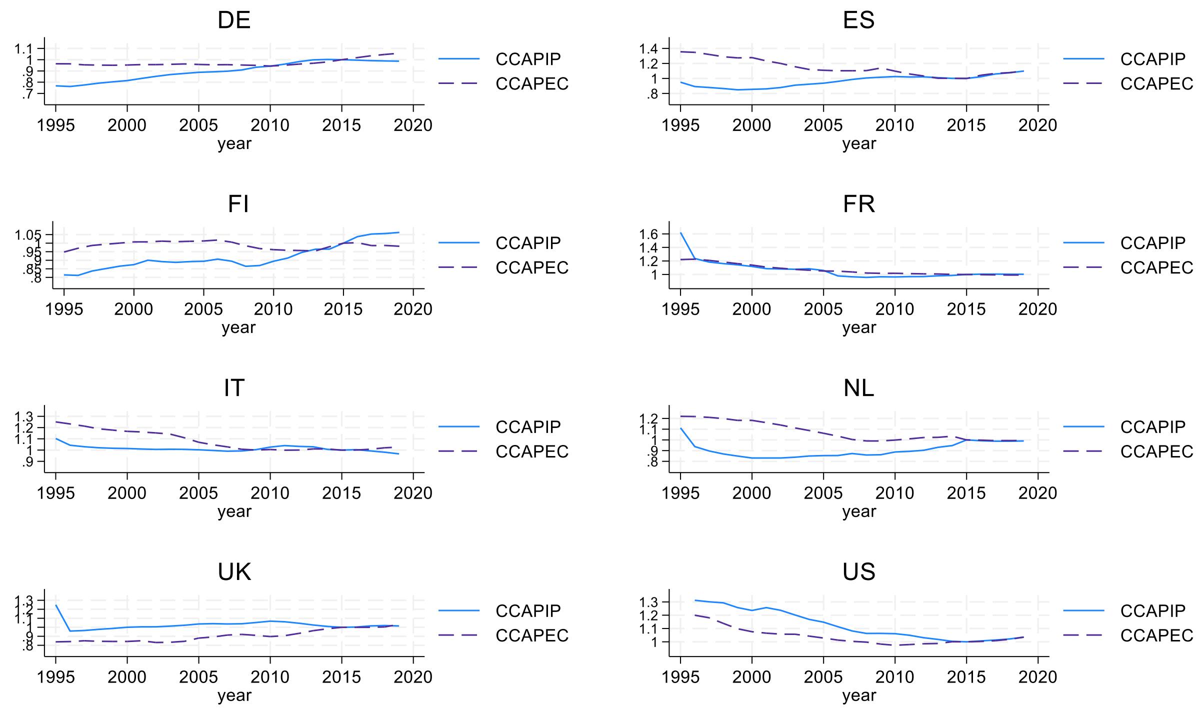
However, if we consider individual countries, we get a different picture. Figure 5 panel A shows trends in the ratio of ICT over total capital services for each country, averaged across all industries. Consistent with the aggregate trend, most countries exhibit a steady increase in ICT intensity, highlighting the widespread diffusion of digital technologies. However, Germany stands out as an exception, displaying a relatively flat trend over the period. Panel B shifts the focus to the two components of intangible capital, namely, innovative properties and economic competencies. Here, cross-country heterogeneity becomes more pronounced. Investment in innovative properties shows a clear upward trend in Germany, Spain, and Finland, suggesting a strong commitment to R&D and technological development. In contrast, France and, perhaps more unexpectedly, the United States exhibit a declining trend. Italy and the United Kingdom show relatively stable levels over time, indicating limited change in this asset category. Economic competencies display a declining trend in most countries. The United Kingdom is the notable exception, where this intangible asset type has increased, potentially reflecting investments in workforce development, managerial practices and organizational capital (Blundell et al. 2022). These divergent patterns suggest that while ICT investment has become a common feature across advanced economies, the accumulation of other intangible assets remains uneven.

Figure 4. Trends in the technology indicators across countries

4.A. Digital technologies, ICT over total capital services



4.B. Intangible assets: innovative properties (CCAPIP) and economic competencies (CCAPEC) over total capital services



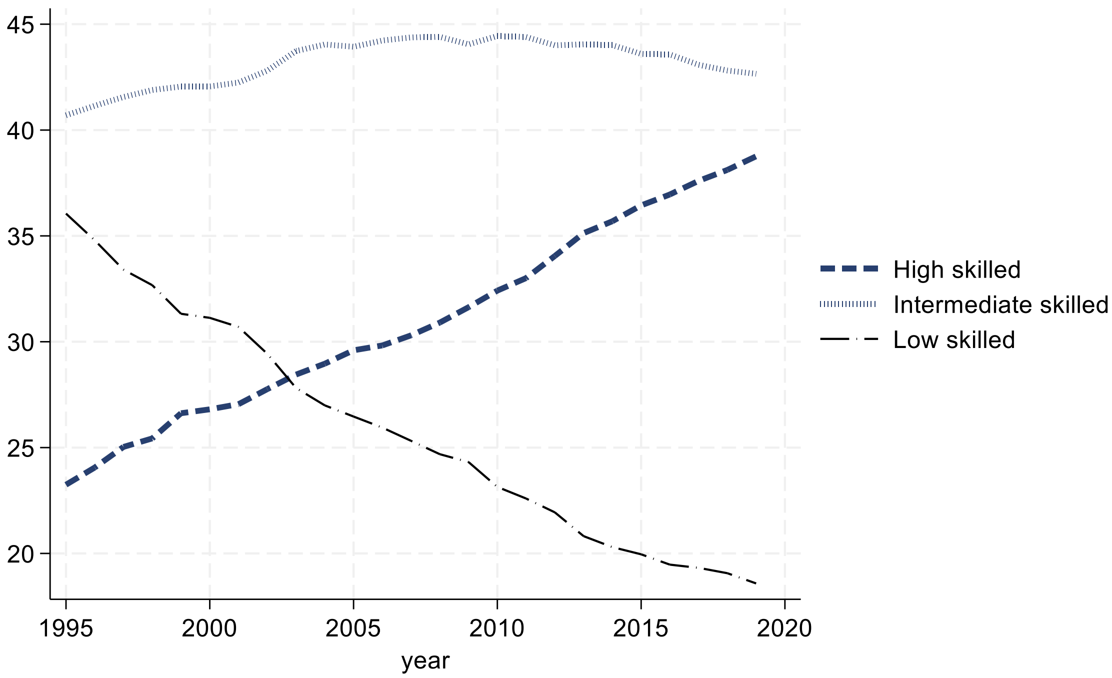
Notes: EUKLEMS & INTANProd and authors' calculations.

