What do Europeans do at work? A task-based analysis: European Jobs Monitor 2016

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The European Foundation for the Improvement of Living and Working Conditions (Eurofound) is a tripartite European Union Agency, whose role is to provide knowledge in the area of social and work-related policies. Eurofound was established in 1975 by Council Regulation (EEC) No. 1365/75 to contribute to the planning and design of better living and working conditions in Europe.

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Introduction

Europe continues its recovery from the economic slump caused by the global financial crisis in 2008, exacerbated by the euro zone single currency crisis in 2010–2011. In 2014–2015, aggregate employment levels rose faster than at any time since 2008 and over four million new jobs were created in the 28 EU Member States.

The fifth annual European Jobs Monitor report looks at employment shifts at Member State and aggregate EU level from the second quarter of 2011 to the second quarter of 2015. Part 1 presents the jobs-based approach, used to describe employment shifts quantitatively (how many jobs were created or destroyed) and qualitatively (what kinds of jobs). This approach relies on breaking employment down into detailed 'job' cells, with a job defined as 'a specific occupation in a specific sector', for example, a health professional in the health sector, or a skilled craft/tradesman in car manufacturing.

A particular focus is placed on the time profile of recent shifts in employment structure. Ranking the jobs according to their wage and educational levels – or a broader multidimensional index of job quality – adds a qualitative dimension to the analysis. In this year's report, a further level of detail is provided by measuring the intensity involved in carrying out different categories of task: physical, intellectual and social in terms of the job's content, methods and work organisation, as well as the tools used (such as information and communication technologies (ICT) and machinery).

Parts 2 and 3 of the report introduce a new set of indicators on the task content, methods and tools used at work. Derived from international databases on work and occupations, these indicators enable the analysis to go beyond characterising jobs by quality alone – to give a detailed account of what Europeans do at work and how they do it. The indicators provide valuable new insights on the structural differences and recent evolution of European labour markets, as well as a better understanding of labour input in the production process and the changing nature of the skills required.

The jobs-based approach has been used since the 1990s to assess the extent to which employment structures in developed economies are polarising, leading to a shrinking middle quintile, or upgrading as the demand for, and supply of, highly qualified workers increases. These are the two main patterns identified in recent analysis of developed economy labour markets, although more recent analysis in the US – corroborated by some evidence in this report – suggests that a downgrading of the employment structure (relatively faster growth at the lower end of the wage distribution) is also emerging as an alternative pattern.

Policy context

The EU's Europe 2020 strategy for smart, sustainable and inclusive growth includes a commitment to fostering high levels of employment and productivity. This implies a renewed focus on the goals of the earlier Lisbon Agenda: 'more and better jobs'. More jobs are needed to address the problem of unacceptably high unemployment rates. But Europe also needs better, more productive jobs if it is to succeed once again in increasing living standards for its citizens in an expanding, integrated global economy. The European Commission's 2012 jobs package ('Towards a job-rich recovery') identifies some sectors in which employment growth is considered most likely: health services, ICT, personal and household services, as well as the promising if hard-to-define category of 'green jobs'.

The jobs-based approach adopted in this report provides up-to-date data about employment levels and job quality in growing and declining sectors and occupations. The tasks-based approach introduced in this report provides a novel perspective on the changing nature of labour input, which can also help to identify emerging trends and new skill requirements.

Key findings

The resumption of employment growth since 2013 has been particularly reflected in increasing levels of employment in low- and mid-paid jobs, jobs where employment declines were sharpest during the two recessionary periods following 2008. This re-emergence of employment growth coincided with a shift away from the more polarised employment shifts observed during the peak recession years, towards a flatter, more equal distribution of new employment across the wage distribution.

The share of part-time work in the EU is increasing rapidly. This trend is the main component in the declining share of workers in traditional, full-time, permanent work, referred to in the report as 'core employment'. Growth of core employment is increasingly confined to top-quintile, well-paid jobs; in all other quintiles of the wage distribution, it is decreasing and largely being replaced by non-standard employment.

The types of tasks carried out at work can be used to characterise the different occupations in European labour markets and to better understand the diversity of economic structures and their evolution in recent years. There seems to be a typical path of change in the task profile of countries, linked to economic development: physical, routine and machine-use tasks are in decline, while intellectual (especially literacy) tasks, social tasks and ICT use are experiencing steady growth. However, there are significant exceptions, which indicate different paths of development and specialisation: for instance, serving tasks (which tend to be repetitive and involve low intellectual demands) have grown very significantly in some countries such as Spain and the UK but not in others.

The services category accounts for nearly all net new employment in recent years, with a growing share in 2013–2015 occurring in less knowledge-intensive services such as food and beverages and residential care. There was also an increase of 800,000 jobs in manufacturing since 2013 and evidence of a recomposition of employment in this sector towards higher-paid jobs.

There has also been a gradual closing of the gender gap, but despite the recent growth in higher-paid jobs for women being greater than that of men, women account for over two-thirds of those employed in the lowest quintile.

Jobs (occupation–sector combinations in this approach) consist of coherent bundles of tasks. Even if a particular factor of change, such as computerisation, affects a particular type of task, such as routine methods, the overall impact on the employment structure will ultimately depend on how a particular task is bundled with others. Training and educational policies should take this bundling into account, identifying complementarities and incorporating them in the educational curricula.

Although the distribution of tasks in the working population is fundamentally structured by occupations and sectors, it can also change within the same job or occupational category. This within-job change can go in the opposite direction towards structural change, which means that a focus on the latter can be misleading. For instance, in recent years, routine task methods have shrunk in structural terms (because the most routine occupations are in decline), while at the same time traditionally non-routine occupations have become considerably routinised.

Part 1: Monitoring recent employment shifts in the EU 2011–2015

Introduction

Part 1 describes recent (primarily 2011–2015) structural shifts in employment in European labour markets using a jobs-based approach. It shows how net employment shifts, at country and aggregate EU level, have been distributed across jobs in different quintiles of the wage distribution. In this approach, a job is understood as a given occupation in a given sector; for example, a teaching professional in the education sector, or a sales worker in retail. The jobs-based approach first breaks down employment into jobs as defined by NACE and then ranks them in terms of their job quality. The principal criterion for ranking jobs is the wage, although alternative job rankings based on the average educational level of job-holders and a multidimensional measure of non-pecuniary job quality have also been developed (see Eurofound 2013, Part 3 and Annex 2 for details on construction of these alternative indices).[1] A simple graphical representation of observed employment shifts in terms of wage (or education or job quality) quintiles shows whether recent employment growth is stronger at the top, middle or bottom of the job distribution and how it is distributed by other demographic or labour market status variables such as gender, country of birth, employment or professional status.

[1] The education-based job rankings have been subsequently revised using the same data (EU-LFS quarterly data to 2015 Q2) used for most of the employment estimates.

Labour market context 1

Aggregate labour market performance in Europe in mid-2015 showed signs of normalisation after a long, post-global financial crisis period of either stagnation or outright contraction. Employment growth in the EU has been positive since early 2013 and has picked up pace from late 2014 onwards, notwithstanding the latest phase of euro zone turbulence during 2015. Over four million net new jobs were created between 2013 Q2 and 2015 Q2 (equivalent to a yearly employment growth of around 1%, compared to pre-crisis yearly growth rates of around 1.4%).

