Working in an immaterial world: intangible assets and the Supply and Demand for skilled labour

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Abstract

We use the latest EUKEMS database for the period 1995-2018, to explore the relationship between intangible assets and the demand for skills disentangling the effects of skill biased technological change. We focus on 8 large European nations, Austria, Germany, Spain, Finland, France, Italy, the Netherlands and the UK and test whether intangibles have a role to play in explaining the wage premium in the race between technology and the supply of skills. Our findings indicate that there is a declining wage premium for high skilled workers compared to others in the labour market in the majority of countries and across the majority of industrial sectors. We find little evidence of a technology impact for high skilled workers but do find a strongly negative supply impact. Overall, we identify the productivity slowdown as a genuine phenomenon and not simply attributable to mismeasurement of these inputs.

JEL Codes: J23; J31; O33

Key words: Intangibles; Skills; Labour demand; ICT

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1. Introduction

The wage gap between the lowest and the highest paid has been increasing over time (OECD, 2015), exacerbating trends in global inequality. At the same time, we have seen a new wave of digital technologies – the 'fourth industrial revolution' - which, when initially introduced, require complementary skilled workers to reap the productivity benefits. This suggests that technology change is biased towards skills and the demand for high skilled workers has increased over time. Many developed regions have seen significant expansion of the number of high skilled workers as a share of total workers, increasing the supply of high skilled labour. The extent to which the supply effect dominates over the demand effect (or not) will determine whether the wage premium for high skills continues to grow. This underpins the Race model presented by Autor et al (2020) and Acemoglu and Autor (2011) which builds on the seminal work of Tinbergen (1975) modelling skill biased technological change.

Since the global financial crisis in 2007, however, the increasing trend in the skill wage premium has reversed. In the US the flattening of the wage premium is discussed in Valletta (2018) and Beaudry et al. (2016). In Europe there is evidence to suggest a decline in the wage premium, primarily due to a more rapid increase in the supply of high skilled labour relative to the demand (Green and Henseke 2021). There is an indication that this varies by country (Crivellaro 2016) and a greater understanding of the causes of this decline is therefore warranted, particularly in the face of modest European economic 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. While these are not new to industrial organisation (Veblen, 1908), their measurement and importance to the knowledge economy is greater and are considered an integral part of knowledge capital. 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). 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, a more nuanced finding highlights the increased dispersion of productivity across sectors. Thus, industrial structure matters.

Given the importance of accurately measured intangible capital to the knowledge economy, its relationship with labour is fundamental to the interplay with technology in the production function. Thus, this analysis seeks to separate the role that intangibles play as well as technologies in contributing to the high skilled wage premium, we also identify the extent to which it affects the elasticity of substitution. Finally, we estimate a model to explore skill biased technological change (SBTC).

Using the latest EUKLEMS industry-country database, we explore the relationship between skills, technology and intangible assets for 8 European countries over the past 25 years (1995-2018). We divide our analysis into 2 sub-periods, distinguishing pre- and post-financial crisis as this event has greatly affected productivity performance in many countries and, therefore, it is likely to have affected wages.

The main objective of this paper is to understand whether supply or demand factors are at the root of this decreasing wage inequality between skilled and unskilled workers. This paper seeks to understand the prevailing forces over time. Specifically, this paper aims to explore the following research questions:

- Can intangibles explain the wage premium in the race between technology and the supply of skills?
- What is the relationship between ICT, intangibles and the demand for skills?
- When considering intangible assets, is the technology still skill biased?

Are intangibles contributing to the skill biased technical change phenomenon – in addition to or instead of ICT capital?

Our findings suggest that since the financial crisis, there has been a decline in the premium associated with high skills, relative to other workers, in all countries and in most industries in our sample. Both demand and supply factors are associated with this decline. On the demand side, our results show that rather than being skill biased, technology has led to skill downgrading particularly after the financial crisis. Intangible assets further contribute to this phenomenon, being negatively associated with the skill wage premium. On the supply side, the increasing number of workers educated at the tertiary level is putting a downward pressure on the wage of the highly skilled, relative to the low skilled.

This paper is structured as follows. In section 2 we provide a review of the literature at the nexus of skills, technology and intangibles in production. Section 3 provides the theoretical framework and specifies the hypotheses to be tested. In section 4 we provide a brief overview of the primary data sources used and provide an overview of employment and wage patterns of high skilled workers, averaged across the selected nations, sectors and time. In section 5 we present our findings. Section 6 provides a discussion and conclusion of our analysis, as well as 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 at the firm, industry, and cross-country levels (Chun, 2003; O'Mahony et al, 2008; Goldin and Katz, 1998). Specifically, there has been concern surrounding the extent to which technology might be labour saving (having welfare implications for workers) or labour augmenting. Early models focussed on factor augmentation for skilled workers (Tinbergen, 1975) and have been criticised for firstly assuming that skills and tasks are directly mapped (one-to-one) and secondly assuming that technology is exogenous and inherently skill biased (Acemoglu and Autor, 2011).