3.2 The supply side: the increase in the number of graduates

As discussed above, the supply of workers educated at the tertiary (degree) level has increased substantially over the past 20 years. Figure 5, reports the share of different types of workers over time, averaged over countries and industries. This shows that there has been a steady rise in the shares of workers with a university degree, from just below 25% in 1995 to nearly 40% in 2019. This increase has largely been at the expense of the low skilled worker share, which has fallen from approximately 36% to 18%. In contrast, the intermediate skill share has seen more muted changes over time.

Figure 5: Average employment shares for different types of workers (%)

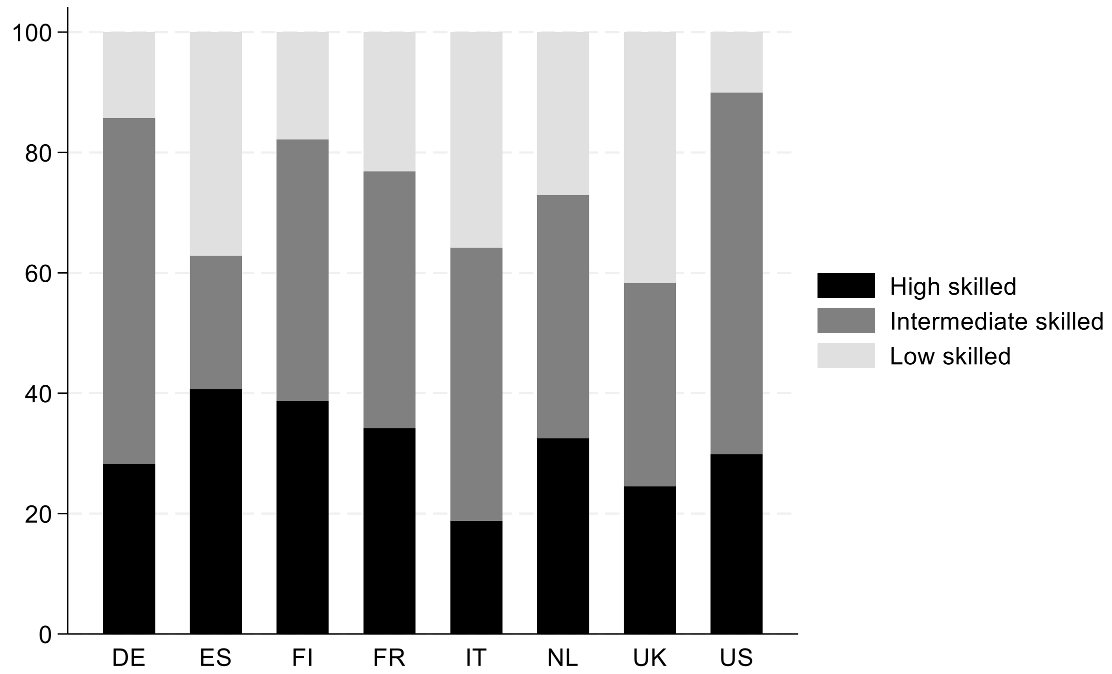
(Total sample)



Source: EUKLEMS & INTANProd and authors' calculations

To gain an insight into country differences, Figure 6 shows the proportion of high, intermediate and low skilled workers in each country and reveals the heterogeneity in our sample. For example, we find a high proportion of intermediate skilled workers in Austria and Germany where the provision of education at the intermediate level has a large uptake. On the other hand, the share of intermediate skilled workers is particularly low in Spain, while it is comparable in the remaining countries. Italy is characterised by the lowest share of high skilled workers. Although Italy, like most Western countries, has experienced an increase in the average level of education, the number of graduates remains below the OECD average. In 2020, 20% of the 25-64-year-olds had tertiary education compared to the EU average of 32.8% (OECD 2021).

Figure 6: Average employment shares by skill type



Source: EUKLEMS & INTANProd and authors' calculations

While data exist in EUKLEMS & INTANProd to consider 3 skill groups, there is some uncertainty about whether the distinction between low and intermediate skills is consistent across all countries. We therefore focus our empirical analysis on the differences between high skilled (graduates) and all other (lower) skilled workers.

4. Theoretical framework

We analyse the relationship between the wage premium and technology, following the setup which has been typically referred to as the canonical model (Carneiro and Lee, 2009, Acemoglu and Autor, 2011, Bowlus et al., 2023 among others). We begin by specifying the following CES production function with two types of labour input, skilled (H) and low-skilled (L), and two terms representing factor augmenting technologies, A_l and A_H:

(1) $$Y = \left[\beta (A_l L)^{\frac{\sigma-1}{\sigma}} + (1-\beta)(A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The coefficient β is a distribution parameter, while σ represents the elasticity of substitution between skilled and low-skilled workers. Values of $\sigma > 1$ indicates that there is substitution between the two types of labour, while $\sigma < 1$ indicates the presence of a complementary relationship. In what follows, to simplify the notation we omit the distribution parameter, β.