Perhaps as importantly, employment growth tended to be more equally distributed after many years of sharply diverging national labour market performance, notably within the single currency zone. Of those countries that suffered particularly disruptive downturns post-2008, Ireland, Portugal and Spain all recorded above-average employment growth since 2013. The recovery of labour markets in the Baltic states began even earlier, around 2011.

Unemployment has also belatedly begun to decline. It is still very high, at over 9% in 2015 (and 10.5% in the euro zone Member States) and significantly higher than in the main comparator countries, Japan and the US (3.3% and 5% in November 2015, respectively).[2] But the period 2013–2015 saw the first sustained decline in the aggregate EU unemployment rate since the global financial crisis (sustained meaning greater than 12 months' duration and greater than one percentage point fall). Improved performance was broadly shared. Between 2013 Q2 and 2015 Q2, only five Member States recorded an increase in unemployment rate, of which only one (Finland) had an increase greater than one percentage point.

There has been however some caveats to this positive assessment of labour market performance in recent years. Employment levels in the EU remain just over three million (-1.4 %) below those recorded in mid-2008. This is unprecedented in the modern era where employment growth has been structurally increasing, mainly as a consequence of the increased participation of female workers. No other recent recession has required seven years to recapture the employment shed during the downturn and the decline in labour inputs is greater than a simple headcount approach would indicate. There has been an accelerating expansion of part-time work in recent years. The net headcount decline of 3.3 million workers since 2008 Q2 is composed of a decrease of 7.7 million full-time workers and an increase of 4.4 million part-time workers. In addition, the average actual working hours of full-time workers in the EU has decreased by over one hour a week (from 41.1 to 40.0 hours).[3] Together, these three factors – fewer workers, a greater proportion of part-time workers and a shortening work week for full-time workers – means that overall hours worked in the EU remain 4.6% below the pre-crisis levels of 2008.

Nonetheless, only two countries experienced a contraction in headcount employment between 2013 Q2 and 2015 Q2 – Belgium and Finland. Employment grew in all other Member States, very modestly in some, such as the Netherlands (+0.4%), Romania (+0.2%), France (+0.1%) and Cyprus (<0.1%), and much more vigorously in Luxembourg (+10.1%) and Hungary (+8%).[4] In absolute terms, the most important contribution to recent employment growth in the EU came from the UK, Spain, Germany

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[2] Though the unemployment rate tends to be an increasingly unreliable basis for comparing labour market performance between the EU and the US. The activity rate – the share of the working age population in the labour force (comprising both employed and unemployed, but not the inactive) – has declined sharply in the US in recent years and is now lower than the equivalent rate in the EU; World Bank data show that in 2014, this was 71.8% in the US compared to 72.1% in the EU (World Bank). The non-employed in the EU are more likely to be unemployed – seeking work – than their counterparts in the US and less likely to be inactive.

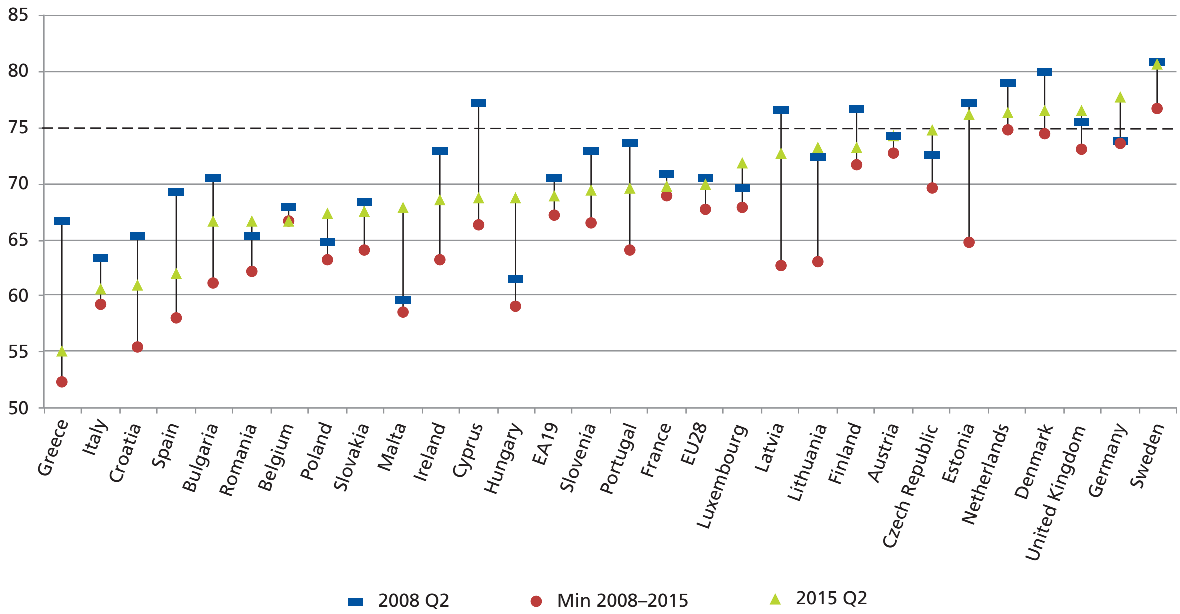
[3] For part-time workers, average actual weekly working hours have been stable since 2008 at 19.9 hrs per week.

[4] EU-LFS data for France since 2014 include employment in the overseas departments (*departements outre mer*, DOM) – about 500,000. To ensure comparability over time, DOM employment figures have been excluded in all the analysis in this report.

and Poland; since 2013 Q2, the number of new jobs in these countries reached over one million in the UK, 700,000 in Spain, and 400,000 in both Germany and Poland.

Europe 2020, the EU's growth strategy from 2010 to 2020, has an overarching employment objective of a 75% employment rate among those aged 20–64 years.[5] As Figure 1 below highlights, the recession and its aftermath slowed progress towards this target – the overall EU employment rate declined from 70.5% in 2008 Q2 to 68.8% in 2011 Q2. In the subsequent four years, however, growth increased to 69.9%.

Figure 1: EU28 employment rates (20–64-year-olds), 2008 Q2–2015 Q2



Note: EA19 = 19 euro zone Member States.
Source: EU-LFS.

Six Member States – the Czech Republic, Denmark, Germany, the Netherlands, Sweden and the UK – are already above the 75% target level. Of the remaining countries, 18 are within 10 percentage points of the target rate, while four Mediterranean Member States – Croatia, Greece, Italy and Spain – are more than 10 percentage points below the target rate. As Figure 1 above illustrates, employment rates in some countries, such as Austria, Belgium and France, demonstrated very little sensitivity to the business cycle, remaining within a tight range since 2008. For those countries where the employment rate response has been more volatile – in part due to the severity of the economic crises experienced – two clusters emerge. In the Baltic states, the employment rate more or less returned to its 2008 rate by 2015. In the second cluster – comprising Croatia, Cyprus, Greece, Ireland and Spain – there was still quite a long way to go by 2015, even though the trajectory in each of these countries improved.

The greater portion of net employment growth occurred in the service sector of the economy, notably the health, professional services, and hotel and restaurants sectors. But there was also positive recent growth recorded among certain sectors that had contracted sharply after the global financial crisis.

[5] Within the Europe 2020 framework, each Member State, with the exception of the UK, has set its own employment rate target or target range for 2020. These range from 62.9% in the case of Malta to 'well over 80%' in the case of Sweden.