Later developments of the model specification allow for both factor augmentation and comparative advantage in skills, as well as allowing for endogenous technological change (Acemoglu and Autor, 2011), which can replace workers. In their study of the US for the 1963-2008 period, Acemoglu and Autor (2011) provide an extensive historical description of the development of the college graduate (high skilled) labour market, in terms of numbers and wage growth. They find a period of rapid SBTC in the 1980s and 1990s and also explore the extent and cause of job polarisation in the US, driven by technology.

Empirical evidence of SBTC in Europe has largely given way to evidence of job polarisation – the recognition that labour markets were becoming hollowed out by technology that requires either high skilled or low skilled workers (Goos et al, 2014). The demand for labour is not subject to a constant technological pressure; as technology becomes established and codified, its skill requirement typically falls (Cappelli, 2014). Labour demand is also affected by the economic cycle and this too affects the demand for skill group differently. Recent work on skill mismatch during recessions suggests that high skilled workers may accept jobs below their skills set and this mismatch often has a long-lasting effect on earnings (Lui et al, 2016) as well as implication for labour productivity. Beaudry et al (2016) focuses on the financial crisis and labour market in the US. In some respects, this paper picks up the US story where Acemoglu and Autor (2011) left off. They find that the technological bias has fallen since 2000, particularly more sharply since 2008 (something we observe also in Europe, in Figure 1). Their main assertion is that with General Purpose Technologies (GPT), waves of technology pass through the labour market and at different points of diffusion, they require different levels of skill.

What also becomes clear through Acemoglu and Autor (2011) is that the role of the supply of labour needs to be disentangled from the demand side effects – something that early models designed to estimate skill biased technological change did not do due to the dependent variable being based on wage bill shares, which confound wages and employment numbers.

There are other capitals that could potentially augment labour differently according to their skills profile. Intangible assets have been identified as playing a significant role in unlocking productivity gains (O'Mahony et al, 2019); indeed, O'Mahony et al (2019) find that, some of the decline in labour share in value added evident in the 1980s and 1990s was offset by intangible assets increasing their labour share. Intangible assets are generally defined according to the Corrado, Hulten and Sichel (2005) definition, which includes three main asset types; digitized information, innovative property and economic competences. Thus, intangibles are seen as a fundamental part of the knowledge economy. As such, they are likely to play a role in the movements of the skill wage premium over time.

Beaudry et al. (2016) claim that the decline in the skill wage premium is associated with decreasing investments in intangible assets after the financial crisis. As intangible assets such as software, R&D and organizational changes, are complementary with high skills, their decline would reduce the demand for skilled labour and the wage premium. This evidence is supported in the analysis of Haskel and Westlake (2022), which also document the decline of investments in intangible assets as one of the causes of the productivity slowdown after the great recession. This, together with the a lower degree of complementarity between technological change and skills, is likely to have played an important role in the decline of the skill wage premium, particularly when met with an increasing supply of workers educated at the tertiary level, who are competing for fewer skilled jobs.

4. Theoretical framework

We use the new intangibles data in EUKLEMS to analyse the relationship between technology, intangibles and skills. In this analysis we use a restricted data set, excluding countries for which there was incomplete data.

Theoretical background

To analyse the relationship between the wage premium and technology, we follow Acemoglu and Autor (2011) in 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 high and lower 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.

Assuming perfectly competitive labour markets, we differentiate equation (1) to obtain the marginal product 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:

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

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) car 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 high killed 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 (O'Mahony et al. 2008). . The second term in equation (5), $\frac{H}{L}$, capture the labour supply effect on the skill premium. Holding technology constant, an increase in the supply of high-skilled labour relative to the lower skilled will decrease the high skill wage premium.

The estimation of equation (5) requires a measure of technology. Existing studies have often captured the effect of technology using a time trend. The sign of the time trend, when positive, indicates the increase in the demand for skills deriving from technology advances (skill biased technical change):

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

However, using a time trend is a crude measure of technology. We refine the specification of the technology term using up to 4 different technology indictors, starting with Total Factor Productivity (tfp), and the ratio of ICT capital services over total capital services (ICAP_IT). We will then account for intangible assets (ICAP_int), both in total and by including the two components of Economic competencies (ICAPEC) and Innovative properties (ICAPInnovaP). Hence, we can rewrite equation (6) as follows:

$$(7) \qquad ln\left(\frac{A_{H,t}}{A_{L,t}}\right) = \gamma_0 + \sum \gamma_i tech_{it} \quad \text{i=1,...4}$$

Where $tech_i$ represents the technology indicator. Combining equation (7) with equation (5) we obtain the final specification that we will use in our empirical analysis:

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

where $\theta_1 = \frac{\sigma-1}{\sigma}\gamma_0$, $\theta_{2i} = \frac{\sigma-1}{\sigma}\gamma_i$, and $\theta_3 = \frac{1}{\sigma}$.

This model has the advantage of clearly distinguishing between demand and supply factors in driving the wage premium. Under the assumption of skill biased technological change, the coefficients of the technology term are expected to be positive. By accounting for different indicators, our approach allows us to evaluate which technology is associated with changes in the wage premium. Overall, the wage premium will increase when the 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 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. From the estimate of θ_3 we can derive an approximate value for the elasticity of substitution, $\sigma \cong \frac{1}{\theta_3}$.