Assuming perfectly competitive labour markets, we differentiate equation (1) to obtain the marginal product (wage) of low-skilled labour, corresponding to the low skill wage:

$$(2) \qquad w_L = \frac{\Delta Y}{\Delta L} = A_L^{\frac{\sigma-1}{\sigma}} \left[A_L^{\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}}$$

In the same manner, we obtain the wage rate for the high skilled:

$$(3) \qquad w_H = \frac{\Delta Y}{\Delta H} = A_H^{\frac{\sigma-1}{\sigma}} \left[A_H^{\frac{\sigma-1}{\sigma}} \left(\frac{H}{L}\right)^{-\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}}$$

Dividing (3) by (2) we derive the skill premium – the high skilled wage divided by the low-skilled wage:

$$(4) \qquad \omega = \frac{w_H}{w_L} = \left(\frac{A_H}{A_L}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{H}{L}\right)^{-\frac{1}{\rho}}$$

Taking the logarithmic transformation, equation (4) can be rewritten as follows:

$$(5) \qquad ln\omega = \frac{\sigma-1}{\sigma} ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma} ln\left(\frac{H}{L}\right)$$

The first term in equation (5), the (log) ratio $\frac{A_H}{A_L}$, captures the technical change effect on the skilled wage premium. This effect will be positive in the presence of skill biased technical change, a phenomenon that has been widely documented in earlier work as discussed above. The second term in equation (5), $\frac{H}{L}$, captures the labour supply effect on the skill premium. Holding technology constant, an increase in the supply of skilled labour relative to the low-skilled will decrease the skill wage premium.

The estimation of equation (5) requires a measure of technology, often proxied by a time trend (Katz and Murphy, 1992, Acemoglu and Autor, 2011):

$$(6) \quad ln\left(\frac{A_{H,t}}{A_{L,t}}\right) = \gamma_0 + \gamma_1 Trend$$

However, a time trend is a crude measure of technology. We refine the specification of the technology term adding two additional technology indictors, the ratio of ICT capital/intangible capital services to total capital services. We also consider the effect of the two components of intangibles, economic competencies and innovative properties. Hence, we can rewrite equation (6) as follows:

$$(7) \qquad ln\left(\frac{A_{H,t}}{A_{L,t}}\right) = \gamma_0 + \gamma_1 Trend + \sum \gamma_j tech_{it} \quad \text{j=2,…3}$$

Where $tech_j$ represents all technology indicators. Combining equation (7) with equation (5) we obtain the final specification for our empirical analysis:

$$(8) \qquad ln(\omega_{it}) = \theta_0 + \theta_1 Trend + \theta_{2j} \sum tech_{it} - \theta_3 ln\left(\frac{H_{it}}{L_{it}}\right) + \varepsilon_{it}$$

Where $\theta_0 = \frac{\sigma-1}{\sigma}\gamma_0$, $\theta_1 = \frac{\sigma-1}{\sigma}\gamma_1$, $\theta_{2i} = \frac{\sigma-1}{\sigma}\gamma_i$, and $\theta_3 = \frac{1}{\sigma}$. The subscript '$i$' indicates the industry dimension of our analysis. Equation (8) includes an error term, ε_{it}, capturing other factors or shocks, that can drive the wage premium of skilled workers, not included in the model. Following related contributions, in the benchmark model we assume that these factors are exogenous.

This model distinguishes between demand and supply forces driving the wage premium and allows us to derive testable hypotheses. Under the assumption of complementarity between skills and technology, the coefficients of the technology terms are expected to be positive, hence our first hyothesis can be formulated as:

H1: $\theta_{2i} > 0$ (indicating evidence of skill biased technical change – the demand side effect)

By accounting for different indicators, we can evaluate which technology is more strongly associated with changes in the wage premium. Overall, the wage premium will increase when technological developments lead to an increase in the demand for skills which is larger than the increase in the ratio of high skilled worker over those who are lower skilled. The sign of $\frac{H_{it}}{L_{it}}$ is expected to be negative as an increase in the supply of high skilled labour relative to the lower skilled will put a downard pressure on the skill premium. Hence our second hypothesis is formulated as follows:

H2: $\theta_3 < 0$ (the supply side effect)

The coefficient θ_3 is generally interpreted as the inverse of the elasticity of substitution hence estimates of the elasticity can be derived from the regression coefficient. The larger the elasticity – which indicates an easier substitution between high and low skilled labour - the lower the response of relative wages to changes in the supply of skills. From equation (5) it is also evident that the greater the elasticity of substitution, the larger the impact of technology on the skill premium.

5. Empirical analysis

5.1 The Race between technology and skills: benchmark model

We begin our empirical analysis with the estimation of Equation (8) using a Fixed Effect (FE) estimator to account for unobserved heterogeneity. Residuals are clustered by industry and country. Results are reported in Table 3. The first column uses only a linear trend to capture technology, while in column (2) we add ICT and in column (3) we include total other intangibles. In the last column we disaggregate total other intangibles into the two components, innovative properties and economic competencies (column 4).

As expected, the coefficient associated with the ratio of high to low skilled workers is negative and statistically significant, capturing the supply side effect. That is, an increasing supply of workers educated at the tertiary level is negatively correlated with the skill wage premium. Our estimates suggest that a 1% increase in the relative supply of high-skilled workers decreases the graduate wage premium by approximately 0.21%, an effect that is consistent across all models. This coefficient is lower compared to the estimates for the US reported in Acemoglu and Autor (2011), which range between -0.5 and -0.6, over the 1963-2008 period. [2] The different group of countries and time period considered are likely to be the reason for this divergence. Consequently, our estimated σ, the elasticity of substitution between high-skilled and low-skilled labour, is higher than the most commonly estimated value of approx. 1.6 (Katz and Murphy 1992, Autor et al. 2008, Acemoglu and Autor 2011). However, recent work by Havranek et al. (2024) shows that correcting for publication and attenuation bias, the implied value of the elasticity of substitution is around 4, ranging between 2 in developing countries and 6 in the US. Our estimated σ of approximately 4.8 is consistent with this evidence and suggests that "..skilled and unskilled labour is substantially more substitutable than commonly thought" (Havranek et al. 2024). Our results are also consistent with the analysis in Bowlus et al. (2023) and Card and Lemieux (2001).