There was steady, if modest, growth in manufacturing employment between 2013 Q2 and 2015 Q2. The year 2015 was the first year since 2008 that the construction sector workforce increased, albeit marginally. Of course, in neither case did the recent gains come anywhere close to redressing the huge losses experienced over the previous seven years, when over nine million jobs were lost in the two sectors. New jobs were also seen in the public administration sector over the last two years (2013 Q2 - 2015 Q2) following years of contraction, indicating some relaxation of the restrictions on public sector hiring.

Jobs-based approach: Methodology

This part of the report focuses on how the structure of employment in Europe changed in the four-year period 2011 Q2 – 2015 Q2.[6] In order to do this, a 'job' is taken as the unit of analysis. Increasingly, EU employment policy is phrased in terms of 'jobs'. 'More and better jobs' was the headline phrase of the Lisbon Agenda and the 'New skills for new jobs' initiative is central to its successor, Europe 2020.

Here, a job is defined as an occupation in a sector. This is an intuitively attractive definition and corresponds to what people think of when describing their job, or to how an employer advertises a new job opening – for example, a customer service worker in the retail sector or a health professional (such as a doctor) in the health sector.

This definition is also useful for theoretical and empirical reasons. The two concepts of occupation and sector correspond to two fundamental dimensions of the division of labour within and across organisations. The sector classification designates the horizontal distribution of economic activities within a country across organisations generating different products and services. The occupation classification provides an implicit hierarchy of within-organisation roles – senior managers, line managers, professionals, associate professionals, production staff, and so on. Established international classifications of occupation – the International Standard Classification of Occupations (ISCO) – and sector – *Nomenclature statistique des activités économiques dans la Communauté européenne* (NACE) – mean that it is relatively easy to operationalise the jobs-based approach using the standard labour market data sources, such as the EU Labour Force Survey (EU-LFS), with a good level of international comparability.

The jobs-based approach requires not only the definition of a job in an intuitive, conceptually coherent and empirically practical way, but also some means of evaluating these jobs in relation to their quality. The job–wage has been the main proxy of job quality in much jobs-based analysis, originating in the work of Nobel Laureate Joseph Stiglitz in the 1990s (CEA, 1996) and subsequently refined by Erik Olin Wright and Rachel Dwyer (2003) and others. The analysis that follows relies mainly on a wage-based measure to rank jobs.

[6] In all of the charts that follow, 2011 Q2–2015 Q2 is the timeframe used. Occasionally, shorthand reference in the text is made to 2011–2013 and 2013–2015, but unless otherwise noted, it is based on second-quarter data from the relevant year.

Methodological note on the jobs-based approach

The main, simplified steps of the jobs-based approach are as follows:

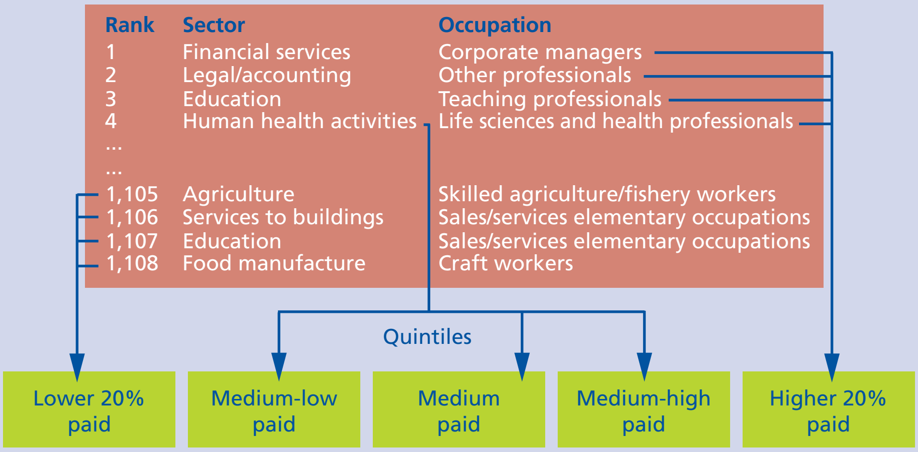
1. Using the standard international classifications of occupation (ISCO 08) and sector (NACE Rev 2.0) at two-digit level, a matrix of jobs is created in each country, with each job an occupation in a sector. In total, there are 43 two-digit occupations and 88 two-digit sectors, generating 3,784 job cells. In practice, many of the theoretical job cells do not contain employment; there are unlikely to be many skilled agricultural workers in financial services, for example. The country total of job cells with employment varies between around 400 and just over 2,000, and is largely determined by country size and labour force survey sample size.

2. The jobs in each country are ranked based on some criterion, mainly the mean hourly wage. The job–wage rankings for each country used in this report are based on combining data from the EU-LFS annual data files for 2011–2014 and aggregated data from the Structure of Earning Survey (SES) for 2010.[7] These sources allow the creation of country job–wage rankings for 28 Member States.

3. Jobs are allocated to quintiles in each country, based on the job–wage ranking for that country. The best-paid jobs are assigned to quintile five, the lowest-paid to quintile one. Each quintile in each country should represent (as close as possible) to 20% of employment in the starting period. Thereafter, the job-to-quintile assignments remain fixed for each country. The focus then shifts to the EU-LFS employment data and the change in the stock of employment at quintile level during a given period in each country, such as 2011 Q2–2015 Q2.

Figure 2 illustrates in simplified format the three steps outlined above, using as examples some of the highest- and lowest-paid jobs that employ large numbers at EU level. (While the jobs are correctly assigned in terms of EU quintile, the individual job–wage ranks of 1–4 and 1105–1108 are for illustrative purposes only.)

Figure 2: Job rankings and quintile assignments carried out for each country

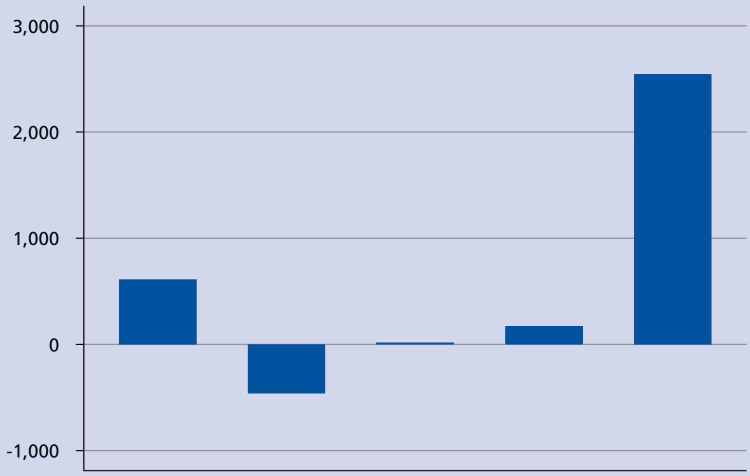


[7] Because the job–wage (and education) rankings have been recalculated using more recent years of EU-LFS data, there may be some minor differences in results reported in this annual report and those in previous reports.

4. Net employment change between starting and concluding periods (in persons employed) for each quintile in each country is summed to establish whether net job growth has been concentrated in the top, middle or bottom of the employment structure. This generates a series of charts similar to Figure 3. Except where otherwise indicated, all charts in the report describe net employment change by quintile for the indicated country or for the EU as a whole. The EU aggregate charts are based on the application of a common EU job–wage ranking.