4. The EUKLEMS database, 1995-2018

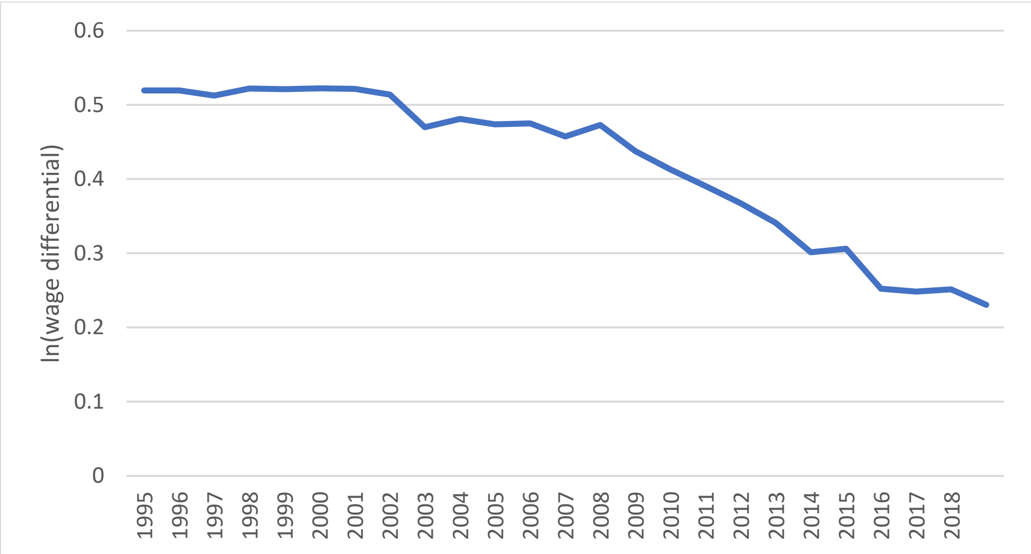
EUKLEMS is a harmonised set of country and industry national accounts developed initially by a number of European Institutes led by GGDC and NIESR that have subsequently been extended and developed with further funding from the European Commission (see O'Mahony and Timmer 2009). The latest vintage has been produced by a consortium of research institutes led by LUIS (Jona-Lasinio et al, 2019) who have updated the database as well as incorporating intangible capitals, 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, the EUKLEMS database covers the period 1995 to 2018. 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.

Our analysis focusses on 8 European countries for which full data are available. These are Austria, Germany, Finland, France, Italy, Spain, The Netherlands and the UK. This sample of European nations includes the largest EU economies and the UK (which was part of the EU at the time). As well as some smaller nations with high GDP per head. For these countries, EUKLEMS contains complete data on intangible assets, capitalised at the sectoral level (19 sectors) for the period 1995 to 2018.

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

Figure 1 presents log graduates/non graduates annual wage premium from 1995-2018, constructed as an average of the wage premium for our sample of countries and for all industries A to S (NACE2 sector codes). This figure suggests the presence of a structural break in 2008, in conjunction with the financial crisis. Although there was a slightly decreasing trend before 2008, the wage premium starts decreasing faster after the financial crisis, moving from a high skill (graduate) premium of 52 log points in 1995 to a log premium of 23 log points in 2018. This means that in 1995, a graduate worker was earning 68% more than intermediate and low skilled and this differential declines to 26% in 2018. It is perhaps also worth noting that this European trend does not replicate the findings presented in Acemoglu and Autor (2011) which finds a positive trend in the wage differential for the US over the period 1963-2008. It is however more consistent with findings for Europe from the IMF, cited in Brunello and Wruuck (2021) and covering later years.

Figure 1: Mean wage premium of high skilled workers, 1995-2018



Source: EUKLEMS Authors' calculations

Naturally these aggregate trends mask differences across countries and industries. Table 1 shows country averages for the pooled sample and for the two subperiods, 1995-2007 and 2008-2019. This clearly shows that even when we focus on individual countries, we find the same pattern: the average high skill wage premium in lower everywhere after the financial crisis. Note also the significant decline in the wage premium in Austria in the later half of the period.

Table 1: Average wage premium for high skills in each EU-8 country

	1995 - 2018	**1995-2007**	**2008-2019**
Austria	0.308	0.528	0.048
Germany	0.570	0.585	0.552
Spain	0.412	0.422	0.401
Finland	0.367	0.385	0.346

France	0.409	0.450	0.361
Italy	0.500	0.609	0.371
Netherlands	0.595	0.734	0.431
UK	0.270	0.298	0.238

Source: EUKLEMS Authors' calculations

These changes can also 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 1995-2018 period and for the period before (1995-2007) and after the financial crisis (2008-2018). Before the financial crisis, the wage premium for skilled workers ranged between 38% (32 log points) in the Information and Communication industry and 90% (64 log points) in Administrative and Support Service activities, with Manufacturing also characterised by an 84% (61 log points) difference in wages between high and lower skilled workers. After the financial crisis the wage premium for skilled workers declines substantially in all industries and particularly in Agriculture and in Real Estate activities. The premium also declines in the Financial and insurance sector (from 39 to 24 log points) but not enough to single out this industry as a possible driver of the lower wage premium after the financial crisis.