As for the technology indicators, a first thing to notice is that a simple linear trend might not fully capture the relationship between technology and the wage premium. In column (1) the linear trend coefficient is statistically significant, but it loses significance when we include the other technology indicators. Digital technologies, captured by the ratio of ICT over total capital assets are always positive and significant, revealing complementarity between this technological asset and high skilled labour. Our estimates consistently show that a 1% increase in ICT is associated with an increase of the skill premium by about 0.05%. The role of intangible assets, on the other hand, is not clearly identified—whether considered as a single aggregate (column 3) or when distinguishing between its two components: innovative properties and economic competencies (column 4). Hence, the benchmark model does not reveal a significant relationship between intangibles and the skill premium.

[2] Crivellaro (2013) study a similar relationship using individual level data for a group of EU countries. Estimates of the coefficients for the supply effect are substantially lower than those reported here, ranging between -0.01 and -0.02, over the 1994-2005 period. Their model is extended using labour demand factors and indicators of institutional framework, and thus not directly comparable to our findings.

Table 3: The race between technology and the demand and supply of skills: ICT and Total Intangible assets. Fixed Effect estimates, 1995-2019

	(1)	(2)	(3)	(4)
VARIABLES	1995-2019	1995-2019	1995-2019	1995-2019
ln(High/Low skilled)	-0.213***	-0.209***	-0.211***	-0.207***
	(0.042)	(0.041)	(0.040)	(0.041)
Trend	0.005***	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
ln(ICT/Tot K)		0.052***	0.047***	0.056***
		(0.017)	(0.018)	(0.018)
ln(Intang/Tot K)			-0.021	
			(0.018)	
ln(Innov. Properties/Tot K)				0.003
				(0.031)
ln(Econ.Comp/Tot K)				0.022
				(0.041)
Constant	0.254***	0.308***	0.304***	0.313***
	(0.060)	(0.066)	(0.064)	(0.067)
Implied σ	4.69	4.78	4.74	4.83
Observations	3,350	3,335	3,287	3,335
R^2	0.2041	0.2218	0.2245	0.2225
Number of id	134	134	134	134
FE	YES	YES	YES	YES
Time dummies	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets are clustered at the industry and country level. Data weighted using each industry total value added share in 2005.

5.2 A dynamic specification of technology, labour supply and skilled wage premium

There are several shortcomings with the analysis discussed in the previous section: first, the simple static model, although a useful benchmark to compare our results to the existing literature, may not be the correct representation of how technological changes affect the labour market. In fact, the static nature of the model is at odds with the inherently dynamic process which characterizes the effect of technological shocks on the labour market (Liu et al. 2007, Beaudry et al. 2016) and in particular the delayed impact of new technologies, requiring investments in complementary assets such as human capital and organizational changes (Basu et al. 2004, Basu and Fernald 2007, Brynjolfsson and Hitt 2003). Second, if the data is non-stationary, the static model can produce spurious results (O'Mahony and Vecchi 2009). Third, as discussed in Blundell et al. (2022), the relationship between technical change and the skill premium is not *one size fits all* and there are likely to be differences across countries, industries and technologies. However, the static model, by imposing common coefficients across all units, cannot account for such differences.

In addition, the error term in equation (8) is generally considered to be exogenous, based on the reasonable argument that, at the country level, the ratio of high-skilled to low-skilled labour is predetermined, as educational choices are made prior to market entry. However, when using industry level data, high skilled workers could switch endogenously from one sector to the other in response to changes in sectoral wage differentials. This will generate cross industry correlations that might bias our results. Endogeneity can also arise if our technology indicators do not fully capture technology shocks, in which case their correlation with the error term cannot be ruled out.

To address these issues, we re-fourmulate equation (8) an Autoregressive Distributed Lag model (ARDL) to capture dynamic effects. For simplicity, we assume a maximum lag order of 1 (ARDL 1,1,1) as follows:

$$(9) \qquad ln(\omega_{it}) = \rho_0 + \rho_{it} \ln(\omega_{t-1}) + \varphi_{01ji} \sum tech_{it} + \varphi_{11ji} \sum tech_{jit-1} - \sigma_{01i} ln\left(\frac{H_{it}}{L_{it}}\right) - \sigma_{11i} ln\left(\frac{H_{it-1}}{L_{it-1}}\right) + \varepsilon_{it}$$

In equation (9) we explain movements in the wage premium as a function of contemporaneous and lagged values of the supply and demand factors, and lagged values of the dependent variable. Rewriting equation (9) as an Error Correction Model (ECM) provides a clear separation between the short and long run relationships between technology, labour supply and the wage premium:

$$(10) \quad \Delta ln(\omega_{it}) = \vartheta[\ln(\omega_{it-1}) - \alpha_{0i} - \alpha_{1ij} \sum tech_{jit} - \alpha_{10i} ln\left(\frac{H_{it}}{L_{it}}\right)] + \delta_{01i} \Delta \ln(\omega_{it-1}) + \delta_{11ij} \sum \Delta tech_{jit} + \delta_{21i} \Delta\left(\frac{H_{it}}{L_{it}}\right) + \mu_{it}$$

The coefficient ϑ represents the speed of adjustment to the long-run equilibrium. This coefficient is expected to be significant and negative, when such a long-run equilibrium exists. Assuming that the ARDL(1,1,1) is the correct lag specification for our dynamic process, the estimation of equation (10) will produce consistent estimates in the presence of endogeneity (Pesaran 2007).

To address issues related to workers' mobility across industries in response to wage differentials, we include corrections for cross-sectional dependence, using the cross-sectional averages of all variables in the model. This will also account for other types of cross-sectional links arising from knowledge spillovers and common shocks (Chudik et al. 2011, Eberhardt and Teal 2020).