The resulting quintile charts give a simple graphical representation of the extent of employment change in a given period – as well as an indication of how that change has been distributed across jobs of different pay. (A similar classification of jobs can be done using job-holders' skills or a broad-based, multidimensional indicator of job quality as a ranking criterion – see Annex 3.) Figure 3, for example, illustrates employment change for the EU28 during 2011 Q2–2015 Q2 using the job–wage quintiles. The figure should be read from the leftmost bar cluster (quintile 1 representing the lowest-paid jobs) to the rightmost cluster (quintile 5 representing highest-paid jobs). Net employment change is represented on the vertical axis, generally in thousands but sometimes in annual percentage change. The dominant feature of the chart is the addition of around 2.5 million well-paid jobs (top quintile) over the period.

Figure 3: Net employment change (in thousands) by job–wage quintile, EU, 2011 Q2–2015 Q2



Note: EU28 data. Q2 data in each year.
Source: EU-LFS (authors' calculations).

This method also offers further possibilities of breaking down these net employment changes by such categories as gender, employment or professional status and working time (full- or part-time); these categories are used later in this part of the report. For a more extensive description of the data processing involved, please refer to Annex 1. Further background documentation includes Eurofound (2008a), as well as extensive material in the annexes of previous European Jobs Monitor annual reports – see Eurofound (2008b, 2011, 2013, 2014) – where the same jobs-based approach was used.

2

Employment shifts in the EU, 2011–2015

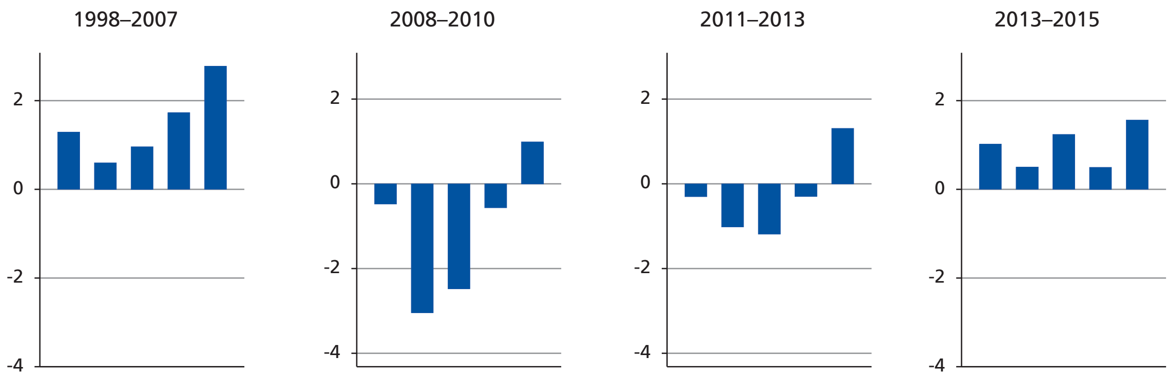
This part of the report uses the jobs-based approach to describe employment developments by job–wage quintile, primarily during the period 2011 Q2–2015 Q2. Overall trends in the EU are looked at first, followed by a description of the varying patterns of change in the individual Member States. Thereafter, employment change is broken down into its components in terms of major sectoral aggregations, worker characteristics (gender and age) and employment characteristics (full- or part-time, temporary or permanent contract). The objective is to show how the broad outlines of employment change identified in the quintile charts, intersect with other dimensions of labour market development, such as the rapid recent growth in part-time work, the increasing share of female employment and the increasing share of services in total employment.

The four-year period of 2011 Q2–2015 Q2 naturally divides into two phases. The first stage of employment decline coincides with the second, so-called 'double-dip' recession that followed the global financial crisis and covers 2011 Q2–2013 Q2 in this analysis. During this time, some 1.2 million job losses were added to the five million previously lost during the global financial crisis period (2008–2010). As already noted, 2013 Q2 marks a turning point; between that quarter and 2015 Q2, some significant employment growth occurred, with approximately 4.2 million net new jobs created in the EU.

As Figure 4 illustrates, these new jobs have been more evenly spread across the wage distribution, with only a light skew towards top quintile employment and each of the job–wage quintiles experienced employment growth during 2013–2015 for the first time since the global financial crisis. Recessionary job destruction was concentrated in the middle and mid–low wage quintiles, notably as a result of the disproportionate share of job losses in the manufacturing and construction sectors. These are sectors in which employment is predominantly in mid-paid jobs. As aggregate economic and labour market performance began to normalise (from 2013 onwards), the sharpened employment polarisation observed during the period of employment contraction gave way to more balanced growth during 2013–2015.

Employment continued to grow in well-paid, high-skilled jobs in the top quintile throughout 2008–2013, albeit at a more modest pace than in the long period of employment expansion that preceded the 2008 global crisis. Bottom-quintile employment also tended to be more resilient than the mid-level quintiles, suffering relatively modest losses.

Figure 4: Employment change (percentage per annum) by job–wage quintile, EU, 1998–2015



Notes: Different EU country aggregates due to data availability as follows: EU23 (no data for Cyprus, Malta, Poland or Romania), 1998–2007, based on annual LFS data. EU28 for remaining periods, based on second quarter data in each year.
Source: EU-LFS, SES (authors' calculations).

The one consistent feature of employment shifts over all periods is the relative outperformance of the top quintile. Well-paid jobs added employment even during the peak crisis period (2008–2010) and contributed disproportionately in all periods to overall employment growth.

Upgrading and polarising employment shifts

The debate about shifts in employment structure in developed economies has so far been largely oriented around two main patterns of growth – upgrading and polarisation. Each has its own underpinning narrative – skill-biased technological change (SBTC) in the case of upgrading and routine-biased technological change (RBTC) in the case of polarisation.

With upgrading employment shifts, the expected pattern is a more or less linear improvement in employment structure, with the greatest employment growth in high-paid (or high-skilled) jobs, the weakest growth in low-paid (or low-skilled) jobs, and middling growth in the middle. With polarisation, the main difference is that the relative positions, in terms of employment dynamics of the middle and bottom levels of the job distribution, are swapped: employment growth is weakest in the middle and relatively stronger at both ends of the job–wage distribution, leading to a 'hollowed middle'.

In both accounts, the principal driver of employment change is technology and its principal effect is to increase the demand for skilled labour in capital-rich, developed economies at the expense of less-skilled labour. Higher skills endow their possessors with the capacities to utilise and master new technologies, enhancing their productivity. But while technology tends to act as a complement to those with higher skills, it is more likely to substitute those with lower skills whose job tasks are more easily machine-replaceable.

The main explanation of the differences in the two accounts (SBTC and RBTC) relates to where in the wage distribution – at the bottom or in the middle – those jobs most susceptible to technological displacement lie. Exponents of RBTC claim that the most vulnerable jobs are routine jobs with a high share of easily codifiable tasks (for example, routine clerical and manufacturing or production jobs). Such jobs happen to predominate in the middle of the wage distribution in developed economies (Autor, Katz and Kearney, 2006). Less routine jobs – personal services at the bottom of the distribution and knowledge-intensive professional services at the top – are less easy to automate and therefore less vulnerable to replacement by machines. In practice, employment changes observed at country level only approximate such schematic predictions; they are a mix of both or are some hybrid shape. In the EU as a whole, over the periods covered by this report's analysis from 1998, employment shifts have tended to be upgrading but with some evidence of polarisation, a trend that becomes more obvious during recessions.