Table 2: Average wage premium for high skilled workers by industy

	1995-2018	**1995-2007**	**2008-2018**
Agriculture, Forestry and Fishing	0.54	0.61	0.20
Mining and Quarrying	0.56	0.62	0.46
Manufacturing	0.57	0.61	0.45
Electricity, Gas, Steam and Air Conditioning Supply	0.38	0.45	0.29
Water Supply; Sewerage, Waste Management and Remediation Activities	0.38	0.42	0.28
Construction	0.48	0.57	0.40
Wholesale and Retail Trade; Repair of Motor Vehicles	0.56	0.57	0.44
Transportation and Storage	0.37	0.48	0.29
Accommodation and Food Service Activities	0.45	0.41	0.26
Information and Communication	0.26	0.32	0.23
Financial and Insurance Activities	0.26	0.39	0.24
Real Estate Activities	0.69	0.58	0.39
Professional, Scientific and Technical Activities	0.37	0.46	0.32
Administrative and Support Service Activities	0.55	0.64	0.52
Public Administration and Defense	0.38	0.41	0.22
Education	0.36	0.37	0.36
Human Health and Social Work Activities	0.48	0.61	0.46

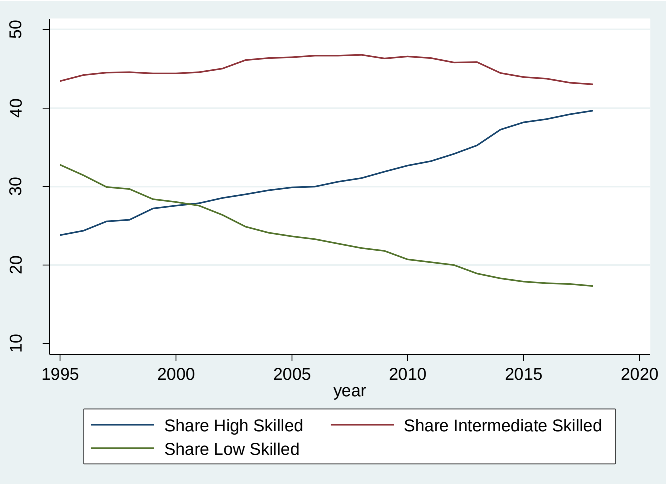
Arts, Entertainment and Recreation	0.39	0.48	0.27
Other Service Activities	0.47	0.53	0.42

Source: EUKLEMS. Authors' calculations

As well as the decline in the high skill wage premium, we observe an increase in the supply of workers educated at the tertiary level, as shown in Figure 2, which reports the share of different types of workers over time, averaged over countries and industries. This figure shows that there has been a steady rise in the shares of workers with a university degree, from approximately 25% in 1995 to 40% in 2018. This increase has largely been seen to be at the expense of the low skilled worker share, which has fallen from approximately 32% to 18%. In contrast and in aggregate, the intermediate skill share has seen little change over time.

Figure 2: Average employment shares for different types of workers

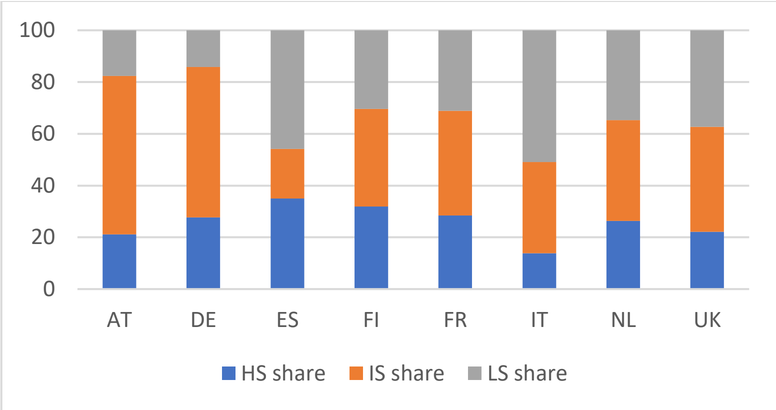
(EU-8 average)



Source: EUKLEMS Authors' calculations

To gain an insight of country differences, Figure 3 shows the proportion of high, intermediate and low skilled in each country included in our sample. This indicates the presence of heterogeneity across 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, consistently with expectations. In fact, although Italy, like most Western countries, has experienced an increase in the average level of education, the number of graduates is below the OECD average. In 2020, of the 25-64-year olds, 20% had tertiary education compared to the EU average of 32.8% (OECD2021).