5.3 Results for the dynamic specification

Results from a set of panel unit root tests, presented in Appendix Table A.1 cannot reject the null hypothesis of a unit root, revealing the non-stationarity of our data (Im, Pesaran and Shin 2003, Pesaran 2007). The presence of cross-sectional dependence is tested using a battery of tests, reported in

Appendix Table A.2. Most tests reject the null hypothesis of weak cross-sectional dependence, against the alternative of strong cross-sectional dependence.

Table 4 presents results from two dynamic specifications, expressed as an Error Correction Model (ECM): the Pooled Mean Group estimator (PMG) (Pesaran et al. 1999) and an augmented version that accounts for cross-sectional dependence, (PMG+CSD) (Pesaran 2006). Both estimators impose homogeneity restrictions on the long-run parameters, while deriving the error correction coefficient and the other short-run parameters of the model by averaging across groups. [3] Estimates account for the role of total intangible assets and the two separate components. As the time trend was not found to be statistically significant in Table 3, we have dropped it from the estimation of the dynamic specification. In all models, the Error Correction term (ECM) is negative and statistically significant as expected when a valid long run relationship exists.

Our results confirm the negative relationship of the relative supply of high skilled workers on the skill premium, and they are mostly consistent with the size of the coefficients reported in Table 3, except for column (3). Also, the impact of ICT does not differ significantly from our previous results, confirming the positive technology effect on the skill premium. The main difference observed when using a dynamic model lies in the improved identification of the role of intangible assets. Both estimators predict a positive effect of total intangibles on the skill premium (columns 1 and 3), an effect that appears to be driven by economic competencies (columns 2 and 4). As economic competencies capture organizational changes typically associated with new digital technologies, this finding is consistent with the discussion in Blundell et al. (2022), which suggests that IT induces a shift in organizational structure toward more decentralised decision-making—favouring highly skilled workers, as they are better equipped to navigate flexible work environments.

More surprising is the negative—albeit statistically insignificant—coefficient on innovative properties, especially given that a large portion of these intangible assets consists of investments in R&D, which typically require highly skilled labour. However, this result is not unique in the intangibles literature. O'Mahony et al. (2021, Table 4), using an earlier release of the EU KLEMS data show that innovative properties are responsible for the decline in the labour share of the highly skilled. This negative effect may be explained by the fact that these investments lead to the introduction of new technologies that are substituting for 'abstract' skills, as documented in vom Lehn (2018). The diffusion of AI, which is replacing not only routine repetitive tasks, but also cognitive tasks typically associated with tertiary education, could strengthen this effect over time (Susskind 2020). Contemporary large language models (LLMs) and other generative AI systems are increasingly functioning as general-purpose technologies,

[3] An alternative technique, the mean group (MG) estimator, also discussed in Pesaran et al. (1999), involves the estimation of separate equations for each industry and the computation of the mean of the estimates, without imposing any constraint on the parameters. However, if some parameters are the same across groups, efficiency gains are made by imposing homogeneity.

capable of executing a broad spectrum of cognitive tasks, ranging from creative production to various forms of reasoning (Korinek 2024).

Table 4: The race between technology and the demand and supply of skills: dynamic model, 1995-2019

	(1)	(2)	(3)	(4)
	PMG	PMG	PMG+CSD	PMG+CSD
ln(High /low skilled)	-0.202***	-0.210***	-0.144***	-0.202***
	(0.008)	(0.008)	(0.010)	(0.009)
ln(ICT/Tot K)	0.073***	0.064***	0.029***	0.061***
	(0.009)	(0.008)	(0.009)	(0.008)
ln(Intangibles/Tot K)	0.021**		0.012	
	(0.009)		(0.009)	
ln((Innovative properties/Tot K)		-0.004		-0.005
		(0.010)		(0.011)
ln(Economic competencies/Tot K)		0.037**		0.057***
		(0.015)		(0.014)
ECM	-0.360***	-0.386***	-0.455***	-0.492***
	(0.025)	(0.026)	(0.026)	(0.027)
Constant	0.106***	0.116***	0.154***	0.149***
	(0.012)	(0.014)	(0.014)	(0.017)
Implied σ	4.95	4.76	6.94	4.95
Observations	3,153	3,201	3,153	3,201
Number of id	134	134	134	134

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.3 AI-creating vs AI-using industries.

Although our estimator controls for cross sectional heterogeneity, common long-run effects in very diverse industries might hide the differential impact of technology on the demand for skills. In recent years, the acceleration of AI developments has spurred increasing interest in their possible labour market consequences (Autor et al. 2024). AI has widely expanded computers' ability to perform tasks generally associated with (highly skilled) humans, such as learning, reasoning and problem solving, hence the implications for future skills demand and for the skill wage premium are likely to be very important. In our data, AI assets-types are already included in ICT and intangible assets. In fact, as discussed in Corrado et al. (2021), AI has hardware and software components, which are included in ICT, as well as developments of new algorithms, which falls within R&D and innovative properties, and market research and IT consulting services, which are part of organizational capital. There is also increasing awareness of the different ways AI operates across industries, something that is particularly relevant in our study.

A particularly important distinction is between AI users and AI creative or innovative sectors. While the use of AI spreads across a wide range of industries, the creation of new AI applications is concentrated in only a few sectors. These have been identified in Calvino et al. (2024) using the share of AI patents by industry, following the approach described in Baruffaldi et al. (2020). The Calvino et al. (2024) newly developed taxonomy of AI intensity identifies two sectors with the highest share of AI innovation (IT Services and Media Services) each with 14% of AI patent application filed between 2017 and 2021. These are followed by five additional sectors, identified as having filed between 3% and 5% patent applications in the same period (Manufacturing of Computers and Electronics, Transport and Storage, Telecommunications, Finance and Insurance Services, Legal, Accounting and Scientific services).

