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The rising value of interpersonal job tasks for graduate pay in Europe

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Abstract

We analyse how wage differentials and employment among Europe's tertiary graduates have changed with task content. Using individual-level income data for 25 European countries from 2004 to 2015 from the European Survey of Income and Living Conditions and the European Labour Force Survey, we find that the value of interpersonal tasks has increased: across Europe, a standard deviation higher intensity of interpersonal job tasks is associated with a 0.4 percentage point higher annual growth rate in wages. Second, problem-solving tasks have become a less important share of graduates' employment: occupations that were a standard deviation more intensive in problem-solving tasks annually grew 1.1 percent more slowly. An analysis with granular, job-level data from Britain for the period 2001-2017 confirms both trends. There is suggestive evidence that the relative value of interpersonal tasks rose more in countries where the prevalence of high-involvement work practice had risen more.

Highlights

- The value of interpersonal tasks among graduates has increased in Europe.

- European graduates are increasingly moving away from jobs that are intensive in problem-solving tasks.

- These trends are similar to those seen in the United States.

Key words: wage dispersion, employment, job tasks, tertiary education, Europe, trends

JEL codes: J23, J24, J21, J31, J44

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Introduction

Graduate labour markets have been expanding and transforming in the 21st century. The aim of this paper is to use the lens of a task-based approach to reveal salient features of the changing dispersion of graduate earnings and employment across 25 European countries over the period 2004-2015. It contributes to the literature on rising graduate heterogeneity and the nascent economic literature on the value of interpersonal tasks and social skills for labour market outcomes. By comparing these wage and employment trends across countries with patterns of organisational and technological change, we also provide suggestive novel evidence on the factors behind the changing value of interpersonal job tasks.

The task-based approach has proved useful for understanding skilled labour markets in the United States, where the growth of cognitive job tasks has faltered since 2000 following a period of steady expansion during the 1980s and 1990s (Beaudry *et al.*, 2016). Faced with sluggish demand, college graduates have increasingly moved down the job ladder with adverse consequences for their access to top jobs, relative earnings, and wage growth (Beaudry *et al.*, 2014, 2016). Employment in numeracy intensive jobs with few interpersonal tasks have diminished (Deming, 2017). Compared with the 1980s, earning returns to cognitive tasks were smaller in the 2000s (Castex and Dechter, 2014), while routine and interpersonal job tasks have become more important for graduate wages (Altonji *et al.*, 2014; Deming, 2017). Technological change is the leading explanation for the initial rise of cognitive job tasks and the subsequent stagnation (Autor *et al.*, 2003; Goos *et al.*, 2009, 2014; Van Reenen, 2011; Michaels *et al.*, 2014). The hypothesis of routine-biased technological change, put forward by Autor et al (2003), proposes that the rapid development and adoption of information and communication technology (ICT) complemented high-skill labour in cognitive jobs while replacing middle-skill labour in routine jobs. Within this task-based approach to labour demand, the recent slowdown in the expansion of cognitive job tasks is consistent with the maturation of ICT (Beaudry *et al.*, 2016), and/or the diffusion of high-skill automation that can substitute labour in a range of cognitive intensive job task domains (Frey and Osborne, 2017; Acemoglu and Restrepo, 2018).

European evidence on graduate labour market trends, however, is more mixed and piecemeal. By 2018 over 40% of 30-34 year-olds held a tertiary qualification across EU countries; up by 16 points from 2002. Graduate labour supply grew everywhere (Green and Henseke, 2019). This common trend towards mass tertiary education contrasts, however, with notably varying graduate labour market trends across countries. For example, in the UK and Portugal, residual wage inequality within graduates has widened by field of study, degree level and degree class over the last decades (Lindley and McIntosh, 2015; Green and Henseke, 2016; Lindley and Machin, 2016; Naylor *et al.*, 2016; Almeida *et al.*, 2017), whereas in Germany dispersion among graduates has remained more stable (Klein, 2016; Reinhold and Thomsen, 2017; Henseke, 2018). Overall, graduate wage inequality has risen in some but not in all European countries since 2004. Over the same period, graduate employment outside the range of high-skill occupations – sometimes referred to as overeducation – has grown in most countries, stayed stable in some, and even declined in a few cases (Green and Henseke, 2017).

The context for this heterogeneity in graduate labour market trends in Europe is the familiar variation in educational and, in particular, labour market institutions -- including the dominant management practices. The task framework has proved useful in illuminating trends in the structure of earnings and employment between education groups in Europe (e.g., Goos *et al.*, 2009, 2014). To help understand dispersions among graduates, however, there is a need also to investigate how the relationship of job tasks with earnings and employment has changed over time within the graduate workforces across European countries.

Our focus is on problem-solving tasks (sometimes referred to as ‘cognitive’ tasks) and on interpersonal (sometimes referred to as ‘social’) tasks.[1] Public discourse on graduate employability has emphasised the value of interpersonal skills for some time. The ability to work in teams, problem-solving, and verbal communication skills with people inside and outside the organisation top the list of the “10 skills employers most want in graduates” according to Forbes (2014). The same set of core

[1] Both job task domains are considered ‘bottlenecks’ for job automation (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018).

competencies is frequently referenced in research on graduate employability (Osmani *et al.*, 2015). Interpersonal competencies are found to be essential for graduate employment across different countries (Andrews and Higson, 2008; Tymon, 2013; Humburg and van der Velden, 2015) and a wide range of professions such as engineering (Riemer, 2007; Passow, 2012), computer science (Polack-Wahl, 2000), public health (Biesma *et al.*, 2007), or accountancy (Gray, 2010). Yet there is a paucity of evidence on how the value of problem-solving and interpersonal skills has changed within the graduate workforce in more recent years.

An exception is Green (2012) who examines for Britain the changing use of cognitive and interpersonal job tasks over the period 1997-2006. He finds that problem-solving and interpersonal task use expanded and that their intensities increased with employee involvement and computer use. He shows that the rising intensity of cognitive and interpersonal job tasks can explain the expansion of graduate jobs over the study period.

Here, what we present is a comprehensive pan-European study, covering the experiences of graduates in 25 countries. Based on wages, task and employment data drawn from the European Survey of Income and Living Conditions, the European Labour Force Survey and Britain's Skills and Employment Survey, we find that there are large and changing wage differentials among graduates associated with cognitive and interpersonal task use. Strikingly, interpersonal tasks are becoming more important for graduate wages. An increase of interpersonal task intensity by a standard deviation is associated with a 0.4 point higher annual wage growth across the 25 countries. A separate analysis with individual level job data from the UK supports this result. Across Europe, the wages associated with interpersonal tasks widened especially in countries where high-involvement work practices became more widespread, and where further computerisation stalled. Together, these factors account for 42% of the cross-country variation in changes in the 'returns' to interpersonal tasks.

We also find that, as in the US, the graduate job mix in Europe moved away from problem-solving task use in several countries. We find evidence that this change correlates with relatively slow computerisation, but not the spread of high involvement management systems. The separate estimates from the UK confirm this move away from problem-solving job tasks.

The remainder of the paper is organised as follows. Section 2 reviews the international literature on job tasks and graduate labour market trends. Section 3 discusses the data, operational definitions and measurement. The main empirical model and findings are given in section 4, both for all European countries and with an application to Britain. Section 5 concludes.

Background: job tasks and the graduate labour market

To explain the slowdown in the demand for cognitive skills in the United States, two hypotheses have been put forward.

First, it is argued that information and communication technology (ICT) – conceived as a “general-purpose technology” whose diffusion had helped to raise productivity across the economy – has matured, with negative consequences for the demand for skilled labour. Beaudry et al (2016) argue that the US had reached the period of maturation where the productivity gains from ICT were largely exhausted by around 2000. Maintenance of the current stock of operational knowledge implies a lower employment share for cognitive tasks, and less demand for high-skilled labour. The result is a slowdown in productivity growth and a growing fraction of tertiary graduates outside graduate employment.

Second, artificial intelligence (AI) may have begun to automate job tasks that were previously performed by skilled, that is, mostly graduate labour (Brynjolfsson and Mitchell, 2017; Brynjolfsson *et al.*, 2018). Building on the insights of the task-based approach, this new general-purpose technology may automate a range of job tasks whilst introducing new task or complementing human labour in the performance of hard to automate job tasks (Autor, 2015; Acemoglu and Restrepo, 2019; Walport, 2017). The net effect of automation on the demand for skilled labour is *a priori* unclear. Current research generally expects low risks of automatability of graduate jobs (Arntz *et al.*, 2017; Frey and Osborne, 2017; Dengler and Matthes, 2018;

Nedelkoska and Quintini, 2018). Automation is thought likely, not to replace entire graduate occupations but rather to incrementally change the job tasks mix within them. Hard-to-automate tasks – such as those involving interpersonal interaction or autonomous problem-solving – may even gain in importance (Acemoglu and Restrepo 2018; Brynjolfsson and Mitchell, 2017; Frey and Osborne, 2017).

We also draw on recent literature focusing on interpersonal skills. Decentralisation of decision-making processes through high-involvement work practices (for example, in the deployment of semi-autonomous teams, job autonomy, or worker participation) may have increased the need to communicate, cooperate and coordinate between workers through consultation, negotiation, or persuasion (Green, 2012); decentralisation can also partially explain the rising demand for graduate labour (Blundell *et al.*, 2016). The adoption of ICT may have contributed to the wider implementation of high-involvement work practices (Eurofound, 2013; Boxall and Winterton, 2018; Menon *et al.*, 2018). Moreover, customisable and thus non-routine production processes add new tasks around emotional labour, listening, persuading or negotiation in face-to-face interactions with clients or costumers for a larger share of workers (Levy and Murnane, 2004; Hunter et al., 2001; Remus and Levy, 2017). As automation progresses and organisations continue to adopt high-involvement work practices, the job task mix is expected to continue to shift with skilled labour's comparative advantage (Acemoglu and Autor, 2011). As a result, social job tasks are likely to become more important in the labour market, consistent with evidence that, across the whole workforce, employment and pay associated with interpersonal skills has been on the rise in the wider workforce in the US and the UK (Green, 2012; Borghans *et al.*, 2014; Deming, 2017; Deming and Kahn, 2018; Edin *et al.*, 2018). Drawing on these insights, Deming (2017) proposes a general task-based model of team work where workers use social skills to cooperate in the production of tasks. The model predicts that the job task mix will become richer in interpersonal job tasks and that workers' social skills become more valuable in the determination of wages with time. US data on skills and earnings supports both conjectures and suggests a growing complementary between social and cognitive skills, especially among college graduates (Weinberger, 2014).