What both patterns show – and what the theoretical explanations that predict them agree on – is that there has been relatively strong top-quintile employment growth. Until recently, this has been one of the empirical regularities of jobs-based analysis in developed world labour markets.

It is of note, however, that recent analysis of the US labour market by David Autor has pointed to relatively stronger growth in the lower part of the wage distribution in the US during 1999–2012, accompanied by relatively stagnant growth in the middle and top of the wage distribution (Autor, 2015, p.20). This analysis also finds echoes in the conclusions of previous work on the US and selected European labour markets. In the US, patterns of employment shift tended to change in a negative direction each decade from the 1960s through to the 1990s (Wright and Dwyer, 2003). A clear upgrading picture in the US in the 1960s became progressively more polarised in succeeding decades. The trend in employment shift patterns in the US observed over a long period has therefore been downward, from clearly positive structural upgrading in the 1960s to more ambiguous patterns in the succeeding decades, culminating in downgrading shifts from 2000 onwards.

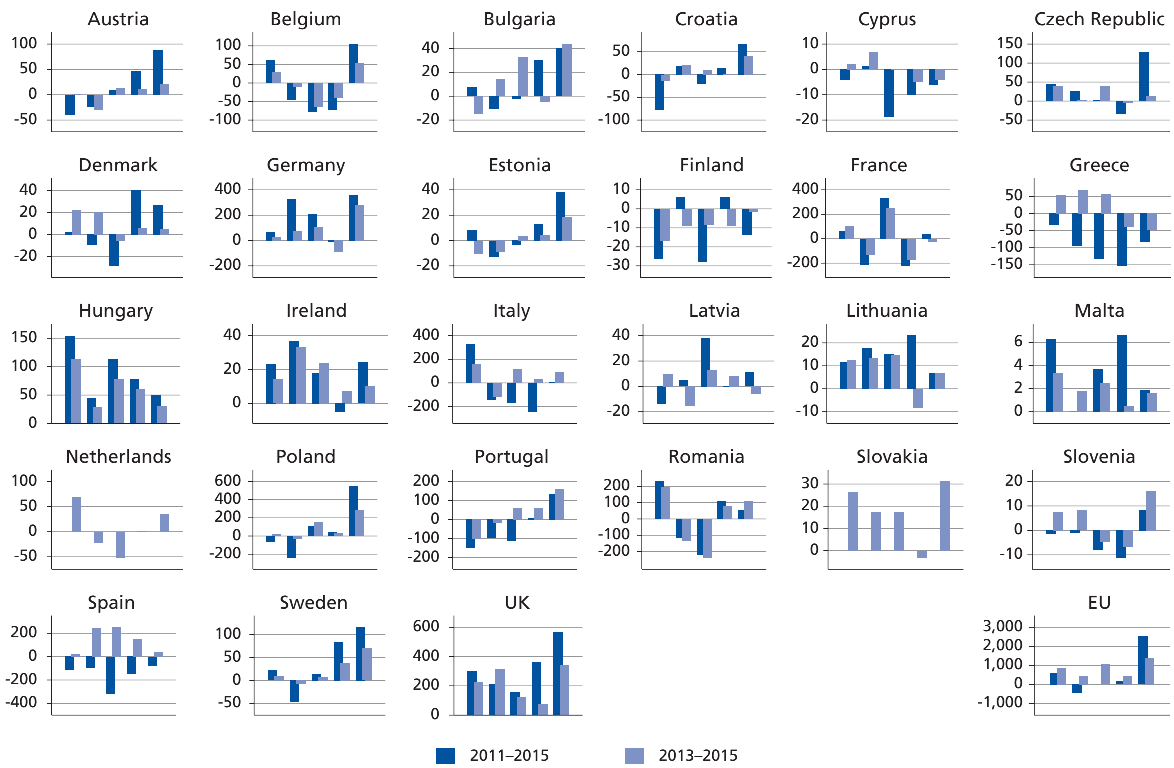
Neither of the orthodox, technology-based explanations of shifts in labour demand is consistent with such downgrading employment shifts. This suggests that other determinants may be playing a stronger role in structural employment change than previously indicated. The two most commonly cited alternative sets of determinants are: globalisation and trade; and labour market institutions (such as wage bargaining regimes, union representation, (de)-regulation and the interaction between welfare regimes and work).

How do recent EU data compare with that observed in the US? The pre-crisis employment expansion in the EU was mainly upgrading but with some polarisation. The crisis itself has been clearly polarising but with some upgrading (the top quintile continued to grow). The most recent pattern (2013 Q2–2015 Q2) is one of balanced growth with only a very mild upgrading skew. There is, as yet, no indication of actual downgrading in the aggregate EU data, though recent employment shifts are clearly less upgrading than those observed in the pre-crisis period. It is also the case that recent data at national level from some countries point to relatively faster growth in low-paid jobs over recent years. Are developments in the US a lead indicator of what may come to pass in more EU Member States? Only time will tell.

Employment shifts in Member States

Figure 5 presents net employment change between 2011 Q2 and 2015 Q2 by wage quintile for 27 Member States.

Figure 5: Employment change (in thousands) by job–wage quintile, EU, 2011 Q2–2015 Q2



Note: Data for Germany for 2012 Q2–2015 Q2. See Annex 2 for treatment of data breaks in France, Germany, the Netherlands and Slovakia. Luxembourg excluded for data reasons.
Source: EU-LFS, SES (authors' calculations).

Over the four-year period 2011–2015, Hungary and Italy both experienced an obvious downgrading pattern of employment shift. In each of these countries, employment growth was strongest in the lowest-paid jobs and weaker in higher-paid jobs. Other countries with relatively greater growth at the bottom included Greece, Ireland, the Netherlands, Romania and Slovakia. The two main patterns of employment shift – upgrading and polarisation – describe developments in most of the remaining Member States. With reference to 2011–2015, the most obvious examples of upgrading countries are Austria, Bulgaria, Croatia, Poland, Portugal, Sweden and the UK. Clear examples of polarisation can be seen in Belgium, Cyprus, the Netherlands and Spain. A number of other Member States exhibit a combination of the two patterns: Czech Republic, Denmark, Germany, Estonia and Slovenia.

At aggregate EU level over 2011–2015, there was upgrading with some polarisation – relatively faster growth in the bottom than in the middle. However, this involved a more even spread of job gains across the wage distribution, as employment growth accelerated from mid-2013 onwards. Particular contributory factors include the strengthening of employment growth after 2013 in mid-paid jobs in France and Spain, and in low- and mid-paid jobs in other, more populous Member States such as Italy and the UK.

Growing and declining jobs

The quintile charts show where, in the job–wage distribution, employment is being created and destroyed, but they do not identify the specific jobs responsible for the observed shifts. In practice, even though the number of jobs with employment identified using the jobs-based approach ranges from around 400 to 2,000 by country depending on size, a small number of jobs account for a high share of employment in all countries. One-quarter of EU employment is concentrated in just 11 jobs and one-half in 60 jobs. Employment shifts in jobs that employ the largest proportion of workers tend to influence the shape of the quintiles most.