Except for the manufacturing of computers and electronics, our data allows the identification of the following AI-creating sectors, as those that most closely align with the Calvino et al. (2024) taxonomy: Information and Communications, Transport and storage, Finance and Insurance and Professional and Scientific Activities. We classify all remaining industries as AI users. Although the acceleration of AI developments begins approximately in 2015, hence most of our data predates the most recent AI booms, changes in skills demand are likely to have taken place over a longer time period.

Focusing on our preferred model (PMG+CSD), we re-run our regression for two groups of industries: intensive AI-creating sectors and AI using sectors. Results in Table 5 reveal substantial differences across these two broad sectors. First, the coefficient on the relative supply of high-skilled workers is considerably lower for the AI creative industries compared to the AI users. This implies a higher elasticity of substitution between high and low skilled in the former compared to the latter (6.33% compared to 5.75%), suggesting a stronger skill biased technical change effect in AI creating industries. Second, the impact of technology is considerably larger in AI creating industries compared to the rest of the economy, particularly when considering innovative properties. A 1% increase in investments in innovative properties leads to an increase in the skill premium by 0.239% in AI innovative industries while the effect in AI users is negative (-0.021). Economic competencies are positive and significant in both industries, although their effect is more precisely estimated for the AI users. Hence the distinction between the two sectors highlights a differential role for innovative properties and reveal a strong complementarity between innovative properties and skilled labour but only in the most innovative industries.

Table 5: The race between technology and the supply of skills: AI-creating vs AI using industries, 1995-2015 (PMG + CSD)

VARIABLES	(5) AI creative	(9) AI users
ln(High /low skilled)	-0.158***	-0.210***
	(0.015)	(0.012)
ln(ICT/Tot K)	0.087***	0.076***
	(0.018)	(0.010)
ln((Innovative properties/Tot K)	0.239***	-0.021*
	(0.024)	(0.013)
ln(Economic competencies/Tot K)	0.070*	0.051***
	(0.036)	(0.015)
ECM	-0.581***	-0.476***
	(0.061)	(0.030)
Constant	0.231***	0.122***
	(0.039)	(0.017)
Implied σ	6.33	4.75
Observations	764	2,437
Number of id	32	102

Notes: Pooled Mean Group estimates with controls for CSD. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

While industry differences are important when considering technological changes, another interesting aspect is accounting for countries' role in the innovation process. In fact, as the technological leader, the US has experienced early developments and diffusion of new technologies (Blundell et al. 2022). This might affect the demand and supply for skills differently compared to European countries, who are typically technological followers. In addition, European labour markets are characterised by tighter legislation and less flexible working arrangements compared to the US, which might contribute to slower adjustment in terms of supply and demand for skills and hence the skill wage premium.

To understand whether the US role as a technology leader might affect our results, we re-estimate the dynamic model for the European countries only. Results in Table 6 are broadly consistent with those for the full sample although when excluding the US, the positive impact of both ICT and innovative properties is lower in the AI innovative sectors. Hence, differently from Blundell et al. (2022) we do not find strong evidence of differences between leader and follower countries in the way technology impacts wage outcomes.

Table 6. AI innovative vs AI users industries (excluding the US) 1995-2019, (PMG + CSD).

	(1)	(3)
VARIABLES	AI creative	AI users
ln(High /low skilled)	-0.148***	-0.218***
	(0.014)	(0.013)
ln(ICT/Tot K)	0.079***	0.070***
	(0.021)	(0.013)
ln((Innovative properties/Tot K)	0.291***	-0.014
	(0.029)	(0.014)
ln(Economic competencies/Tot K)	-0.002	0.043***
	(0.040)	(0.016)
ECM	-0.538***	-0.422***
	(0.068)	(0.031)
Constant	0.210***	0.088***
	(0.042)	(0.015)
Implied σ	6.76	4.59
Observations	672	2,184
Number of id	32	102

Notes: Pooled Mean Group estimates with controls for CSD. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.5 Investigating changes in the relationship between technology and the graduate wage premium in recent years.

The period under investigation was one of rapid technological change and economic disruption. Thus, an interesting extension of our analysis is to account for changes in the relationship between skills and technology over time. Figure 1 clearly shows that the decline of the skill premium becomes particularly pronounced after 2005. We therefore test for the presence of possible changes in the effect of technology over time by splitting the time period at the 2005 cut-off year and re-estimating our model for the period 2006-2019. Results are presented in Table 7. The first column presents estimates for all industries, while columns (2) and (3) distinguishes between AI innovative and AI using industries.

Table 7: The race between technology and supply of skills – 20106-2019

	All industries 2006-2019	AI-creating sectors 2006 -2019	AI user sectors 2006 -2019
ln(High /low skilled)	-0.331***	-0.239***	-0.294***
	(0.007)	(0.028)	(0.011)
ln(ICT/Tot K)	0.167***	0.355***	0.148***
	(0.007)	(0.032)	(0.010)
ln((Innovative properties/Tot K)	0.052***	0.361***	0.016
	(0.008)	(0.028)	(0.010)
ln(Economic competencies/Tot K)	-0.003	-0.313***	0.029**
	(0.013)	(0.032)	(0.014)
ECM	-0.619***	-0.554***	-0.633***
	(0.046)	(0.097)	(0.053)
Constant	0.156***	0.223***	0.148***
	(0.030)	(0.055)	(0.032)
Implied σ	3.02	4.18	3.401
Observations	1,876	448	1,428
Number of id	134	32	102

Notes: Pooled Mean Group estimates with controls for CSD. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results for all industries (column 1) show a larger negative effect of the relative supply of high skilled workers on the wage premium (-0.331 vs -0.202) compared to the full period estimates, hence the implied elasticity of substitution is lower (ranging between 3.02 and 4.18) compared to the results for the full sample (ranging between 4.75 and 6.33). The effect of ICT is substantially larger for the 2006-2019 period compared to the 1995-2019 period, suggesting an overall stronger complementarity between this indicator of technical progress and high-level skills in more recent years. We also find a positive effect of innovative properties, suggesting that in later years accumulation of this asset type has resulted in an increasing premium for the highly skilled.