The pace and timing of these changes are expected to vary across countries. Compared with the US, European countries start with a lower and widely varying pool of graduate labour (OECD, 2019). There are large differences in management style and skills (Bloom, Sadun *et al.*, 2012; Bloom, Genakos, *et al.*, 2012; Bloom, Schweiger, *et al.*, 2012), including in the use of high-involvement management practices (Zoghi and Mohr, 2011; Eurofound, 2013, 2015). Since the mid-1990s Europe's capital intensity started to fall behind the US as ICT investment soared and relative labour costs in Europe decreased (O'Mahony and Timmer, 2009). Differences in labour market institutions such as minimum wages, union coverage, employment protection, or the prevalence of occupational licensing and the importance of the public sector can influence employment growth of different types of jobs and the evolution of the wage structure (Bryson, 2014; Magda *et al.*, 2016; Aaronson and Phelan, 2017; Campos *et al.*, 2017; Koumenta and Pagliero, 2018). Finally, different levels of income and development as well as demographic composition across countries can further affect the relative demand for goods and services (Goos *et al.*, 2014), with implications for the evolution of earnings and high-skill employment. In all, clear differences between the US on one hand and European economies on the other as well as differences within European may alter the incentives to adopt new technologies and shape their consequences on the job mix and wage structure.

In sum, it can be expected that graduates in Europe have an advantage in carrying out cognitive problem-solving and interpersonal tasks, and that graduates' pay differs with the job tasks they perform. With technological and organisational change in the 21st century, it is expected that the value of interpersonal tasks for graduate pay will have risen, and that, if Europe follows the US there will have been a significant change in the job task mix. We expect the changes in graduate wage dispersion and the employment structure to covary across countries with the diffusion of high-involvement working practices and further computerisation.

Data

Earnings

To examine graduate wage trends, this paper uses individual earnings data from the European Survey of Income and Living Conditions (EU-SILC) for up to 13 consecutive years from 2004 to 2016 for 25 European countries. EU-SILC is a programme of output-harmonised nationally representative surveys of the adult population on topics such as income, social inclusion, living conditions, employment and health. Data collection started in 2003 in Austria, Belgium, Denmark, Greece, Ireland and Luxembourg. We restrict the sample to countries that were member states of the EU (minus Latvia and Malta) by 2004 plus Norway and Switzerland. By 2008 all 25 countries in our sample contributed data to EU-SILC. We limit the analysis to workers aged 25-59 with completed tertiary education, who were in work for at least a full-time equivalent month in the year preceding the survey interview. For the analysis, we use full-time equivalent gross monthly labour income which was derived from data on annual labour income and information on the employment history for the year before the interview. Derived monthly values were then deflated using the national consumer price index and converted into purchasing power adjusted Euro. Although the earnings measure is based on income rather than wages, the distribution is largely consistent with wage data from the Structure of Earnings Survey (Fernández-Macías *et al.*, 2017). The same outcome has been in deployed in a study of wage inequality within and between occupations in Europe (Fernández-Macías and Arranz-Muñoz, 2019). We removed graduates who worked in agriculture or in the armed forces and those who had negative or zero labour income. Our sample for analysis, then, comprises over 545,000 observations from the following countries: Austria, Belgium, Cyprus, Czech Republic, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Sweden, Slovenia, Slovakia, and the United Kingdom.

The public-use file of EU-SILC classifies jobs to 2-digit occupation codes based on the International Standard Classification of Occupations (ISCO). Until 2010 occupations were coded to the ISCO-88 classification; from 2011 it used ISCO-08.[2] The occupation codes reduced to the first digit from 2013 in the Slovenian sample and from 2014 in the German sample. Because our job task variables are defined at the 2-digit occupation level, we limit the sample from these two countries to years with sufficiently detailed occupation codes. EU-SILC also includes broad industry categories based on aggregated one-digit industry codes from the Classification of Economic Activities in the European Community (NACE). Until 2007, industry information was coded to NACE revision 1. Starting in 2008, countries switched to report industry codes based on NACE revision 2. For the analysis, we collapsed the categories into five consistent groups: 'Mining, Manufacturing, Construction', 'Wholesale, Accommodation', 'Business Services', 'Finance', and 'Public and Other Services'.

To support the analysis, we deploy individual-level data from the British Skills and Employment Survey Series (SES) 2001, 2006, 2012, and 2017. The SES is a series of repeated cross-sections of workers aged 20-60 years and their jobs in Great Britain. The first survey of the series was fielded in 1986. Since 1997, the survey asks respondents, both about their earnings and in detail about the importance of more than 30 job tasks covering cognitive, manual and interpersonal activities. This makes it a worldwide unique individual-level data source that combines consistent, worker-reported job tasks with earnings information over the last two decades. Since 2001, the series has grouped jobs according to the British Standard Classification of Occupation 2000. Fieldwork on the most recent wave of the survey was completed in early 2018. The surveys have been successfully used in previous research to study the value of job tasks for earnings (e.g., Dickerson and Green, 2004; Green, 2012; Green *et al.*, 2016; Williams and Bol, 2018). For more information on the SES series see Felstead et al (2015).

[2] Although considered a minor update, ISCO-08 led to substantial changes in how some workers in non-graduate health and teaching jobs were classified. Because of the relatively coarse occupation codes in the public-use files and varying coding practices across countries, we decided not to attempt to harmonise the occupation codes into a common classification.

Employment

Information on graduate employment, weekly hours worked, and the occupational compositions of the workforce comes from the European Labour Force Survey (EU-LFS). EU-LFS is collected at the national level. It includes a common set of variables across countries such as usual working hours, harmonised classifications and definitions of occupations, industries, and educational attainment. As with the EU-SILC, our analysis sample is again restricted to tertiary graduates in the age bracket 25-59 years who were in employment in the reference week in the set of 25 countries; we exclude members of the armed forces and subsistence farmers from the sample; and the occupation classification switched in 2011 from ISCO-88 to the ISCO-08 standard.

The switch in the occupation classification introduces a break that can make it harder to assess the medium-term changes in the graduate job mix. The British Quarterly Labour Force Survey provides consistent occupation and industry codes over the study period. We use these data to examine the changing job mix among graduates in an uninterrupted panel in a robustness analysis.

Job tasks

To measure job tasks, the necessary data come from SES in 2012 and 2017, which code individual jobs simultaneously to the ISCO-88 and ISCO-08 nomenclature. In the task literature, country-specific sources are sometimes deployed to proxy job task intensity elsewhere. For example, Goos et al (2014) use US-American O*NET data to study job polarisation in Europe. The advantages over O*NET are threefold: the job task data is reported by workers in a European country; we can map the task information without crosswalks into the occupation nomenclature in European data; and we can switch between job and occupation-level analysis when appropriate.

To quantify *problem-solving job tasks*, we borrow from work by Eurofound (2016) and Fernández-Macías and Hurley (2017). The index of *problem-solving* tasks is the mean over worker-reported information on the importance of thinking of solutions to problems, analysing complex problems in depth, and working out cause of problems, as well as the need to learn new things, the level of job variety, the lack of short, repetitive tasks, and the degree of choice over the way in which to do the job.

Responses are scaled to the bracket (0,1). Cronbach's alpha of the resulting scale is 0.77, which is acceptable. For descriptive purposes we define "problem-solving rich" occupations to be those in the top 20% of occupations on the problem-solving index. Examples include: chief executives, science and engineering and information and communications technology professionals.

To measure *interpersonal job tasks*, we combine information on the importance of working with a team, dealing with people, listening carefully to colleagues, making speeches, and persuading others from the British Skills and Employment Surveys. Workers report on the importance of these tasks on a five-point scale ranging from 'essential' (scored 1) to 'not at all important' (scored 0). The responses across the task items are averaged to derive an index of interpersonal task use. Cronbach's alpha is 0.75. The scale is further averaged by two-digit ISCO occupations to obtain the importance of interpersonal tasks by occupations. "Interpersonal task rich" occupations are then defined as the top 20% on the index. Examples include: teaching professions, chief executives and administrative and commercial managers.

The derived job task indices are set to a mean of zero and a standard deviation of one in the pooled dataset of 2-digit ISCO-08 and ISCO-88 occupations. Although conceptually and empirically distinct, there is a clear correlation between the importance of problem-solving and interpersonal job tasks across occupations (r=0.71), which is indicative of task bundling within jobs. An online annex provides further details on the derivation of the work task items and lists the occupation codes and their task intensities.

Findings

Our aim is to document the changing value of problem-solving and interpersonal tasks, both in Europe as a whole and within individual European countries, as well as the changing task composition of graduates' jobs. To what extent are the patterns of change consistent across Europe, and can we account at all for the dissimilarities? Are the changes similar to those found in the US?

To provide the context, we begin by describing the trends in graduate wages and employment across Europe, broken down by problem-solving rich, or interpersonal task rich occupations. We then set out an empirical estimating model drawn from the literature, through which we can estimate trends in the value of problem-solving and interpersonal tasks for graduates, and in their compositions. These key estimates are then presented, followed by a robustness study using individual job-level data in the case of Britain. Finally, in order to help understand the variable pattern of change across European countries, we examine the relationship of the estimated changes in graduates' task values and the task-employment structure with the diffusion of high-involvement working practices and further computerisation.

Description of Graduate Wage and Employment Trends

As could be expected, graduate wages were substantially higher in problem-solving rich and interpersonal task rich occupations. Specifically, in the pooled sample across all years and countries we find that graduates in problem-solving rich or in interpersonal task rich occupations earned on average, respectively, 35% or 22% higher monthly earnings. These are economically substantial differences: for comparison one might note, as an example, that the pay premium of tertiary degrees over upper secondary qualifications in OECD countries is 54% (OECD, 2018). The differences are found consistently across most countries – one exception being the Scandinavian countries, where interpersonal task rich occupations do not command a pay premium.

These task-based wage differentials are matched by similar differences in the deployment of graduate labour. The number of total graduate working hours was substantially higher in problem-solving rich and interpersonal task rich occupations. Across the 25 countries, the number of graduate working hours was almost three times higher in problem-solving rich occupations than in less problem-solving rich occupations. Interpersonal task rich occupations were approximately 75% larger in terms of graduate deployment. In other words, graduate labour is predominantly deployed – as expected – in occupations that require high levels of problem-solving and interpersonal communication.