Figure 3: Average employment shares by skill type

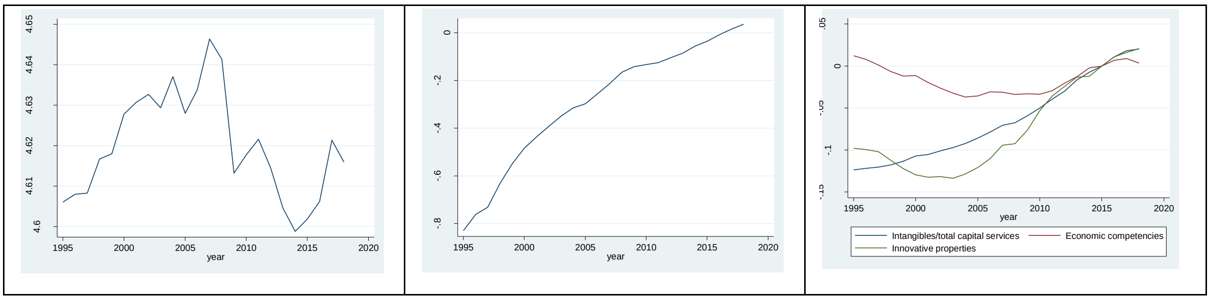


Source: EUKLEMS Authors' calculations

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

In Figure 4 we present movements over time in the technology indicators used in our analysis, averaged across countries and industries. Except for TFP, which declines after the financial crisis, ICT and other intangible assets, expressed as a proportion of total capital services, show an increasing trend, which begins around the year 2004 and continues after the financial crisis. Hence, the data for this group of countries does not show evidence of the decline in investments in intangible assets, discussed in Beaudry et al. (2016) and Haskel and Westlake (2021).

Figure 4: Trends in the technology indicators.



Notes: EUKLEMS data, authors' calculations. ICT, total intangibles, innovative properties and economic competencies are expressed as a proportion of total capital services.

5. Results

5.1. The Race between technology and skills

We begin with the estimation of equation (8) using a fixed effect model. Results are reported in table 3, where we estimate the model for the whole time period, 1995-2018. The first column uses a linear trend to capture technology, while in column (2) we substitute the linear trend with total factor productivity. In columns (3) and (4) we include additional innovative assets, starting from ICT and total intangibles (3) and finally dividing total intangibles into the two main components, economic competencies and innovation properties.

Table 3: The race between technology and skills 1995-2018

Dependent variable: log wage difference between high skilled and low skilled workers (wage premium)

VARIABLES	(1)	(2)	(3)	(4)
lh_ratio	-0.2715***	-0.2746***	-0.2854***	-0.2859***
	(0.0077)	(0.0078)	(0.0094)	(0.0094)
trend	0.0000			
	(0.0002)			
ltfp		-0.0028	0.0003	-0.0010
		(0.0241)	(0.0248)	(0.0245)
lCAP_IT			0.0312***	0.0270***
			(0.0097)	(0.0095)
lCAP_int			-0.0500**	
			(0.0240)	
lCAPEC				-0.0232
				(0.0207)
lCAPInnovaP				-0.0283**
				(0.0125)
Constant	0.1688***	0.1745	0.1510	0.1564
	(0.0090)	(0.1117)	(0.1146)	(0.1135)
Elasticity of substitution $\hat{\sigma}$	**-3.7**	**-3.64**	**-3.51**	**-3.50**
Observations	3,400	3,254	3,193	3,193
R-squared	0.2774	0.2835	0.2871	0.2879
Number of id	143	140	136	136
FE	YES	YES	YES	YES
Time dummies	NO	NO	NO	NO

Notes: fixed effect estimates. Robust standard errors in brackets.

As expected, the coefficient on the ratio between high skilled and low skilled workers (hours) is negative and statistically significant. The estimates suggest that the evolution of the skill premium during the 1995-2018 period was characterised by an elasticity of substitution of approximately 3%, a result that is robust across the different specifications. The size is consistent with estimates in Acemoglu and Autor (2011) and indicates that an increase in the supply of skilled workers has led to a decline in the demand for unskilled labour. Results also show an insignificant effect of both the time trend and TFP, suggesting little impact of technical change over the period. The only positive effect from the demand side comes from the ratio of ICT capital services over total capital services with a coefficient of 0.0312 in column (3) and 0.0270 in column (4). Hence, the only skill biased technical change effect derives from investments in ICT. Intangibles assets, on the other hand, are not found to be complementary with high skilled labour: a 1% increase in intangible capital services (as a proportion of total capital services) decreases the skill premium by 0.05%.

A particularly interesting extension of this model is to account for different time periods. Figure 1 and the discussion in the previous section clearly show that the decline of the skill premium is mainly a feature of the post financial crisis period. We can take the year 2008 as identifying a structural change and we re-estimate equation (8) adding a dummy variable taking the value of 1 for the 2008-2018 period and equal to 0 otherwise; we also interact this dummy with all our right-hand side variables. Results are presented in Table 4. A structural break test is reported at the end of table and indicates that there is no evidence of a structural break.