The outcome is substantially different when we separate AI-creating industries from the rest of the economy, in column (2) and (3). In the former, the effect of ICT is particularly strong, with an estimated coefficient of 0.355 vs 0.148 among AI users. We also find a large and positive effect from innovative properties in the AI-creating industries while their impact on AI-using sectors is not statistically significant. Among the latter, economic competencies are still positive and statistically significant, with an estimated coefficient just below the estimates for the full time period in Table 5. Hence, apart from a larger ICT effect, we do not find substantial differences in the relationship between technology and the wage premium in this group of industries since 2005.

On the other hand, in the AI-creating industries, our results suggest a more important role for innovative properties in recent years, suggesting a period of intensifying research effort in the years leading up to the launch of ChatGPT. While research effort, captured by innovative properties, has led to an increase in the demand for high skilled labour, and hence producing an upward pressure on their relative wage, organizational changes have played against the highly skilled in this most innovative group of industries, as indicated by the large and negative coefficient on economic competencies. Similar results are found when focusing on European countries (see appendix table A.3). A possible explanation for this result is that the skill required for the two types of investments are substantially different. Investments in research effort requires highly technical skills, primarily related to qualification in Science, Technology, Engineering and Maths (STEM). These are likely to command premium wages, particularly in those industries where these skills are necessary for developing new technologies. On the other hand, economic competencies may require more general skills, for example managerial or marketing skills, which might command relatively lower pay for graduates rather than non-graduates. Separating these skill mix effects would require detailed information on pay by occupation and industry, which is beyond the scope of this paper.

6. Conclusions and discussion

The evolution of the labour market in OECD countries is both influenced by, and responds to, changes in other production inputs. In this paper we have explored the extent to which skill demand factors, proxied by technology, and skill supply, captured by the ratio of graduates over no-graduates, have driven the decline in the skill wage premium. Our analysis has provided a long run perspective that incorporates both ICT capital and intangible capital services as separate technology indicators, allowing for heterogeneous technology effects. Our findings for 6 large European countries, the UK and the US show that the wage premium associated with high skilled labour has been declining, particularly after the mid-2000s.

Using a dynamic version of the canonical model and adopting an estimation strategy that accounts for non-stationarity and cross-sectional dependence, two main results emerge from our analysis: first, ICT consistently complements high skilled labour, an effect that intensifies in recent years. Second, the role played by other intangible assets differs depending on the asset type. In the most innovative sectors – AI creating industries - we find that innovative properties strongly complement skilled labour, and the effect intensifies after 2005. In the rest of the economy the two assets that drive the wage premium are ICT and economic competencies. Overall, our analysis concludes that technology is still skill biased. In addition, given that economic competencies include investments in organizational capital that complement new technologies, our evidence provides some support to the assumption of skill biased organizational change, as discussed in Blundell et al. (2022), but only in AI-using sectors. Hence, distinguishing between AI-creatives and AI users has allowed us to capture differences in the way technology and skill demand interact with wages. It also suggests that country-level analyses cannot fully capture the impact of technology on the economy and that the industry perspective is important for policy recommendations, particularly for policies related to education and training. These will be necessary to retrain workers, whose jobs may be replaced by technology and upskill those employed in low-skilled jobs who might not benefit from technology advances.

Given the complementarities between technology and the demand for skills, supply factors remain the main driver of the declining wage premium across the board, consistent with Crivellaro (2013). Although holding a degree is still associated with higher earnings, this advantage has diminished over time, particularly since 2005. This may be due to a skill downgrading trend, whereby high skilled workers are moving into lower skilled occupations, increasing the competition between education groups for increasingly scarce well-paid jobs (Valletta 2018). Additionally, phenomena such as job polarization and overeducation offer complementary, non-mutually exclusive explanations. Promoting changes in university curricula to better prepare students for changes in the labour market brought about by technological changes is another policy recommendation.

Future analysis might fruitfully consider using information on age and gender, which could be incorporated into the specifications of the race model, to explore possible differences in the wage premium over different worker characteristics. For example, Bowlus et al. (2023) recommends accounting for differences in skills across cohorts to derive correct estimates of the elasticity of substitution between high and low skill workers. This issue may be less relevant in our study as our sample cover a relatively shorter period of time - and our estimates are close to those in Bowlus et al. (2023). However, it is an important recommendation for future work. Future analysis will also be able to follow how AI developments will continue to affect the labour market and the wage premium. Tech groups are currently poaching top engineers, pushing their wages to extremely high levels (Financial Times, 2025). This suggests that the wage premium might increase but only for STEM qualified workers, employed in top high-tech jobs. The outcomes for the majority of workers who are excluded from these ‘dream’ occupations are still uncertain.