Next, we present a raw description of how employment in problem-solving rich and in interpersonal rich occupations, and wage differentials by these categories have evolved over the years 2004-2015. Table 1 displays the average annual change in log wages (columns (1) to (3)) and log total graduate working hours (columns (4) to (6)), overall and by job task domains across Europe.

Table 1: Graduate wage and employments trends across occupational' job task profiles, Europe, 2004-2015

	Δ log graduate wages			Δ log graduate hours worked per year		
	(1) Total	(2) Problem-solving rich occupations	(3) Interperson-al rich occupations	(4) Total	(5) Problem-solving rich occupations	(6) Interperson-al rich occupations
Pooled	0.004	0.006	0.006	0.043	0.039	0.023
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)
	-0.000	-0.000	0.002	0.037	0.033	0.012
EU15	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.007)
	0.000	0.004	0.002	0.055	0.055	-0.015
AT	(0.004)	(0.007)	(0.007)	(0.014)	(0.011)	(0.039)
	-0.003	-0.004	-0.002	0.034	0.051	0.042
BE	(0.002)	(0.004)	(0.004)	(0.007)	(0.006)	(0.020)
	0.014	0.017	0.022	0.052	0.063	0.056
CH	(0.007)	(0.009)	(0.009)	(0.008)	(0.020)	(0.034)
	-0.011	-0.008	-0.009	0.049	0.051	0.060
CY	(0.006)	(0.011)	(0.011)	(0.010)	(0.017)	(0.029)
	0.007	0.013	0.008	0.059	0.039	0.033
CZ	(0.005)	(0.007)	(0.011)	(0.008)	(0.012)	(0.018)
	0.002	-0.001	-0.007	0.028	0.028	0.030
DE	(0.006)	(0.008)	(0.013)	(0.011)	(0.019)	(0.010)
	0.011	0.004	0.009	0.005	0.002	-0.011
DK	(0.004)	(0.006)	(0.005)	(0.012)	(0.031)	(0.049)
	0.027	0.022	0.026	0.009	0.006	0.023
EE	(0.007)	(0.010)	(0.009)	(0.010)	(0.018)	(0.026)
	-0.033	-0.043	-0.030	0.018	0.008	-0.033
EL	(0.007)	(0.011)	(0.011)	(0.008)	(0.016)	(0.024)
	0.000	0.004	0.005	0.027	0.034	0.031
ES	(0.006)	(0.006)	(0.007)	(0.006)	(0.010)	(0.020)
FI	0.017	0.021	0.019	0.016	-0.011	-0.011

	(0.003)	(0.006)	(0.006)	(0.007)	(0.014)	(0.025)
	0.002	0.000	0.008	0.042	0.035	-0.017
FR	(0.006)	(0.008)	(0.010)	(0.013)	(0.023)	(0.027)
	-0.019	-0.023	-0.009	0.074	0.051	0.082
HU	(0.006)	(0.007)	(0.007)	(0.011)	(0.013)	(0.034)
	-0.013	-0.011	-0.009	0.044	0.048	0.030
IE	(0.004)	(0.005)	(0.005)	(0.009)	(0.016)	(0.025)
	-0.035	-0.027	-0.035	0.054	0.028	0.017
IT	(0.010)	(0.020)	(0.029)	(0.007)	(0.012)	(0.010)
	0.029	0.042	0.026	0.031	0.070	0.045
LT	(0.007)	(0.013)	(0.009)	(0.018)	(0.031)	(0.082)
	-0.011	-0.018	-0.010	0.042	0.059	-0.004
LU	(0.006)	(0.006)	(0.005)	(0.014)	(0.015)	(0.029)
	-0.009	-0.001	-0.003	0.024	0.021	0.022
NL	(0.004)	(0.008)	(0.007)	(0.009)	(0.014)	(0.021)
	0.013	0.015	0.015	0.030	0.044	-0.002
NO	(0.005)	(0.008)	(0.007)	(0.009)	(0.015)	(0.012)
	0.017	0.021	0.021	0.094	0.059	0.075
PL	(0.004)	(0.008)	(0.007)	(0.008)	(0.009)	(0.013)
	-0.024	-0.027	-0.031	0.074	0.073	0.015
PT	(0.011)	(0.017)	(0.015)	(0.015)	(0.033)	(0.015)
	0.017	0.013	0.019	0.048	0.038	0.021
SE	(0.004)	(0.006)	(0.008)	(0.006)	(0.014)	(0.020)
	-0.038	-0.034	-0.037	0.064	0.035	0.012
SI	(0.005)	(0.009)	(0.007)	(0.010)	(0.010)	(0.020)
	0.041	0.049	0.042	0.063	0.040	0.016
SK	(0.006)	(0.008)	(0.015)	(0.011)	(0.026)	(0.021)
	-0.015	-0.019	-0.019	0.040	0.042	0.034
UK	(0.007)	(0.008)	(0.008)	(0.004)	(0.009)	(0.009)
N	549,297	162,515	241,981	12,159	3176	1814

Columns (1)-(3): average annual difference in log wages by occupations' job task intensities in EU-SILC (N=545,281). Weighted estimates from least square regression of log monthly wages on linear time trend, a dummy variable to indicate the break in ISCO classification and country-specific slopes and intercepts using survey weights (giving each country an equal weight). Estimates for the total graduate workforce (1), graduates in problem-solving rich (top 20% of ISCO occupations on problem-solving score) (2), and interpersonal rich occupations (top 20% of ISCO occupations on interpersonal task score) (3). Columns (5)-(8) show average annual differences in log total graduate working hours from 12,159 year-country-occupation-sector cells derived from EU-LFS (excluding cases from country-occupation-sector cells with less than 75 observations total). Estimates form a least square regression of total working hours on a linear time trend, and a dummy that indicates the break in the ISCO classification, with country-specific slopes and intercepts. Standard errors in parentheses.

As can be seen in column (1), graduate wage growth across all occupations varied substantially across countries. For example, in Italy monthly graduate wages fell by 3.4 percent (exp(-0.035)-1) per year on average in real terms, in the UK real graduate wages dropped by 1.5 percent on average, whereas in Sweden graduate monthly wages rose by 1.7 percent per year. This accumulates. Over a decade, the difference in growth rates between Sweden and the UK implies a widening of the earnings gap between graduates in the two countries by almost 38%. Overall, graduate wages stagnated or fell in 13 of the countries over this period. In the pooled sample for all Europe, average graduate wage growth was glacial at only 0.4 percent per year, with little differences across problem-solving rich, and interpersonal rich occupations.

Unsurprisingly, there is a strong correlation of wage growth in the total graduate workforce with the growth rates for graduates in problem-solving and interpersonal-rich occupation groups. Nonetheless, at country-level, there are some differences between the overall growth rate of wages and the growth rates in specific occupation groups. For example, graduate wages in interpersonal-rich occupations grew faster than the average in almost three quarter of the countries in the sample.

While wage growth was muted, as can be seen from column (5) graduate employment expanded at more than 4 percent per year on average across Europe. At this rate, the stock of graduate labour would double every 16 years. The expansion was particularly fast in Portugal (exp(0.074)-1 ≈ 7.7%) and in Central and Eastern European countries such as Poland (9.9 %), Hungary (7%), and Slovakia (6.5%). Graduate employment tended to expand more rapidly outside problem-solving rich occupations, both overall and in most countries (all but nine), similar to findings by Beaudry et al (2016) for the US. Similarly, graduate employment also tended to grow faster outside of interpersonal task rich occupations.

Empirical Model

Drawing on Altonji et al (2014) and theoretical work by Acemoglu and Autor (2011), Goos et al (2014) and Deming (2017), the basic estimation model to examine trends in wage differentials is specified as follows:

(1) $$lwage_{ijnct} = \beta_{task}\left(task_j \times tt_{ct}\right) + \eta Z_{it} + \delta_{jnc} + \gamma_{cnt} + \varepsilon_i$$

$lwage_i$ is the monthly gross labour income of individual i in occupation j and industry n from country c in year t. The variable $task_j$ represents the intensity of either problem-solving or interpersonal job tasks in occupation j. The variable tt_{ct} is a linear time trend that counts the number of years from the first year of observation in country c up to survey reference year t. The parameter of interest is β_{task}. It summarises the differences in the annual growth rate of wages along the job task intensity scales. A positive coefficient for problem-solving and interpersonal tasks would indicate a further widening of the existing pay differentials within graduates. Since we are interested in how wage differentials change across occupations' task intensities, we include a set of country-industry-occupation fixed effects, δ_{jnc}, which will absorb any cross-sectional differences in graduate wages across occupation-industry-country cells. To accommodate the break in the occupational classification, the model includes occupation dummies for both the old and new ISCO classification. This set of dummies will condition out both time-invariant country-specific influences on graduate wages stemming from, for example, variations in the level of development, labour market institutions or education systems, and pre-existing wage differentials between occupations and industries within countries. Besides time-invariant differences across countries, there may also be variation in national business cycles, productivity growth, or shifts in demand for products and services from specific industries. To capture these country-industry-period effects, the model includes a set of period dummies for each country-industry cell, γ_{cnt}. This separates the changing wage differential across occupations from common trends within countries and industries.

Finally, to account for potentially confounding influences from concurrent changes in the make-up of the graduate workforce, we also condition on individual-level demographic characteristics, Z_{it}. These include age, presence of dependent children in the household, full time equivalent months worked in the last year (<6, 6-11, 12+), migration status, and the interactions of these variables with an indicator variable for gender.

All wage regressions are weighted using the survey weights provided by EU-SILC; rescaled to weight each country equally. Standard errors are clustered at country-industry-occupation level. The key parameter of interest is β_{task}, which indicates whether the value of the tasks among graduates is rising or falling.

To analyse changes in graduate employment, our dependent variable is the log of total graduate hours worked within an occupation-sector-country-year cell. The estimation model is structured in the same way as equation (1):

$$lhours_{jnct} = \beta_{task}\left(task_j \times tt_t\right) + \delta_{jnc} + \gamma_{nct} + \varepsilon_{jct} \tag{2}$$

$lhours_{jnct}$ is the log of total graduate hours worked within occupation j in sector n in country c in year t, δ_{jnc} represent a set of occupation-sector-country fixed effects, and γ_{nct} are sector-country-year dummies.