When including interactions, in all specifications we found a larger elasticity of substitution in the post-financial crisis period (the coefficient on the H/L ratio becomes smaller in absolute values), compared to the base period and the difference is statistically significant at the 1% significance level. This elasticity is approximately 5%, indicating that highly skilled workers are increasingly substituting the low skilled. Our time trend as an indicator of technology is still insignificant column (1) while the correlation between the high skill premium and TFP, which was insignificant before the financial crisis, becomes negative although weakly significant in the 2008-2018 period column (2). The skill biased technical change effect deriving from investments in ICT disappears after the financial crisis column (3), when the effect turns negative. This indicates that a 1% increase in ICT capital intensity reduces the skill premium by approximately 0.05% (0.0543-0.1076), offsetting the positive association in the pre-crisis period. As for intangibles, the negative association between intangible capital services and the skill premium in table 2, is only statistically significant in the post-crisis period. This negative association is driven by investments in innovative properties. Results in column (4) show that a 1% increase in the ratio of innovative properties over total capital services reduces the skill premium by approximately 0.11%.

Table 4: Testing for structural change in the race model

Dependent variable: log wage difference between high skilled and low skilled workers (wage premium)

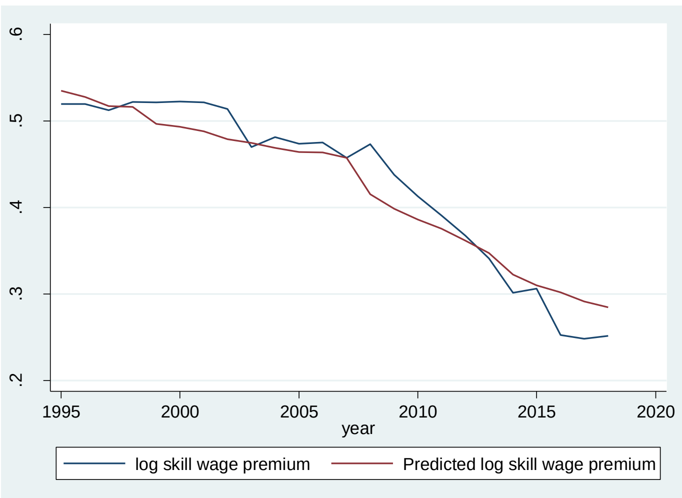
VARIABLES	(1) lwage_prem	(2) lwage_prem	(3) lwage_prem	(4) lwage_prem
$ln\left(\frac{H_{it}}{L_{it}}\right)$	-0.2411***	-0.2521***	-0.2501***	-0.2470***
	(0.0103)	(0.0104)	(0.0108)	(0.0108)
$ln\left(\frac{H_{it}}{L_{it}}\right) * D2008$	0.0289***	0.0294***	0.0297***	0.0305***
	(0.0053)	(0.0054)	(0.0055)	(0.0055)
trend	-0.0001			
	(0.0002)			
*trend*D2008*	0.0002			
	(0.0004)			
ln(TFP)		-0.0073	-0.0283	-0.0341
		(0.0244)	(0.0252)	(0.0245)
Ln(TFP)*D2008		-0.0908*	-0.0686	-0.0083***
		(0.0522)	(0.0530)	(0.0021)

Ln(ICT/TK)			0.0543***	0.0534***
			(0.0105)	(0.0105)
Ln(ICT/TK)*D2008			-0.1076***	-0.1377***
			(0.0300)	(0.0281)
ln(Int/TK)			-0.0052	
			(0.0243)	
ln(Int/TK)*D2008			-0.1525***	
			(0.0565)	
Ln(EC_comp/TK)				-0.0199
				(0.0208)
Ln(EC_comp/TK)*D2008				0.0085
				(0.0394)
lCAPInnovaP				0.0002
				(0.0128)
lCAPInnovaP*D2008				-0.1129***
				(0.0296)
D2008	-0.0193	0.4135*	0.2802	
	(0.0123)	(0.2415)	(0.2453)	
	(0.0138)	(0.1145)	(0.1190)	(0.1156)
Test structural change (P value)	<0.001	<0.001	<0.001	<0.001
Observations	3,400	3,254	3,193	3,193
R-squared	0.2901	0.2952	0.3082	0.3096
Number of id	143	140	136	136
FE	YES	YES	YES	YES

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The test for structural change is a test for the joint significance of the time dummy and all interaction terms. The null hypothesis is rejected in all specifications, supporting the presence of a structural change in our data.

Using the results from column (4), we plot the skill premium together with the prediction in Figure 5. The model captures reasonably well the main trends in the data, with a mild underprediction of the wage premium between 1998 and 2008 and an overprediction towards the end of the sample period. Both series suggest a reversion of the decline in the last two years, just before the Covid-19 pandemic.

Figure 5: Actual and predicted skill wage premium



Overall our results indicate that in the period following the financial crisis technology has been de-skilling, while high skilled labour has increasingly substituted the low skilled. This suggests that some skill downgrading is taking place. As discussed in Beaudry et al. (2016) with reference to the US economy, around the year 2000 the demand for skills started to decline and high skilled workers moved down the occupational ladder and increasingly displaced lower-educated workers in less skill-intensive jobs. These effects became particularly apparent after the financial crisis. The pattern in the high skill premium in the 8 European countries depicted in Figure 5, is consistent with this explanation as we observe an initial decline after 2000 and a stronger negative trend after the financial crisis. This outcome is also consistent with the literature on the skill mismatch among graduates, showing that there is a large proportion of graduates employed in non-graduate jobs, whose earning are below those working in graduate occupations (Vecchi et al. 2021).