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Appendix

Figure A.1 Skill wage premium, country level estimates

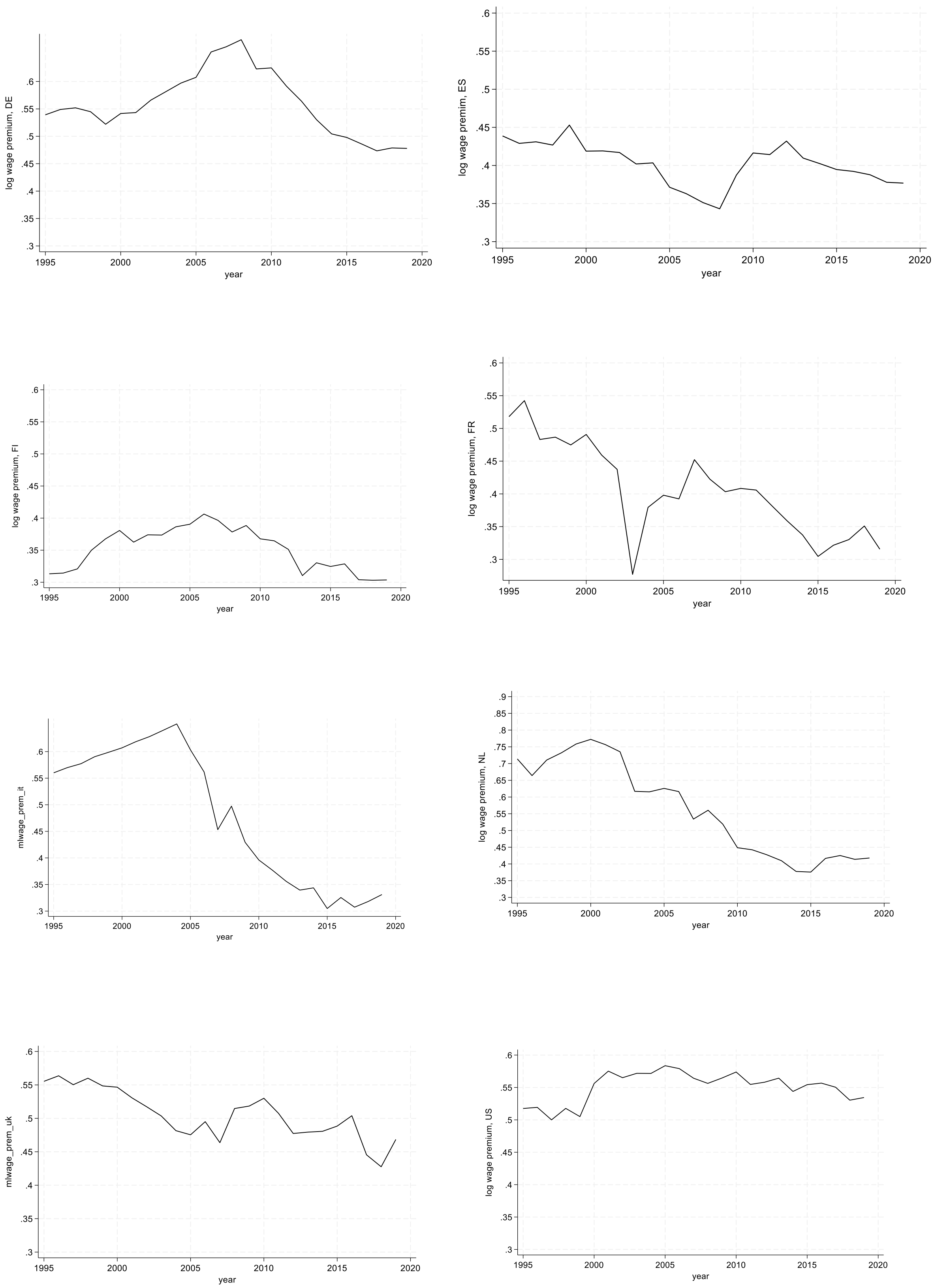

Table A.1

Unit root tests, 1995-2019

Variable	Im, Pesaran and Shin (2003)	Pesaran (2003)
ln(wage premium)	-0.988	2.723
	(0.162)	(>0.995)
ln(High/low skilled)	9.794	0.064
	(>0.995)	(0.525)
ln(ICT capital)	5.350	0.926
	(>0.995)	(0.823)
ln(Economic competencies)	3.225	9.725
	(>0.995)	(>0.995)
ln(Innovative Properties)	2.091	5.274
		(>0.995)
	(0.982)	
ln(Total intangibles)	0.821	5.995
	(0.794)	(>0.995)

Notes: the tests are for 134 cross sections, n = 3,350 observations. All variables are in levels and weighted using the 1995 average value added across all units. P values in brackets. Both tests are based on the null hypothesis that all panels have a unit root. The Pesaran (2003) test for unit root controls for cross-sectional dependence.

Table A.2

Tests for cross sectional dependence, 1995-2019

Variable	Pesaran (2015, 2021)	Juodis and Reese (2022)	Pesaran and Xie (2021)
ln(wage premium)	55.320	-1.120	13.100
	(0.000)	(0.265)	(0.000)
ln(High/low skilled)	369.730	-3.070	0.770
	(0.000)	(0.002)	(0.440)
ln(ICT capital)	186.610	-1.800	81.650
	(0.000)	(0.073)	(0.000)
ln(Economic competencies)	14.440	-2.150	28.050
	(0.000)	(0.032)	(0.000)
ln(Innovative Properties)	12.300	-1.800	3.560
	(0.000)	(0.071)	(0.000)
ln(Total intangibles)	1.840	-2.520	-0.870
	(0.065)	(0.012)	(0.386)

Notes: the tests are for 134 cross sections, n = 3,350 observations. All variables are in levels and weighted using the 1995 average value added across all units. Standard errors in brackets. All tests are based on the null hypothesis of weak cross-sectional dependence against the alternative of strong cross-sectional dependence.

Table A.3

The race between technology and the supply of skills, Europe, 2005-2019

VARIABLES	(1) All sectors	(3) AI innovative	(5) AI users
ect1	-0.572***	-0.562***	-0.582***
	(0.048)	(0.110)	(0.058)
lh_ratio	-0.290***	-0.389***	-0.287***
	(0.010)	(0.020)	(0.011)
lCAP_IT	0.131***	0.250***	0.124***
	(0.010)	(0.021)	(0.010)
lCAPIP	0.008	0.261***	0.008
	(0.009)	(0.025)	(0.010)
lCAPEC	0.064***	-0.168***	0.072***
	(0.013)	(0.035)	(0.014)
Constant	0.133***	0.182***	0.121***
	(0.026)	(0.064)	(0.030)
Observations	1,666	392	1,274

Notes: Pooled Mean Group estimates with controls for CSD. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1