To estimate equation (2), we collapse the labour force survey data into an unbalanced panel of year-country-sector-occupations cells. Because the occupation classification switches from ISCO-88 to ISCO-08 in 2011, we treat occupations based on the old and new nomenclature separately. We distinguish public sector industries (public administration, health, and education) from other industries. Cells are weighted by their mean employment rate within countries over the years 2004-2015. To reduce noise from poorly measured means, we drop country-sector-occupation cohorts with a total of less than 75 observations from the analysis. This leaves 12,159 observations from 2,084 country-sector-occupation cohorts.

Changing wage differentials by job tasks across Europe

Table 2 reports the estimates for β_{task} from pooled regressions across all 25 countries and across the EU-15, and from separate regressions for each country. Rows (1) and (2) summarise the pooled results across all countries. The first row displays the results from separate regressions for each job task domain, and the second row the results from a combined regression with both job tasks entered. The third and fourth row repeat this for the potentially more homogenous group of countries that formed the EU-15. Rows (5)-(29) summarise country-specific findings from separate regression for each job task domain.

Table 2: Changing graduate wage differentials across European countries, 2004 to 2015. Dependent variable: Log real gross monthly wages (in PPP-EUR)

	Time trend interacted with		
	(1) Problem solving	(2) Interpersonal	N
(1) Pooled (separate)	0.0027**	0.0039***	544,790
	(0.0010)	(0.0010)	
(2) Pooled (combined)	0.0001	0.0039**	544,790
	(0.0013)	(0.0013)	
(3) EU-15 (pooled)	0.0031*	0.0054***	361,041
	(0.0012)	(0.0012)	
(4) EU-15 (combined)	-0.0011	0.0061***	361,041
	(0.0016)	(0.0015)	
(5) AT	0.0137*	0.0124**	14,787
	(0.0058)	(0.0046)	
(6) BE	0.0085**	0.0062*	26,858
	(0.0027)	(0.0024)	
(7) CH	0.0154***	0.0113*	18,683
	(0.0040)	(0.0045)	
(8) CY	0.0047	0.0033	16,692
	(0.0042)	(0.0050)	
(9) CZ	0.0089	0.0099	14,977
	(0.0057)	(0.0059)	
(10) DE	0.0040	0.0092	36,967
	(0.0065)	(0.0049)	
(11) DK	0.0009	-0.0015	14,785
	(0.0032)	(0.0033)	
(12) EE	0.0041	0.0022	17,104
	(0.0037)	(0.0032)	
(13) EL	-0.0057	-0.0036	18,738
	(0.0051)	(0.0067)	
(14) ES	0.0082*	0.0127**	41,923

	(0.0036)	(0.0048)	
(15) FI	0.0040	0.0086*	35,935
	(0.0027)	(0.0035)	
(16) FR	-0.0016	0.0025	34,744
	(0.0032)	(0.0029)	
(17) HU	0.0002	0.0009	19,223
	(0.0059)	(0.0055)	
(18) IE	0.0059	0.0012	16,772
	(0.0034)	(0.0034)	
(19) IT	0.0193***	0.0201**	26,149
	(0.0050)	(0.0063)	
(20) LT	-0.0012	-0.0012	15,937
	(0.0072)	(0.0060)	
(21) LU	-0.0104	0.0027	15,994
	(0.0065)	(0.0067)	
(22) NL	-0.0025	0.0108*	21,976
	(0.0046)	(0.0047)	
(23) NO	-0.0015	0.0024	13,451
	(0.0054)	(0.0056)	
(24) PL	0.0013	-0.0001	31,823
	(0.0043)	(0.0045)	
(25) PT	0.0025	0.0067	9,390
	(0.0115)	(0.0123)	
(26) SE	-0.0097**	-0.0068	14,075
	(0.0037)	(0.0043)	
(27) SI	0.0050	-0.0018	19,795
	(0.0048)	(0.0048)	
(28) SK	-0.0052	-0.0018	16,064
	(0.0042)	(0.0041)	
(29) UK	0.0072*	0.0073*	31,948
	(0.0032)	(0.0030)	

Weighted least square regressions in a sample of 25-59 year-old tertiary graduates across 25 European countries over the years 2004 to 2016 of log real gross monthly earnings on a time trend interacted with job task scales, (country-)occupation-industry fixed effects, industry-year dummies and individual level control variables. Controls includes age, dependent children in the household, full time equivalent months worked in the last year (<6, 6-11, 12+), migration status, and the interactions of these variables with an indicator variable for gender and its main effect. Row (1) reports results from separate regressions for each job task domain pooled across all countries. Row (2) displays results from a pooled regression of all job task jointly. Rows (3) and (4) replicate this for the former EU-15 countries. Rows (5)-(29) summarise results from country-specific regressions for each job task domain separately. Weights from EU-SILC (each country weighted equally in pooled analyses). Standard errors are reported in parentheses. * p < .05, ** p < .01, *** p < .001

The pooled estimates indicate that wage differentials widened along job task domains. For problem-solving tasks, the coefficient of beta in the first cell of the first row, 0.0027 with a standard error of 0.001, implies that graduate wages grew 0.27 percentage points faster per year with each standard deviation more in occupations' problem-solving task intensity. Likewise, for interpersonal task use, wage differential between occupations with a standard deviation difference in the interpersonal task scale widened by 0.39 points. Over a ten-year period, this amounts to widening wage differentials of roughly three to four percent along either of these job task domains.

However, when both work tasks are included in a combined model, interpersonal tasks 'soak up' the effect of problem-solving tasks (row 2). In these specifications, there is no evidence that wage growth differed by problem-solving tasks. But the growth rate differential according to interpersonal tasks remained at 0.39 percentage points per year.

For the countries of the former EU-15, the overall pattern is similar but stronger in magnitude. Interpersonal job tasks emerge as a clear differentiator for graduate wage. A standard deviation higher intensity of interpersonal job tasks across occupations is associated with a 0.6 percentage point higher annual growth rate of wages in the combined model. In sum, the estimates indicate that graduate wage differentials have widened across Europe along job task domains, with the trend driven mainly by a rising wage premium associated with interpersonal job tasks.

The trajectories vary across countries (rows 5-29). There were significant (p<=0.1) changes in wage differentials along either job task domain in 12 countries. Based on the point estimates, wage growth rose with the importance of interpersonal job task in 18 of the 25 countries, in 10 countries these changes reaching levels of statistical significance (p<=.1). There is no country in the dataset where graduate wages grew significantly faster in occupations with a lower importance of interpersonal tasks.

Thus, there is some indication that the rising value of interpersonal tasks among graduates is not a localised effect but a potentially wider phenomena consistent with common cross-country antecedents.

Finally, so far both males and females are included in our sample. In order to check whether there are gender differences we split the sample by male/female and found that the overall pattern of change varies little by gender. These separate analyses can be found in the online appendix.

Employment patterns and the job task mix

The previous findings indicate that in some but not all countries wage differentials widened in a way that is consistent with the rising importance of interpersonal-tasks. We now use the data on hours worked from the EU-LFS over the period 2004-2015 to examine how the job task composition in the graduate workforce has changed. We restrict the analytical sample again to 25-59-year-old tertiary graduates from across the same set of 25 European countries as above. Beaudry et al (2016) document a move out of cognitive jobs among US college graduates after 2000. We assess how far there was a similar trend across Europe; if at all. Table 3 reports the estimates of β_{task} for equation (2):

Table 3: Change in graduate labour demand across job tasks domains from 2004 to 2015 - Dependent Variable: Log (hours worked/1,000)

	Time trend interacted with		
	(1) Problem solving	(2) Interpersonal	N
(1) Pooled (separate)	-0.011*** (0.002)	-0.007* (0.003)	12,159
(2) Pooled (combined)	-0.011*** (0.003)	0.001 (0.004)	12,159
(3) EU-15 (separate)	-0.012*** (0.003)	-0.009** (0.003)	7,651
(4) EU-15 (combined)	-0.011** (0.004)	-0.002 (0.004)	7,651
(5) AT	-0.025# (0.015)	-0.025 (0.017)	553

(6) BE	0.000	-0.001	534
	(0.008)	(0.008)	
(7) CH	-0.011	-0.005	504
	(0.009)	(0.010)	
(8) CY	-0.011	0.012	425
	(0.014)	(0.016)	
(9) CZ	-0.009	-0.011	405
	(0.010)	(0.011)	
(10) DE	-0.008	-0.007	548
	(0.008)	(0.009)	
(11) DK	-0.014	0.005	507
	(0.014)	(0.021)	
(12) EE	-0.002	-0.000	407
	(0.013)	(0.014)	
(13) EL	-0.021*	-0.012	529
	(0.010)	(0.012)	
(14) ES	-0.001	0.001	575
	(0.005)	(0.006)	
(15) FI	-0.013$^{\#}$	-0.019*	430
	(0.007)	(0.008)	
(16) FR	-0.003	-0.021	524
	(0.019)	(0.016)	
(17) HU	-0.010	0.005	512
	(0.013)	(0.014)	
(18) IE	-0.005	0.000	595
	(0.012)	(0.013)	
(19) IT	-0.031***	-0.021**	553
	(0.008)	(0.007)	
(20) LT	0.017	0.030	485
	(0.016)	(0.023)	
(21) LU	0.024	-0.008	243
	(0.023)	(0.026)	
(22) NL	-0.009	0.004	504
	(0.014)	(0.013)	
(23) NO	-0.001	-0.002	397
	(0.011)	(0.012)	
(24) PL	-0.010	-0.022**	539
	(0.010)	(0.008)	
(25) PT	-0.034$^{\#}$	-0.034$^{\#}$	435
	(0.017)	(0.019)	

(26) SE	-0.010	-0.009	563
	(0.007)	(0.009)	
(27) SI	-0.048***	-0.051***	392
	(0.012)	(0.013)	
(28) SK	-0.024	-0.010	442
	(0.018)	(0.017)	
(29) UK	-0.010*	-0.001	558
	(0.005)	(0.005)	

Fixed effects panel estimates of log total hours worked in the graduate workforce aged 25-59 years across 25 European countries in occupation-industry-country-year pseudo panel from EU-LFS 2004-2015. All regressions include (country-)sector-occupation fixed effects and a set of (country-)sector-period dummies. Row (1) reports results from separate regressions for each job task domain pooled across all countries. Row (2) displays results from a pooled regression of all job task jointly. Rows (1) and (2) replicate this for the former EU-15 countries. Rows (5)-(29) summarise results from country-specific regressions for each job task domain separately. Autocorrelation and heteroscedasticity robust standard errors in parentheses * $p < .05$, ** $p < .01$, *** $p < .001$

The results contrast with the estimated trends for the wage differentials in Table 2. The findings in Table 3 indicate that graduate employment expanded relatively faster in occupations with lower intensities of problem-solving tasks or interpersonal job tasks. The coefficient for problem-solving intensity is negative and remains economically and statistically significant even after conditioning on the interpersonal task use (row 2). Occupations that were a standard deviation more intensive in problem-solving tasks grew 1.1 percent less fast each year, according to the estimated coefficient from the combined model. Over a decade, this amounts to widening gap in graduate labour deployment between occupations of close to 12 percent. On its own, interpersonal task usage is negatively associated with changes in the employment rate (row 1), but this may be because of its relationship with problem-solving tasks. In the combined model, its coefficient is small and statistically insignificant (row 2). Separate results for the EU15 confirm the relative decline of graduate employment in occupations that were richer in problem-solving tasks (rows 3 and 4).