5.2 Focusing on the supply side and skill biased technical change

An early hint of the technological deskilling process of the current technological wave was discussed in Chun (2003), who argued the need to distinguish between different stages of technological diffusion and its relationship with skilled labour. While in the short run the introduction of new technologies demands high-levels of cognitive skills, over time, once the new technology becomes fully implemented and codified, firms can replace highly educated workers with lower paid less educated ones (Brunello and Wruuk 2021). This is also confirmed in the analysis by O'Mahony et al. (2008) with reference to the US wage shares of highly educated IT workers, which had a lower correlation with the ICT technology compared to the UK and France until 2000. This result suggested that the US, having adopted the new technology at an earlier stage, was entering a phase of lower demand for IT-specific skills.

An alternative analytical framework that has been widely used to understand the relationship between technology and the demand for skills, focuses the supply side of the market and aims at explaining movements in the wage bill share for the highly educated workers divided by the total wage bill (Berman et al. 1994, Machin and Van Reenen, 1998, Chun, 2003, O'Mahony et al. 2008):

$$\text{(9)} \qquad \frac{ws_{H,i}}{WT_i} = \beta_i + \beta_w ln\left(\frac{ps_{H,i}}{punsk_i}\right) + \beta_k ln\left(\frac{K_i}{Y_i}\right) + \varepsilon_i,$$

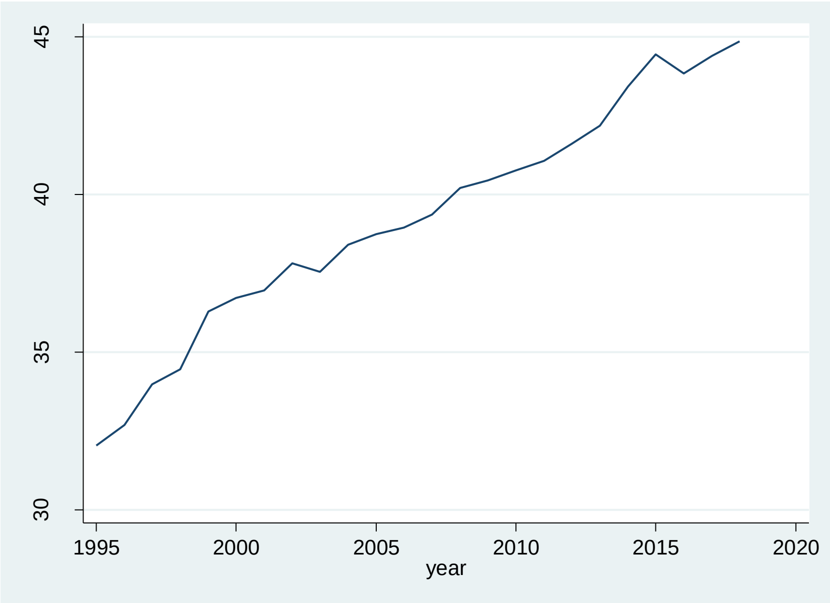
where $ws_{H,i}$ is the high skilled wage bill share in industry i, WT_i is the total wage bill for the same industry. Time subscript have been omitted for simplicity. The first term in equation (9), $\frac{ps_{H,i}}{punsk_i}$, is the ratio between the wage rate of highly skilled workers divided by the wage rate for the unskilled, while the second term is the capital output ratio. To account for the impact of technological change, equation

(9) is augmented with a technology indicator. In our study, we rely on the same indicators used in the previous section (TFP, and the ratio of ICT and intangible capital services over total capital services):

(10) $$\frac{ws_{H,i}}{WT_i} = \beta_i + \beta_k ln\left(\frac{K_i}{Y_i}\right) + \beta_i ln(Tech_i) + \delta_t D_t + \varepsilon_i$$

In equation (10), the relative wage term has been replaced with a set of time dummies (Dt) to deal with endogeneity issues, frequently discussed in the literature (Machin and Van Reenen, 1998, Berman et al. 1994, Chennells and Van Reenen 2002, Chun 2003, O'Mahony et al. 2008). In the presence of capital-skill complementarity the coefficient $\beta_k$is expected to be positive. A positive coefficient for the technology term (β_i) provides support for the presence of skill biased technical change.

Figure 6: High skilled wage bill share over time



Source: EUKLEMS, authors own calculations

Figure 6 reports the overall trend in the high skill wage bill share, as an average across all countries and industries included in our sample. Differently from the wage premium, the wage bill share is characterised by an increasing trend throughout the 1995-2018 period. This suggests that the increase in the wage bill share is mainly driven by the increasing supply of workers educated at the tertiary level. In figure 5 we cannot identify a clear structural change coinciding with the financial crisis. For this reason, the estimation of equation (10) will focus on the pooled sample.