Table 1: Top 10 jobs by employment, greatest growth and greatest loss, EU, 2011 Q2–2015 Q2

Biggest jobs

Occupation (ISCO two-digit)	Sector (NACE two-digit)	Employment		Quintiles		
		Current headcount (millions)	% change 2011–2015	Wage	Education	Job quality
Sales workers	Retail trade	11.98	1.1	1	2	3
Teaching professionals	Education	9.69	2.0	5	5	5
Market-oriented skilled agricultural workers	Crop and animal production	6.51	-7.7	2	1	2
Health professionals	Human health activities	4.75	7.2	5	5	4
Personal service workers	Food and beverage service activities	4.26	11.6	1	2	1
Building and related trades workers	Specialised construction activities	4.04	-12.5	2	2	2
Drivers and mobile plant operators	Land transport and transport via pipelines	3.85	-0.7	3	2	1
Health associate professionals	Human health activities	3.72	-0.4	4	4	3
Business and administration associate professionals	Public administration and defence	2.98	-1.3	4	4	5
Cleaners and helpers	Services to buildings and landscape activities	2.23	13.6	1	1	1

Table 1: (continued)

Fastest gaining large jobs

Occupation (ISCO two-digit)	Sector (NACE two-digit)	Employment		Quintiles		
		Current headcount (thousands)	% change 2011–2015	Wage	Education	Job quality
ICT professionals	Computer programming, consultancy and related activities	1514	38.6	5	5	5
Business and administration professionals	Activities of head offices; management consultancy activities	646	33.6	5	5	5
Legal, social, cultural and related assoc. professionals	Sports activities and amusement and recreation activities	522	23.0	3	4	3
Personal care workers	Households as employers of domestic personnel	532	20.5	1	2	2
Legal, social and cultural professionals	Creative, arts and entertainment activities	661	17.1	4	5	4
Stationary plant and machine operators	Manufacture of food products	739	16.7	2	1	1
Personal care workers	Residential care activities	1918	16.2	2	3	3
Business and administration professionals	Financial service activities	709	16.1	5	5	5
Legal, social and cultural professionals	Legal and accounting activities	1028	15.2	5	5	5
Food preparation assistants	Food and beverage service activities	1021	14.7	1	1	1

Fastest declining large jobs

Occupation (ISCO two-digit)	Sector (NACE two-digit)	Employment		Quintiles		
		Current headcount (thousands)	% change 2011–2015	Wage	Education	Job quality
Sales workers	Wholesale trade	965	-14.4	2	3	4
Building and related trades workers	Specialised construction activities	4039	-12.5	2	2	2
Building and related trades workers	Construction of buildings	2232	-9.0	3	1	1
General and keyboard clerks	Public administration and defence	1306	-8.0	3	3	4
Market-oriented skilled agricultural workers	Crop and animal production	6507	-7.7	2	1	2
Hospitality, retail and other services managers	Retail trade	758	-7.5	4	3	4
Cleaners and helpers	Households as employers of domestic personnel	1439	-6.7	1	1	1
Metal, machinery and related trades workers	Manufacture of fabricated metal products	1552	-6.5	3	2	1
Protective services workers	Public administration and defence	1751	-5.6	4	3	3
Electrical and electronic trades workers	Specialised construction activities	1040	-4.8	3	3	3

Note: EU28, 2015 Q2 data for top 10 jobs by employment. Figures for percentage growth (2011 Q2–2015 Q2) relate to a sample of large-employing jobs only (>500,000, EU28 2015 Q2; n=75) and are calculated based on data from 23 Member States only (excluding France, Germany, Luxembourg, the Netherlands and Slovakia) for data reasons or due to classification breaks.
Source: EU-LFS, SES (authors' calculations).

The first part of Table 1 (see page 13) shows that the two largest-employing jobs in the EU – sales workers in retail (12 million) and teaching professionals in education (9.7 million), together accounting for 10% of all employment in the EU – enjoyed very modest growth over 2011–2015, most of which was concentrated in the most recent two years of that period. The biggest absolute job losses were experienced in blue-collar occupations in construction and agriculture. Employment in construction continued to contract at aggregate EU level seven years on from the construction busts that accompanied the global financial crisis of 2007–2008, though, as noted previously, the rate of contraction slowed significantly after 2013. The failure of the construction sector – in normal times, an especially cycle-sensitive sector – to restore employment growth despite the resumption of output growth, serves as confirmation that its pre-crisis expansion was excessive and unsustainable.

The biggest absolute employment losses were among skilled agricultural workers (more than half a million fewer jobs over 2011–2015), with the relatively large agricultural sectors of Poland and Romania contributing disproportionately to these losses.

The greatest absolute employment growth was recorded in services sectors both at the top of the wage distribution (health professionals) and at the bottom (personal service workers in food and beverage activities, along with cleaners/helpers in services to buildings).

The second and third parts of Table 1 list fast-growing and fast-declining jobs among a job sample restricted to those 75 jobs (occupation by sector) with an EU employment headcount of at least 500,000. The fastest growing job was that of ICT professionals in computer programming and consultancy activities, which has increased by 39% since 2011. It should be noted, however, that this archetypal post of the third industrial revolution employs less than 1% of European workers; even relatively fast growth in such a job contributes only modestly to overall employment. All but one of the fastest growing jobs is in the services sector and four of these are top quintile – white-collar jobs in IT, financial or professional services sectors.

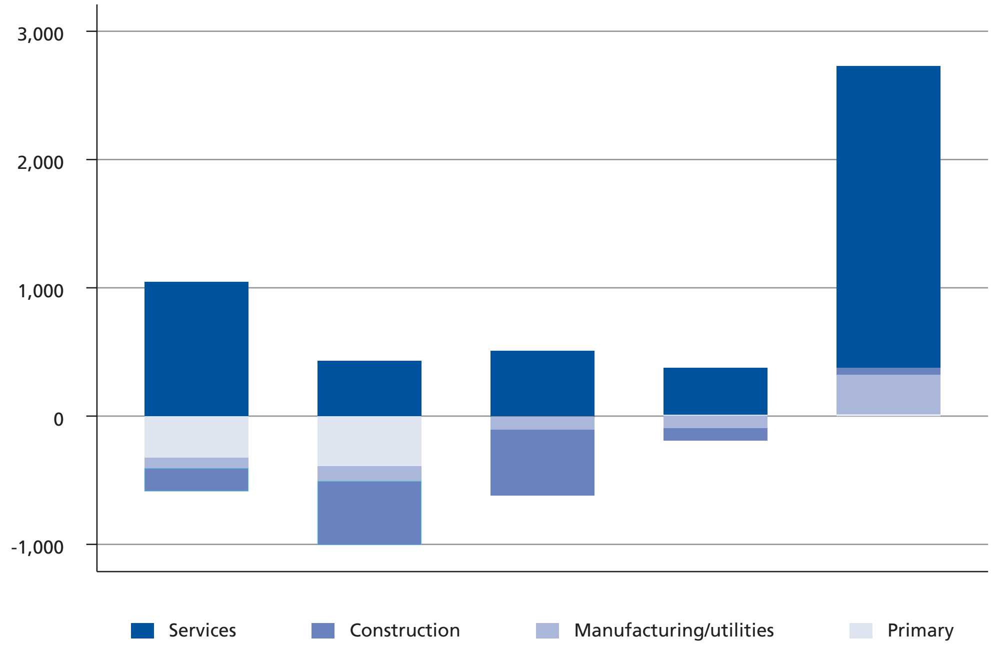
The top ten list of fast declining jobs is comprised mainly of low- and mid-paid jobs. There are no well-paid, top-quintile jobs on it; this is the corollary of the general resilience of top-quintile employment growth. Of the sectors affected, it is no surprise to see the construction sector represented by three distinct jobs for reasons already discussed. Contracting jobs in the public administration include protective services workers (social workers) as well as general and keyboard clerks (routine clerical grades). Employment in the public administration sector is overwhelmingly state-funded and is sensitive, therefore, to widespread public spending restrictions in place in most Member States in recent years (Eurofound, 2015b). Declining employment of retail managers may relate to the vogue for 'management delayering', identified in many recent retail sector restructurings (Eurofound, 2016) whereby previous layers of middle-management have been flattened or eliminated by major retail groups. The stated objective of such restructurings is often to maximise the share of employees in direct customer service. The online migration for retail transactions may also have led to a decline in demand for this role.