Across countries there is, again, some heterogeneity. Statistically significant changes in the job mix of graduates occurred in only 8 out of the 25 countries.

Nonetheless, in all but two countries the point estimate for problem-solving tasks is negative.

The results indicate a weakness in the demand for cognitive skills. If graduates have a productivity advantage in problem-solving and interpersonal task use, the estimates in Table 3 suggest that the demand for skilled labour has not kept pace with the growing supply of tertiary graduates. The negative time trends are similar across gender (for estimates, see the online appendix). In all, the results confirm that as in North America, the share of graduate labour deployed in cognitive tasks such as problem-solving dropped in many European countries.

Case study: Great Britain

One of the limitations of the above analyses is that fixed job task averages at 2-digit occupation level are only an approximation of the kind of jobs people do (Autor, 2013). The approach ignores heterogeneity of job task profiles within occupations. It also ignores differences in job tasks for similar occupations across countries and over time. This limitation is compounded by the switch in the occupational classification from ISCO-88 to ISCO-08 and changes in national occupational classification frameworks which map into the international classification. Such issues are not unusual when analysing change across Europe, with imperfectly harmonised data. Furthermore, if wage inequality and employment changed predominantly within occupations our analysis will have picked up only a fraction of the full dynamic (Fernández-Macías and Arranz-Muñoz, 2019).

One way to test the robustness of our findings surrounding graduate pay and task utilisation across Europe is to attempt to confirm them in the case of a country where high quality data sources are available, in this case, Britain. First, the British SES series permits us to examine the evolution of wage differentials by job tasks at the level of individual jobs rather than occupations and to assess the interplay of changing task returns with workers' job selection based on richer information on individual skill. Second, the British Quarterly Labour Force Survey provides consistent occupation and industry codes which we can use to study the changing job mix among graduates in an uninterrupted occupation-sector panel over the years

2001-2017 at lower levels of disaggregation. We combine data from quarters two, three and four for each year.

As in many other advanced countries, the British graduate labour market has for the last two decades seen a rapid inflow of tertiary-educated students. The major surge in tertiary enrolment began at the end of the 1980s. By 2016, more than 42% of the 25-64-year-olds in the UK held a tertiary-level qualification, up 20 points compared with the situation 20 years earlier. Across all the EU-15 countries, tertiary attainment in this age group rose by 14 points in the same period. However, compared with other countries, the skills advantages of tertiary graduates aged 25-34 years over similar aged adults with upper-secondary qualification is relatively modest in Britain, according to the OECD's Survey of Adult Skills (Henseke and Green, 2017). Meanwhile Britain has had relatively flexible employment relations including low levels of employment protection, declining union coverage, and a national minimum wage. The share of government employment in the UK fell from close to 20% to 15% since 2000, which was one of the largest drops in public sector employment over this period in Western Europe (Eurostat, 2019). While other countries increased labour flexibility, Britain largely maintained its already very flexible setup (Turrini *et al.*, 2015).

Task wage differentials at the level of jobs

We begin by providing estimates of the changing wage differential by job task domains using job-level data from the Skills and Employment Series based on equation (1). The results are displayed in Table 4. Interpersonal tasks emerge again as the key task domain along which graduate wages have differentiated. A standard deviation increase of interpersonal task importance across jobs was associated with a 0.073 log point faster annual growth of graduate earnings in the combined model within narrowly defined sector-occupation cells (column 2).

Problem-solving tasks are individually associated with changing wage differentials, but their effects on wage are absorbed by interpersonal job tasks in the combined regression models as in the data above, where job task were measured at the level of 2-digit occupations.

Table 4: Changing wage differentials by job tasks in Britain, 2001-2017 (Dependent variable: log real gross hourly wages)

Time trend interacted with:	(1) Separately	(2) Combined	(3) Combined - complementarity	(4) Combined – Skills Heterogeneity
Problem-solving	0.0042***	0.0014	0.0009	0.0020
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Interpersonal	0.0078***	0.0073***	0.0066***	0.0070***
	(0.0019)	(0.0020)	(0.0018)	(0.0020)
(Interpersonal X Problem-solving)			0.0028*	
			(0.0011)	
Occupation X Industry	X	X	X	X
Industry X Period	X	X	X	X
Skills heterogeneity (school type, highest math qualification, highest level of tertiary attainment)				X
N	4,975	4,975	4,975	4,975

Weighted least squares regression of real gross hourly wages (in PPP-EUR) from a sample of 25-59 year old employed tertiary graduates outside the primary sector in Great Britain over the years 2001, 2006, 2012 and 2017 using survey weights. All models include age in 5-year bands, ethnicity, dependent children present, and UK region, and their respective interaction with a dummy for female cases. The models include dummies for 193 occupation-sector cells (105 occupations in 0/1 public sector industries, some combinations are missing). Robust standard errors clustered at industry-occupation cells in parentheses * $p < .05$, ** $p < .01$, *** $p < .001$

Source: *Skills and Employment Surveys, 2001, 2006, 2012, 2017*

Next, we aim to better understand whether the rising wage differential associated with interpersonal tasks reflects an overall rising ‘return’ to interpersonal job tasks among graduates and/ or emerging complementarities within job task bundles. The literature suggest that there are increasing complementarities between interpersonal tasks and the importance of computer-use on the job (Green *et al.*, 2016) as well as between cognitive and social individual skills (Weinberger, 2014; Deming, 2017). For this, we add interaction terms for interpersonal tasks with problem-solving tasks and task automatability and their respective time trends to the combined model. The findings in column (3) confirm that the rising value of interpersonal tasks for graduate wages accelerated with the intensity of problem-solving tasks. For example, in jobs with both high levels of interpersonal tasks (interpersonal task scale =1) and problem-solving tasks (problem-solving task scale =1) hourly wages grew on average by around a percent per year, whereas in jobs that were rich in interpersonal tasks (interpersonal task scale =1) but made average use of problem-solving tasks (problem-solving task scale =0) graduate hourly wages grew by 0.65% per year on average. Nonetheless, this does only little to reduce the estimated relative wage growth associated with interpersonal job task use alone.

To disentangle whether the rising wage differential associated with interpersonal job tasks is merely reflecting a changing composition of the graduate workforce (e.g. a growing number of postgraduates, decline of high-level professional qualification), we add in column (4) variables that measure the highest level of qualification in mathematics (degree, A-level, GCSE A*-C, GCSE G-D or below, other), school type (state-comprehensive, state-selective, private, other) and qualification level (undergraduate, postgraduate, professional, other) interacted with a linear time trend to the regression model. For simplicity we refer to these variables as skills. Although skills are associated with wages in both the cross-section (F=11.1, p=0.000) and over time (F=11.0, p=0.000) over and above the occupation-industry fixed effects and industry-period effects, their inclusion does not affect the estimated trend associated with interpersonal task use.

In all, the British job-level data show that even when task use is measured at more granular level and shifts in the skills composition of the graduate workforce are accounted for, the widening wage differential associated with interpersonal tasks remains strongly significant. The magnitude of the estimated wage growth associated with interpersonal job tasks in SES is within the ballpark of the above estimate based on EU-SILC with occupational-level task data (see Table 2, row 29).

Job task mix in the graduate workforce

Next, we explore shifts in job task mix among graduates between 2001 and 2017 in Britain. As with the EU-LFS above, the worker-level information is collapsed into an occupation-sector-year panel. The estimates of equation (2) are summarised in Table 5.

Table 5: Changing job mix among graduates in Britain, 2001-2017. Dependent Variable: log (Total hours worked/1,000)

Time trend interacted with:	(1) individual	(2) combined
Problem-solving	-0.010***	-0.012***
	(0.0025)	(0.0032)
Interpersonal	-0.006*	0.003
	(0.0028)	(0.0036)
N	5,959	5,959
N (groups)	353	353

Fixed effects panel estimates of log total hours worked in the graduate workforce aged 25-59 years in Britain. All regressions include 353 industry-occupation fixed effects (105 occupations, and 4 industry broad industry groups) and year-industry fixed effects. Industries are grouped into a sector that combines manufacturing, mining, utilities and construction, a combined sector for wholesale, accommodation, transport, communication, and other community services, a sector comprising of financial industry, business services, and real estate, and the public sector that combines public administration, education and health services. Clustered standard errors in parentheses * $p < .05$, ** $p < .01$, *** $p < .001$

Source: *UK QLFS, 2001-2017*

The findings in column (1) confirm the move out of problem-solving rich and interpersonal occupations. The magnitude of the estimated effects is substantial. For example, a standard deviation higher importance of problem-solving tasks is associated with a point slower growth of graduate work hours per year. The estimated change associated with the problem-solving domains remains highly statistically significant in a combined model (column 2 of Table 5). This confirms the findings for Britain in Table 3.

In all, at least for the British example we find no contradiction between the findings from European data and those from a high-quality national data source with individual job level information, despite some limitations of the European wide harmonised sources.

The contribution of technological and organisational change

So far, the analysis has focused on common trends across European countries. But is it possible to account for some of the cross-country variations in the evolution of graduate pay differentials and of the job task mix, within the bounds of what is measurable consistently?

The heterogeneous speed with which management practices and computerisation change across Europe are two candidates. Thus, Deming (2017) argues that the rising importance of interpersonal tasks in the workforce results from greater decentralising of decision-making, more team work and greater coordination requirements; similarly Blundell et al (2016) propose that an IT-enabled switch to more decentralised decision making within organisations contributed to the rising demand for graduates in the UK.