5.3. Estimation of the wage share equation

Table 5 presents coefficient estimates for equation (10). In column (1) we use only TFP as a measure of technological change, while in column (2) we include ICT and the two types of intangible assets, economic competencies and innovation properties. Results indicate that the complementary relationship between capital and high skilled labour, usually found in previous work, no longer exists as the capital-output ratio coefficient is not statistically significant. General technological change, captured by TFP, is positively associated with the wage share of high skilled workers, an effect that is robust to the inclusion of intangible assets. Among the latter, only economic competencies are significantly correlated with the wage shares of the high skilled, showing a negative correlation. The coefficient of ICT capital is positive but not statistically significant, indicating that over time digital technologies are longer associated with the demand of high-level skills.

Table 5: Dependent variable: wage bill share of high skilled workers

VARIABLES	(1) 1995-2018	(2) 1995-2018
lCAP_Y	0.128	-1.313
	(0.879)	(0.992)
ltfp	3.433***	2.737**
	(1.050)	(1.173)
lCAP_IT		0.503
		(0.359)
lCAPEC		-2.340***
		(0.626)
lCAPInnovaP		-0.0828
		(0.373)
Constant	16.10***	11.58***
	(3.397)	(3.815)
Observations	3,377	3,193
R-squared	0.414	0.419
Number of id	147	136
FE	YES	YES
TD	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, we investigate the possibility that we might overcontrol for the effect of technical change by considering each technology indicator separately. Results reported in Appendix table A.1 are consistent with those presented above, except for the coefficient of the capital-output ratio which reveals the presence of capital-labour substitution (the coefficient is negative and statistically significant).

These results differ from our previous work (O'Mahony et al. 2008) for the UK and the US. The evidence based on data covering the 1979-2000 period revealed the presence of both capital-skill complementarity and skill-biased technological change, driven by investments in ICT. Overtime, this complementarity has disappeared, a result that is consistent with those presented in Table 4, showing a negative association of ICT with the wage premium, after the financial crisis. Overall, except for TFP, other demand factors have not contributed to the increase in the wage bill share. Working in an intangible economy does not appear to favour the high skilled.

6. Conclusions and discussion

The evolution of the labour market in Europe is both influenced by, and responds to, changes in other production inputs. In this paper we have explored the changes over time of high skilled labour, both in terms of numbers of hours as well as the high skilled wage differential (compared to other workers).

This paper utilises the latest EUKLEMS industry database to provide a long run perspective that incorporates both intangible capital services and ICT capital to explore the extent to which these capitals influence the demand for high skilled workers. Our findings for 8 large European economies for the 25 year period indicates that the wage premium associated with high skilled labour has been declining. This is particularly marked after the financial crisis.

Using the Race model, we find little evidence of general technology change (captured by TFP) influencing the high skilled wage premium. In addition, we see no evidence that intangible capital favours high skilled workers. In the earlier time period, there is evidence that ICT capital services had a positive role in driving the wage premium, but since the financial crisis this effect too has disappeared.

We explore a number of possible explanations for the wage premium decline; firstly, we see that there has been an increase in the supply of workers educated at the tertiary level. A potential explanation for the fall in the skill premium is that this supply has been faster than the demand for skills, probably due to new technologies reaching maturity. Indeed, we find that the complementarity between skills and technologies of the 1990s and early 2000s has decreased. Even the complementarity between skills and ICT, which lasted until the financial crisis, has reversed its course in recent years. Evidence of capital-skills substitution, in relation to ICT, is emerging in the later period. Secondly, we find that the substitutability between high and low skilled workers appears to be increasing, as captured by an increase in the elasticity of substitution over time. We suggest that this is caused by a skill downgrading trend – situations where high skilled workers are moving into lower skilled jobs.

There are some areas for refining our work in subsequent analysis. Firstly, we would like to incorporate gender and age into the specifications to explore possible differences in the wage premium over different dimensions. This is particularly relevant in the policy arena at present where we see increased concern about older workers leaving the labour market, and the hangover from the differential impact of Covid-19 across the genders. A better understanding of this dynamic pre-pandemic will help to better assess the post-pandemic trends. Although our model is doing a good job at capturing the movements in the skill wage premium, endogeneity remains a problematic issue. Therefore another extension of the current analysis is to control for endogeneity, using a suitable instrumental variable strategy. Finally, our analysis so far has excluded the possible role of labour market institutions, that could also play a role in reducing the wage gap between high and low skilled. We leave these extensions for future research.

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Appendix

Table A.1. Estimation of wage share for the high skilled with single technology indicators

VARIABLES	(1) 1995-2018	(2) 1995-2018	(3) 1995-2018
lCAP_Y	-2.088***	-2.598***	-3.092***
	(0.554)	(0.613)	(0.607)
lCAP_IT	-0.0611		
	(0.298)		
lCAP_int		-0.317	
		(0.732)	
lCAPEC			-2.014***
			(0.614)
lCAPInnovaP			-0.299
			(0.360)
Constant	18.86***	16.06***	13.14***
	(3.288)	(3.713)	(3.652)
Observations	3,498	3,264	3,264
R-squared	0.419	0.422	0.425
Number of id	150	136	136
FE	YES	YES	YES
TD	YES	YES	YES