The shift to services

Employment destruction during the post-crisis period was highly concentrated in two sectors – construction and manufacturing – with net losses of over eight million jobs during 2008–2013. The preponderance of mid- and mid–low-paid employment in manufacturing and construction was the principal factor behind the sharp employment polarisation observed during the crisis, as job destruction in these sectors tended to 'hollow out' the employment structure. After 2013, there was some improvement in employment performance in both sectors, as already noted. Figure 6 below illustrates one notable dimension of this improvement – net job growth in both sectors in well-paid, top quintile jobs, even as employment declines in each of the lower four quintiles. This is indicative of upskilling recompositions of the workforce and is especially evident in manufacturing where employment growth was concentrated among science and engineering professionals and, to a lesser extent, business and administrative professionals. Employment shrunk in more traditional blue-collar occupations in manufacturing and, to an even greater extent, in construction. These jobs are mainly found in the low–middle and middle wage quintiles. The primary sectors – agriculture and mining/extractive industries – shed employment in the lowest two quintiles of the wage distribution.

The main message from Figure 6 is the overwhelming contribution of services to net employment growth in 2011–2015, with positive growth in services employment across the wage distribution. Given its weight in overall employment – 70% of employment is now in services – and its even greater weight in employment shifts at the margin, the distribution of services employment growth largely determines overall patterns of change. Upgrading arose from the net addition of over two million top quintile services jobs in 2011–2015. To the extent that one can see polarisation over the period, it is because services employment growth in the bottom quintiles outpaces the corresponding growth in the mid–upper-mid paid quintile. These patterns are reinforced by developments in the other broad sectors, but it is shifts in services employment that dominate the overall picture.

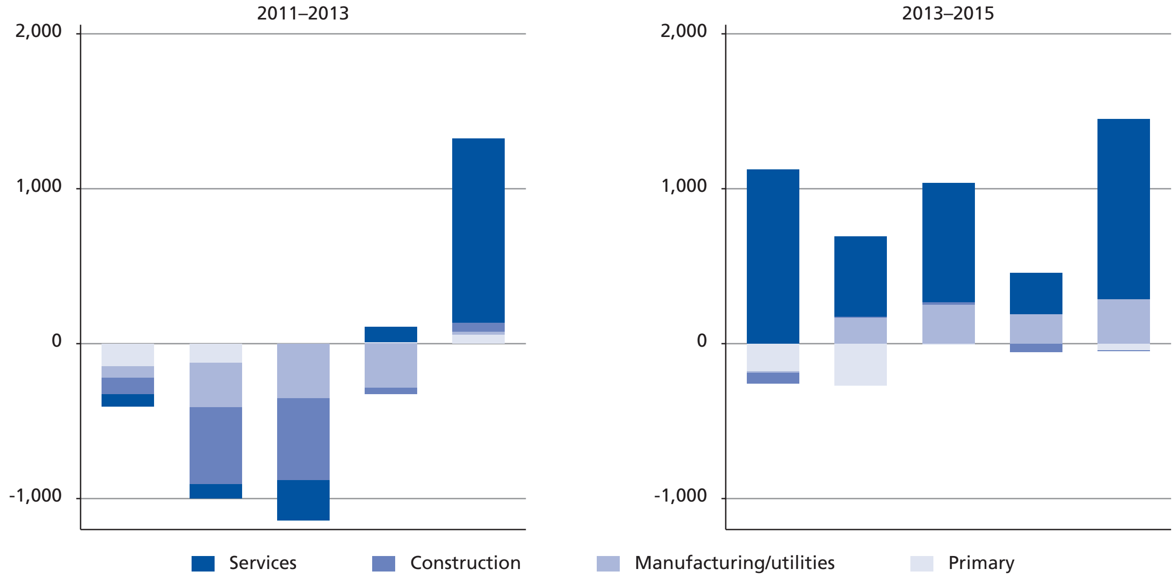
Figure 6: Employment shifts (in thousands) by job–wage quintile and broad sector, EU, 2011 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).

The period 2011 Q2–2015 Q2 comprises two quite distinct phases: an initial phase, up to 2013, of employment decline – the end of the recession that followed the global financial crisis – and a subsequent period of employment growth up to mid-2015.

Figure 7: Employment shifts (in thousands) by job–wage quintile and broad sector, EU, 2011 Q2–2013 Q2 and 2013 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).

Patterns of employment shift before the 2013 turning point are quite different to those that came afterwards. Before this change, there was polarised upgrading, with well-paid services employment notably resilient compared to developments in other broad sectors and lower down the wage distribution. After 2013 Q2, employment growth became much more evenly distributed across the wage distribution. The most important developments post-2013 all tend to mute the polarisation observed during 2011–2013. Indeed, analysis of the recessionary period going back to 2008 shows that:

- services employment growth is strong in the lower half of the wage distribution;
- manufacturing adds employment both at the top and the middle;
- construction sector job losses are relatively minor compared to before.

Within manufacturing, the strongest recent employment gains came in automotive and machinery manufacture, as well as food production. Services account for seven out of 10 jobs in Europe and this sector's share of overall employment is growing as that of the manufacturing and the primary sectors declines: there were 4.7 million net more service sector jobs in 2015 Q2 than there were in 2011 Q2.

Figure 8 (on next page) differentiates between growth in three areas of the services sector: public knowledge-intensive services (public KIS); private knowledge-intensive services (private KIS); and less knowledge-intensive services (LKIS).[8] The left panel shows changes over the earlier two-year period (2011 Q2–2013 Q2), while the right shows the more recent changes (2013 Q2–2015 Q2).