We obtain measures of computerisation and high-involvement work practices at country-level from the European Working Conditions Survey (EWCS). EWCS is a survey of workers, covering all EU and associated countries. Alongside information about job quality, psychosocial stressors and wellbeing, EWCS collects data on the frequency of working with computers, laptop and other handheld devices. To measure high-involvement work practices, we focus on three sub-domains: organisational involvement, task discretion, and working in (semi-)autonomous teams. Organisational involvement combines information on whether workers are consulted over work targets, whether they can influence decisions made that are important for their work, whether they can apply their own ideas, whether they have some say over who they work with, and whether there are regular management meetings where employees can express their views. Task discretion is measured by workers' perceived influence over the order, methods and speed of doing their tasks. To measure semi-autonomous teams, respondents are asked how frequently they work in teams and how much influence the team has over the division of tasks, the team leader and work schedule (Gallie *et al.*, 2012). Each item is recoded to range from zero to one, where one indicates higher involvement. The recoded items are averaged within each of the three sub-domains. Finally, to derive an overall index of high involvement working, we take the average over the three sub-domains.

Changes in computerisation or high involvement work practices can occur through technological changes or from changes in the industrial composition. We perform a simple regression-based decomposition that splits the within country change in computerisation and high involvement working practices between the EWCS waves 2005 and 2015 into a compositional component, that stems from changes related to industry, occupation, workplace size, and sector composition, and a residual component. We use changes of the residual component at the country level between 2005 and 2015 as measures of technological and organisational change, consistent with the idea that either can be conceived as a General Purpose Technology (Beaudry *et al.*, 2016; Bloom *et al.*, 2016). The resulting measures are z-standardised in the sample of 25 countries. Based on these measures, technological change was fastest in Cyprus, Norway and Estonia over the period 2005-2015 while organisational change was fastest in Italy, Spain and Germany. In the UK, both computerisation and high-involvement practices expanded faster than average in international comparison.

We correlate our measures of technological and organisational change with country-specific changes in wage differentials and employment trends (Tables 2 and 3). Overall, there is a weak negative cross-countries association between the change in the wage differentials and employment change (r=-0.212).

Table 6 shows the results from cross-country least square regressions of the changing wage differential (panel a) and employment trends (panel b) on computerisation and the spread of high-involvement management. The table reveals that the rise in the value of interpersonal tasks was greatest in countries where there was the fastest introduction of high-involvement practices. The rise was also slowest where computerisation has risen the most. The rise in the importance of problem-solving skills reported above, however, was fastest (as expected) in countries with the most rapid expansion of computerisation. In robustness analysis we included the percentage change of graduates in the employed workforce. We also re-estimated the regression models with the observed instead of the residual changes in computerisation and high-involvement work practices. Neither changes the substantive findings.

While these simple findings on conditional correlations are, of course, not estimating structural relationships, we take them as suggestive evidence that the differential paces of technological and organisational change across countries are associated with the heterogeneous ways in which graduates' labour market experiences are changing.

Table 6: The association of computerisation and high-involvement work practices for changing job task 'returns' and job task mix across Europe (N=25), 2004-2015.

	(1) Problem-solving	(2) Interpersonal
	(a) Changing Wage Differentials	
Δ Computerisation	-0.036	-0.055**
(z-score)	(0.025)	(0.019)
Δ High involvement	0.069*	0.076**
(z-score)	(0.032)	(0.024)
Constant	0.003*	0.005***
	(0.001)	(0.001)
R^2	0.210	0.419
	(b) Changing Job Mix	
Δ Computerisation	0.122*	0.163**
(z-score)	(0.053)	(0.053)
Δ High involvement	-0.014	-0.037
(z-score)	(0.066)	(0.066)
Constant	-0.011***	-0.008**
	(0.003)	(0.003)
R^2	0.192	0.298

Least square estimation of the wage and employment trend coefficients on changes in computer-usage and high-involvement management at country level. Standard errors in parentheses. # $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

Conclusions

With rising participation since at least the 1990s in tertiary education, graduates in the 21st century have become a central but increasingly diverse group within the labour market. This study has provided a comprehensive assessment of graduate labour market trends across 25 European countries over the period 2004 to 2015. The main limitation of our study is that, in the absence of comparable European-wide task data, we have had to construct task indices on the assumption that occupations have similar task profiles across countries. While our approach is similar to that followed by others, the availability of task data for all countries would be of benefit for studies such as this.

We find, consistent with many studies of the whole labour force, that job tasks are important determinants of wages among European graduates. In particular, there are large and robust positive wage 'returns' for graduates associated with problem-solving and interpersonal task use in Europe. Second, we can report for the first time that interpersonal tasks are becoming more important for graduate earnings in most countries. Across the 25 countries taken together, an increase of interpersonal task intensity by a standard deviation is associated with a 0.4 percentage point higher annual wage growth across the 25 countries. The value associated with interpersonal tasks grew even faster in the countries of the former EU-15.

Third, the graduate job task mix has moved away from problem-solving tasks in all but two countries in the sample. Our fourth finding comes from separate analysis using the high-quality, individual-level British data for the years 2001-2017: this analysis confirms the rising importance of interpersonal task use for graduate pay and the move away from problem-solving rich jobs.

These conclusions – both the rising wage differential associated with interpersonal job tasks and the movement out of problem-solving rich occupations – reveal a transformation of European graduate labour markets that is strikingly similar to the evidence from the United States. Nevertheless, the trends in the mean levels of graduate pay and employment have differed markedly between European countries; and the trends in dispersion within these countries' graduate labour forces have also varied. Our final finding, using the task-based lens, is that differences in technological change and in management practices appear to matter. Task wage differentials widened more in countries where further computerisation stalled, and where high-involvement work practices became more widespread; while graduate employment in problem-solving and interpersonal task intensive occupations rose more in those countries where computerisation rose the most. We consider these last findings to be suggestive pointers for further research that could be based on new data and a structural model of the institutional differences between nations. The relevance of this current study and such a future line of research for education and labour market policy lies in the evident importance of demand-side changes for the distribution of the returns to tertiary education (and the associated financial risks for individuals).

References

Aaronson, D. and Phelan, B. J. (2017) 'Wage Shocks and the Technological Substitution of Low-wage Jobs', *Economic Journal*, 129(May 2016), pp. 1–34. doi: 10.1111/ecoj.12529.

Acemoglu, D. and Autor, D. (2011) *Skills, tasks and technologies: Implications for employment and earnings*, *Handbook of Labor Economics*. Elsevier B.V. doi: 10.1016/S0169-7218(11)02410-5.

Acemoglu, D. and Restrepo, P. (2018) 'Low-Skill and High-Skill Automation', *Journal of Human Capital*, 12(2), pp. 204–232. Available at: https://economics.mit.edu/files/15118.

Acemoglu, D. and Restrepo, P. (2019) 'The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand', *NBER Working Paper*, (25682). Available at: http://www.nber.org/papers/w25682.

Adams, S. (2014) 'The 10 Skills Employers Most Want In 20-Something Employees', *Forbes*, 12 November, pp. 10–12. Available at: http://www.forbes.com/sites/susanadams/2013/10/11/the-10-skills-employers-most-want-in-20-something-employees/%5Cnhttp://www.forbes.com/sites/susanadams/2014/11/12/the-10-skills-employers-most-want-in-2015-graduates/.

Almeida, A. *et al.* (2017) 'Returns to Postgraduate Education in Portugal: Holding on to a Higher Ground?', (10676), pp. 1–45.

Altonji, J. G., Kahn, L. B. and Speer, J. D. (2014) 'Trends in Earnings Differentials across College Majors and the Changing Task Composition of Jobs', *American Economic Review*, 104(5), pp. 387–393. doi: 10.1257/aer.104.5.387.

Andrews, J. and Higson, H. (2008) 'Graduate employability, "soft skills" versus "hard" business knowledge: A european study', *Higher Education in Europe*, 33(4), pp.

411–422. doi: 10.1080/03797720802522627.

Arntz, M., Gregory, T. and Zierahn, U. (2017) ‘Revisiting the risk of automation’, *Economics Letters*, 159, pp. 157–160. doi: 10.1016/j.econlet.2017.07.001.

Autor, D. H. (2013) ‘The “task approach” to labor markets: an overview’, *Journal for Labour Market Research*, 46(3), pp. 185–199. doi: 10.1007/s12651-013-0128-z.

Autor, D. H. (2015) ‘Why Are There Still So Many Jobs? The History and Future of Workplace Automation’, *Journal of Economic Perspectives*, 29(3), pp. 3–30. doi: 10.1257/jep.29.3.3.

Autor, D. H., Levy, F. and Murnane, R. J. (2003) ‘The Skill Content of Recent Technological Change: An Empirical Exploration’, *The Quarterly Journal of Economics*. Narnia, 118(4), pp. 1279–1333. doi: 10.1162/003355303322552801.

Beaudry, P., Green, D. A. and Sand, B. M. (2014) ‘The declining fortunes of the young since 2000’, *American Economic Review*, 104(5), pp. 381–386. doi: 10.1257/aer.104.5.381.

Beaudry, P., Green, D. A. and Sand, B. M. (2016) ‘The Great Reversal in the Demand for Skill and Cognitive Tasks’, *Journal of Labor Economics*, 34(S1), pp. S199–S247. doi: 10.1086/682347.

Biesma, R. G. *et al.* (2007) ‘Using conjoint analysis to estimate employers preferences for key competencies of master level Dutch graduates entering the public health field’, *Economics of Education Review*, 26(3), pp. 375–386. doi: 10.1016/j.econedurev.2006.01.004.

Bloom, N., Genakos, C., *et al.* (2012) ‘Management Practices Across Firms and Countries’, *Academy of Management Perspectives*. Academy of Management Briarcliff Manor, NY , 26(1), pp. 12–33. doi: 10.5465/amp.2011.0077.

Bloom, N., Sadun, R. and Van Reenen, J. (2012) ‘Americans Do IT Better: US

Multinationals and the Productivity Miracle', *American Economic Review*, 102(1), pp. 167–201.

Bloom, N., Sadun, R. and Reenen, J. Van (2016) 'Management as a Technology?', *NBER Working Paper*, (22327). Available at: http://www.nber.org/papers/w22327.

Bloom, N., Schweiger, H. and Van Reenen, J. (2012) 'The Land that Lean Manufacturing Forgot?', *Economics of Transition and Institutional Change*, 20(4), pp. 593–635. doi: 10.1111/j.1468-0351.2012.00444.x.

Blundell, R., Green, D. A. and Jin, W. (2016) 'The UK Wage Premium Puzzle: How did a Large Increase in University Graduates Leave the Education Premium Unchanged?', *IFS Working paper*, 16(1). doi: 10.1920/wp.ifs.2016.1601.

Borghans, L., Weel, B. Ter and Weinberg, B. A. (2014) 'People skills and the labor-market outcomes of underrepresented groups', *ILR Review*, 67(2), pp. 287–334. doi: 10.1177/001979391406700202.

Boxall, P. and Winterton, J. (2018) 'Which conditions foster high-involvement work processes? A synthesis of the literature and agenda for research', *Economic and Industrial Democracy*, 39(1), pp. 27–47. doi: 10.1177/0143831X15599584.

Brynjolfsson, E. and Mitchell, T. (2017) 'What can machine learning do? Workforce implications', *Science*, 358(6370), pp. 1530–1534. doi: 10.1126/science.aap8062.

Brynjolfsson, E., Mitchell, T. and Rock, D. (2018) 'What Can Machines Learn and What Does It Mean for Occupations and the Economy?', *43 AEA Papers and Proceedings*, 108, pp. 43–47. doi: 10.1257/pandp.20181019.

Bryson, A. (2014) 'Union wage effects', *IZA World of Labor*, (July), pp. 1–10. doi: 10.15185/izawol.35.

Campos, M. M. *et al.* (2017) 'Understanding the public sector pay gap', *IZA Journal of Labor Policy*. IZA Journal of Labor Policy, 6(1). doi: 10.1186/s40173-017-0086-0.

Castex, G. and Dechter, E. (2014) ‘The Changing Roles of Education and Ability in Wage Determination’, *Journal of Labor Economics,* 32(4), pp. 685–710. doi: 10.2139/ssrn.2169122.

Deming, D. J. (2017) ‘The growing importance of social skills in the labor market’, *Quarterly Journal of Economics*. Oxford University Press, 132(4), pp. 1593–1640. doi: 10.1093/qje/qjx022.

Deming, D. and Kahn, L. B. (2018) ‘Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals’, *Journal of Labor Economics*, 36(S1), pp. S337–S369. doi: 10.1086/694106.

Dengler, K. and Matthes, B. (2018) *Substituierbarkeitspotenziale von Berufen: Wenige Berufsbilder halten mit der Digitalisierung Schritt*. Available at: http://job-futuromat.iab.de (Accessed: 2 August 2018).

Dickerson, A. and Green, F. (2004) ‘The growth and valuation of computing and other generic skills’, *Oxford Economic Papers*, 56(3), pp. 371–406. doi: 10.1093/oep/gpf049.

Edin, P.-A. *et al.* (2018) *The Rising Return to Non-cognitive Skills*. Available at: www.iza.org.

Eurofound (2013) *Work organisation and employee involvement in Europe*, *Luxembourg*. Luxembourg. doi: 10.2806/35945.

Eurofound (2015) *Workplace practices – Patterns, performance and well-being (3rd European Company Survey)*. doi: 10.2806/85175.

Eurofound (2016) *What do Europeans do at work? A task-based analysis: European Jobs Monitor 2016*. Luxembourg. doi: 10.2806/12545.

Eurostat (2019) *The European economy since the start of the millennium — a* *statistical portrait*. doi: 10.2785/56093.

Felstead, A., Gallie, D. and Green, F. (eds) (2015) *Unequal Britain at Work*. Oxford: Oxford University Press.

Fernández-Macías, E. and Arranz-Muñoz, J.-M. (2019) 'Occupations and the recent trends in wage inequality in Europe', *European Journal of Industrial Relations*. SAGE PublicationsSage UK: London, England, p. 095968011986604. doi: 10.1177/0959680119866041.

Fernández-Macías, E. and Hurley, J. (2017) 'Routine-biased technical change and job polarization in Europe', *Socio-Economic Review*, 15(3), pp. 563–585. doi: 10.1093/ser/mww016.

Fernández-Macías, E., Hurley, J. and Arranz-Muñoz, J. M. (2017) *Occupational change and wage inequality: European Jobs Monitor 2017*. Luxembourg: Publications Office of the European Union. doi: 10.2806/332137.

Frey, C. B. and Osborne, M. A. (2017) 'The future of employment: How susceptible are jobs to computerisation?', *Technological Forecasting and Social Change*. Elsevier B.V., 114, pp. 254–280. doi: 10.1016/j.techfore.2016.08.019.

Gallie, D. *et al.* (2012) 'Teamwork, Skill Development and Employee Welfare', *British Journal of Industrial Relations*, 50(1), pp. 23–46. doi: 10.1111/j.1467-8543.2010.00787.x.

Goos, M., Manning, A. and Salomons, A. (2009) 'Job Polarization in Europe', *American Economic Review*, 99(2), pp. 58–63. doi: 10.1257/aer.99.2.58.

Goos, M., Manning, A. and Salomons, A. (2014) 'Explaining job polarization: Routine-biased technological change and offshoring', *American Economic Review*, 104(8), pp. 2509–2526. doi: 10.1257/aer.104.8.2509.

Gray, F. E. (2010) 'Specific oral communication skills desired in new accountancy graduates', *Business Communication Quarterly*, 73(1), pp. 40–67. doi: 10.1177/1080569909356350.

Green, F. (2012) 'Employee Involvement, Technology, and evolution in job skills: A Task- Based analysis', *Industrial and Labor Relations Review*, 65(1), pp. 36–67. doi: 10.1177/001979391206500103.

Green, F. *et al.* (2016) 'Skills and work organisation in Britain: a quarter century of change', *Journal for Labour Market Research*, 49(2). doi: 10.1007/s12651-016-0197-x.

Green, F. and Henseke, G. (2016) 'The changing graduate labour market: analysis using a new indicator of graduate jobs', *IZA Journal of Labor Policy*, 5(1). doi: 10.1186/s40173-016-0070-0.

Green, F. and Henseke, G. (2017) 'Graduates and "graduate jobs" in Europe: a picture of growth and diversification Graduates and "graduate jobs" in Europe: a picture of growth and diversification', *Centre for Global Higher Education working paper series* , (25). Available at: www.researchcghe.org.

Green, F. and Henseke, G. (2019) *Graduate Employment and Under-Employment: Trends and Prospects*.

Henseke, G. (2018) 'Against the Grain? Assessing Graduate Labour Market Trends in Germany Through a Task-Based Indicator of Graduate Jobs', *Social Indicators Research*, pp. 1–32. doi: 10.1007/s11205-018-1839-x.

Henseke, G. and Green, F. (2017) 'Cross-National Deployment of "Graduate Jobs"', in Polachek, S. W. et al. (eds) *Skill mismatch in labor markets*. Emerald Publishing Limited. doi: 10.1108/S0147-9121201745.

Humburg, M. and van der Velden, R. (2015) 'Skills and the graduate recruitment process: Evidence from two discrete choice experiments', *Economics of Education Review*. Elsevier Ltd., 49, pp. 24–41. doi: 10.1016/j.econedurev.2015.07.001.

Klein, M. (2016) ‘The association between graduates’ field of study and occupational attainment in West Germany, 1980–2008’, *Journal for Labour Market Research*, 49(1), pp. 43–58. doi: 10.1007/s12651-016-0201-5.

Koumenta, M. and Pagliero, M. (2018) ‘Occupational Regulation in the European Union: Coverage and Wage Effects’, *British Journal of Industrial Relations*, pp. 1–32. doi: 10.1111/bjir.12441.

Levy, F. and Murnane, R. (2004) *The New Division of Labor: How Computers Are Creating the Next Job Market*. New York; Princeton; Oxford: Princeton University Press. Available at: http://www.jstor.org/stable/j.ctt1r2frw.

Lindley, J. and Machin, S. (2016) ‘The Rising Postgraduate Wage Premium’, *Economica*, 83(330), pp. 281–306. doi: 10.1111/ecca.12184.

Lindley, J. and McIntosh, S. (2015) ‘Growth in within graduate wage inequality: The role of subjects, cognitive skill dispersion and occupational concentration’, *Labour Economics*. Elsevier B.V., 37, pp. 101–111. doi: 10.1016/j.labeco.2015.03.015.

Magda, I., Marsden, D. and Moriconi, S. (2016) ‘Lower coverage but stronger unions? Institutional changes and union wage premia in Central Europe’, *Journal of Comparative Economics*. Elsevier Ltd., 44(3), pp. 638–656. doi: 10.1016/j.jce.2015.08.001.

Menon, S., Salvatori, A. and Zwysen, W. (2018) ‘The Effect of Computer Use on Job Quality: Evidence from Europe’, *IZA Discussion Paper*, (11298).

Michaels, G., Natraj, A. and Van Reenen, J. V. (2014) ‘Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years’, *Review of Economics and Statistics*, 96(1), pp. 60–77. doi: 10.1162/REST_a_00366.

Naylor, R., Smith, J. and Telhaj, S. (2016) ‘Graduate returns, degree class premia and higher education expansion in the UK’, *Oxford Economic Papers*, 68(2), pp. 525–545. doi: 10.1093/oep/gpv070.

Nedelkoska, L. and Quintini, G. (2018) ‘Automation, skills use and training’, *OECD Social, Employment and Migration Working Papers*, (202). Available at: http://dx.doi.org/10.1787/2e2f4eea-en%0D.

O’Mahony, M. and Timmer, M. P. (2009) ‘Output, Input and Productivity Measures At the Industry Level: the EU-KLEMS Database’, *The Economic Journal*, 119(June), pp. F374–F403. doi: 10.1111/j.1468-0297.2009.02280.x.

OECD (2018) *Education at a Glance 2018: OECD Indicators*. Paris: OECD Publishing (Education at a Glance).

Osmani, M. *et al.* (2015) ‘Identifying the trends and impact of graduate attributes on employability: a literature review’, *Tertiary Education and Management*. Routledge, 21(4), pp. 367–379. doi: 10.1080/13583883.2015.1114139.

Passow, H. J. (2012) ‘Which ABET Competencies Do Engineering Graduates Find Most Important in their Work?’, *Journal Of Engineering Education*, 101(1), pp. 95–118.

Polack-Wahl, J. A. (2000) ‘It is time to stand up and communicate’, in *30th Annual Frontiers in Education Conference*, p. F1G/16-F1G/21. doi: 10.1109/fie.2000.897702.

Van Reenen, J. (2011) ‘Wage inequality, technology and trade: 21st century evidence’, *Labour Economics*, 18(6), pp. 730–741. doi: 10.1016/j.labeco.2011.05.006.

Reinhold, M. and Thomsen, S. (2017) ‘The changing situation of labor market entrants in Germany’, *Journal for Labour Market Research*, 50(1), pp. 161–174. doi: 10.1007/s12651-017-0227-3.

Riemer, M. J. (2007) ‘Communication skills for the 21st century engineer’, *Global Journal. of Engineering Education*, 1(1), p. 890100. Available at:

https://pdfs.semanticscholar.org/6976/2a3c558cbe2a20d59fb362718ac269da8bca.pdf.

Turrini, A. *et al.* (2015) ‘A decade of labour market reforms in the EU: Insights from the LABREF database’, *IZA Journal of Labor Policy*. IZA Journal of Labor Policy, 4(1). doi: 10.1186/s40173-015-0038-5.

Tymon, A. (2013) ‘The student perspective on employability’, *Studies in Higher Education*, 38(6), pp. 841–856. doi: 10.1080/03075079.2011.604408.

Weinberger, C. (2014) ‘The Increasing Complementarity Between Cognitive and Social Skills’, *The Review of Economics and Statistics*, 96(5), pp. 849–861. doi: 10.1162/REST_a_00449.

Williams, M. and Bol, T. (2018) ‘Occupations and the wage structure: The role of occupational tasks in Britain’, *Research in Social Stratification and Mobility*. Elsevier, 53(November 2017), pp. 16–25. doi: 10.1016/j.rssm.2017.11.003.

Zoghi, C. and Mohr, R. D. (2011) ‘The Decentralization of Decision Making and Employee Involvement within the Workplace: Evidence from Four Establishment Datasets’, *British Journal of Industrial Relations*, 49(4), pp. 688–716. doi: 10.1111/j.1467-8543.2010.00838.x.

Appendix

Occupational Task Measures

The measures of occupational tasks come from the British Skills and Employment Survey Series (SES). SES are surveys of the British workforce aged 25-60 years (65 since 2006). The cross-sectional survey is repeated approximately every five years. Since 1997, it includes worker-reported information on the importance of more than 30 job task items in their current job. We use the last waves 2012 and 2017 to measure the intensity of interpersonal task and risk of automation for 2-digit ISCO occupations. The derived job task domains concentrate on bottleneck, or 'non-routine' tasks which are hard to automate (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018).

Problem-solving job tasks

The problem-solving index combines tasks associated with information gathering, evaluation, creativity and complex problem-solving in non-routine jobs.

Table A.1: Complex problem-solving in SES

Variable	Description
brepeat	How often does your work involve carrying out short, repetitive tasks...
bvariety	How much variety is there in your job?
bchoice	How much choice do you have over the way in which you do your job
bnewthin	My job requires that I keep learning new things
ccause	Importance: working out the cause of problems or faults?
csolutn	Importance: Thinking of solutions to problems?'
canalyse	Importance: analysing complex problems in depth?

To derive the indices, items are, first, standardised to the [0,1] range and then averaged. Cronbach's alpha for the scale is 0.77.

Interpersonal job tasks

The interpersonal job task scale combines five items that describe the importance of dealing with people inside and outside the organisation and professional communication. Responses are rescaled to the [0,1] range. Cronbach's alpha for the scale is 0.75.

Table A.2: Interpersonal job tasks in SES

Variable	**Description**
cspeech	importance of: making speeches/ presentations
clisten	importance of: listening carefully to colleagues
cpeople	importance of: dealing with people
cteamwk	importance of: working with a team
cpersuade	importance of: persuading or influencing others

Aggregation of job task scales to 2-digit occupation level

To aggregate to the occupation level, we average the values of the derived job task scales by 2-digit occupations (either ISCO-88 or ISCO-08) within the SES weighted by survey weights and working hours. The resulting scores are z-standardised within the combined pool of ISCO-88 and ISCO-08 occupations.

Table A.3: Task scales by 2-digit ISCO-88 occupations

ISCO – 88	Problem-solving (z-score)	Interpersonal (z-score)
11 Legislators and senior officials	1.18	2.30
12 Corporate managers	0.90	1.27
13 Managers of small enterprises	0.31	0.26
21 Physical, mathematical and engineering science professionals	1.30	0.41
22 Life science and health professionals	1.34	1.26
23 Teaching professionals	0.74	1.57
24 Other professionals	0.76	0.80

31 Physical and engineering science associate professionals	0.73	0.22
32 Life science and health associate professionals	0.87	0.84
33 Teaching associate professionals	0.22	1.31
34 Other associate professionals	0.36	0.51
41 Office clerks	-0.31	-0.27
42 Customer services clerks	-0.31	0.23
51 Personal and protective services workers	-0.40	0.17
52 Models, salespersons and demonstrators	-1.33	-0.19
71 Extraction and building trades workers	0.52	-0.86
72 Metal, machinery and related trades workers	0.74	-0.78
73 Precision, handicraft, craft printing and related trades workers	0.37	-0.93
74 Other craft and related trades workers	0.00	-1.18
81 Stationary plant and related operators	0.10	-0.47
82 Machine operators and assemblers	-0.82	-1.12
83 Drivers and mobile plant operators	-1.63	-1.61
91 Sales and services elementary occupations	-1.82	-1.23
93 Labourers in mining, construction, manufacturing and transport	-1.18	-0.95

Derived job task scales by 2-digit ISCO-88 occupations from EWCS 2010 & 2015 (problem-solving) and SES 2012 & 2017 (interpersonal, task automatability). Restricted to occupations outside of agriculture.

Table A.4: Task scales by 2-digit ISCO-88 occupations

ISCO – 08	Problem-solving (z-score)	Interpersonal (z-score)
11 Chief executives, senior officials and legislators	1.44	2.21
12 Administrative and commercial managers	0.94	1.38

13 Production and specialised services managers	1.00	1.12
14 Hospitality, retail and other services managers	0.41	0.69
21 Science and engineering professionals	1.27	0.57
22 Health professionals	1.05	1.24
23 Teaching professionals	0.66	1.61
24 Business and administration professionals	0.63	1.12
25 Information and communications technology professionals	1.17	0.45
26 Legal, social and cultural professionals	0.82	0.60
31 Science and engineering associate professionals	0.84	0.28
32 Health associate professionals	0.76	0.60
33 Business and administration associate professionals	0.19	0.35
34 Legal, social, cultural and related associate professionals	0.08	0.59
35 Information and communications technicians	0.78	-0.19
41 General and keyboard clerks	-0.11	0.14
42 Customer services clerks	-0.31	0.07
43 Numerical and material recording clerks	-0.11	-0.29
44 Other clerical support workers	-1.07	-0.62
51 Personal service workers	-1.08	-0.50
52 Sales workers	-1.07	-0.19
53 Personal care workers	-0.13	0.30
54 Protective services workers	0.00	0.50
71 Building and related trades workers, excluding electricians	0.43	-0.91
72 Metal, machinery and related trades workers	0.50	-1.01

73 Handicraft and printing workers	0.20	-1.07
74 Electrical and electronic trades workers	1.05	-0.62
75 Food processing, wood working, garment and other craft and related trades workers	-0.22	-1.03
81 Stationary plant and machine operators	-0.64	-0.97
82 Assemblers	-1.46	-1.28
83 Drivers and mobile plant operators	-1.63	-1.61
91 Cleaners and helpers	-2.55	-2.40
93 Labourers in mining, construction, manufacturing and transport	-1.36	-0.96
94 Food preparation assistants	-1.56	-0.47
95 Street and related sales and service workers	-2.26	-0.80
96 Refuse workers and other elementary workers	-1.30	-0.48

Derived job task scales by 2-digit ISCO-08 occupations from EWCS 2010 & 2015 (problem-solving) and SES 2012 & 2017 (interpersonal, task automatability). Restricted to occupations outside of agriculture.

Further Findings

Wage differentials

Table A.5: Changing graduate wage differentials in the pooled sample of 25 countries, males

Time trend interacted with:	(1) Log wages	(2) Log wages	(3) Log wages
Problem-solving	0.0028*		0.0004
	(0.0014)		(0.0017)
Interpersonal		0.0039**	0.0037*
		(0.0014)	(0.0018)
N	255,380	255,380	255,380

See footnote of Table 2 for information on estimator and covariates. Standard errors in parentheses. * $p < .05$, ** $p < .01$, *** $p < .001$

Table A.6: Changing graduate wage differentials in the pooled sample of 25 countries, females

Time trend interacted with:	(1) Log wages	(2) Log wages	(3) Log wages
Problem-solving	0.0038**		0.0017
	(0.0014)		(0.0019)
Interpersonal		0.0041**	0.0028
		(0.0013)	(0.0018)
N	289,410	289,410	289,410

See footnote of Table 2 for information on estimator and covariates. Standard errors in parentheses. * $p < .05$, ** $p < .01$, *** $p < .001$

Employment Trends

Table A.7: Changes in graduate employment across job task domains in the pooled sample, males

Time trend interacted with:	(1) Log (Hours worked/1000)	(2) Log (Hours worked/1000)	(3) Log (Hours worked/1000)
Problem-solving	-0.013***		-0.006
	(0.003)		(0.004)
Interpersonal		-0.012***	-0.008*
		(0.003)	(0.004)
N	7226	7226	7226
Groups	1234.00	1234.00	1234.00
R sq (within)	0.18	0.18	0.18

See footnote of Table 3 for information on estimator and covariates. Standard errors in parentheses. * $p < .05$, ** $p < .01$, *** $p < .001$

Table A.8: Changes in graduate employment across job task domains in the pooled sample, females

Time trend interacted with:	(1) Log (Hours worked/1000)	(2) Log (Hours worked/1000)	(3) Log (Hours worked/1000)
Problem-solving	-0.011***		-0.012*
	(0.003)		(0.005)
Interpersonal		-0.008*	0.001
		(0.004)	(0.006)
N	6225	6225	6225
Groups	1068.00	1068.00	1068.00
R sq (within)	0.23	0.22	0.23

See footnote of Table 3 for information on estimator and covariates. Standard errors in parentheses. * $p < .05$, ** $p < .01$, *** $p < .0$