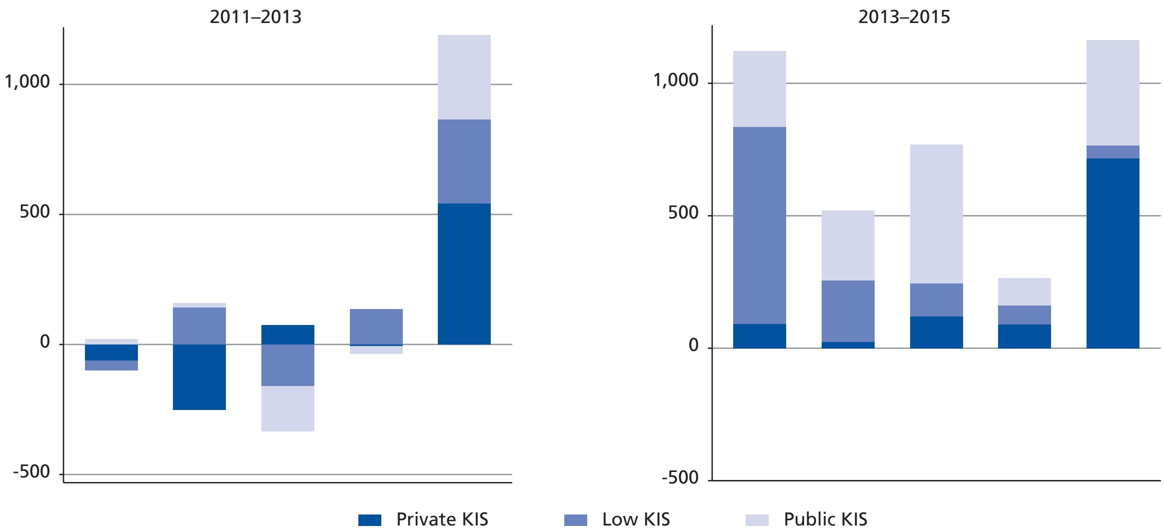
[8] This breakdown relies on the Eurostat aggregation of services sectors into 'knowledge-intensive services' (KIS) and 'less knowledge-intensive services' (LKIS). As there is no specific question in the EU LFS regarding the public or private status of the respondent's employer, it is not possible to estimate accurately the respective shares of public and private sector services employment. To make the distinction in this report, the KIS category has been further broken down into public and private service components. Public KIS comprises the following NACE sector categories: public administration, social security and defence, education, and human health activities. Private KIS comprises all remaining 'knowledge-intensive services' (see Annex 1 for a full list). It should be noted that as a significant minority of workers in the health and education sectors are in fact private sector employees, the public KIS category is an imprecise proxy of public sector employment.

From 2013 onwards, public KIS and low-knowledge intensive services employment both strongly contributed to stronger services employment growth at the lower end of the wage distribution since 2013. The largest absolute gains were in food and beverage services activities (over 560,000), while other predominantly lower-paid sectors, such as services to buildings and residential care activities, also brought significant new employment (between 300,000–400,000 since 2013). These account for the majority of gains in 'less knowledge intensive services' in the bottom quintiles. These gains at the bottom were accompanied by gains in mid-paying jobs in the same sectors (such as food and beverages) or related ones (such as sports, amusements and recreation activities) for associate professional grades.

Simultaneously, there was a resurgence of growth in public KIS (mainly education and health) in the bottom three quintiles, possibly related, in part, to an easing of public spending pressures and associated 'austerity' policies during 2013 Q2–2015 Q2 (see Figure 8). In particular, employment grew for associate professional grades in both education and health; it also grew further down the wage distribution of these sectors, for personal care workers and those in elementary occupations such as cleaners and helpers. An important qualification here is the growing share of private sector employment in the traditionally predominantly state-funded sectors of health and education, as well as increased levels of outsourcing in these sectors (Eurofound, 2015a). In other words, some of the employment growth attributed to public KIS in Figure 8 is likely to occur among private sector employers.

Where less change is observed in the top quintile, employment shifts may be more structural and less cyclical in nature. For example, steady positive growth in well-paid services employment after 2013 Q2 continued at a similar rate to that observed before 2013 Q2.

Figure 8: Employment shifts (in thousands) by job–wage quintile and service sector grouping, EU, 2011 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).

Professional occupations in private sector KIS – which comprises a broad range of activities including media, ICT, consulting, advertising, financial, legal services and accounting – accounted for a growing share of top-quintile employment growth over 2011 Q2–2015 Q2. These occupations saw the addition of just over 700,000 well paid jobs in 2013–2015 alone. Largest gains occurred among business and administration professionals and ICT professionals, as indicated in the list of fastest growing jobs (Table 1).

Patterns of employment change by worker and employment characteristics

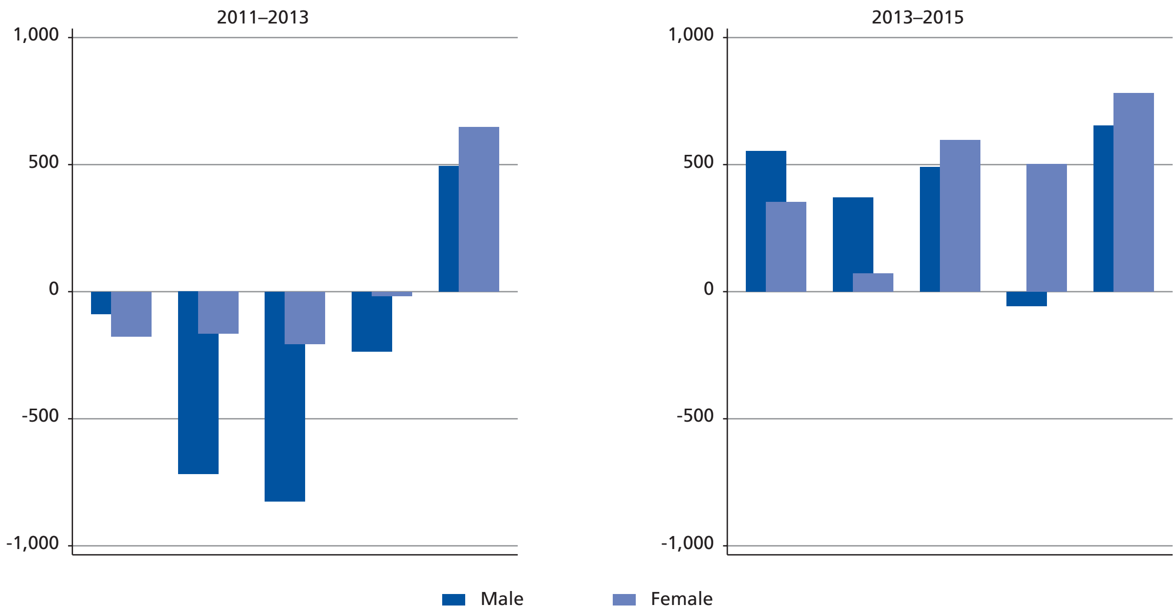
3

In this chapter, recent employment change (2011 Q2–2015 Q2) is analysed by job–wage quintile, according to the background variables of gender, country of birth and employment status. Following on from the discussion in the previous chapter, this analysis also aims to identify any recent shifts in the pattern of employment change by comparing the period 2011–2013 (continuing employment contraction) with 2013–2015 (employment expansion).

Upwardly mobile women and downwardly mobile men

By 2015 Q2, women accounted for 46% of total employment in the EU, the gender employment gap contracting by two percentage points since 2008. This, primarily, reflected the disproportionate impact of the great recession on predominantly male-employing sectors such as manufacturing and construction. In addition, employment levels tended to be much more resilient in predominantly female-employing service sectors, especially in health and education. However, as Figure 9 below illustrates, while employment contraction in 2011–2013 continued to primarily impact men, in 2013–2015, employment gains were more evenly shared by men and women.

Figure 9: Employment shifts (in thousands) by job–wage quintile and gender, EU, 2011 Q2–2015 Q2



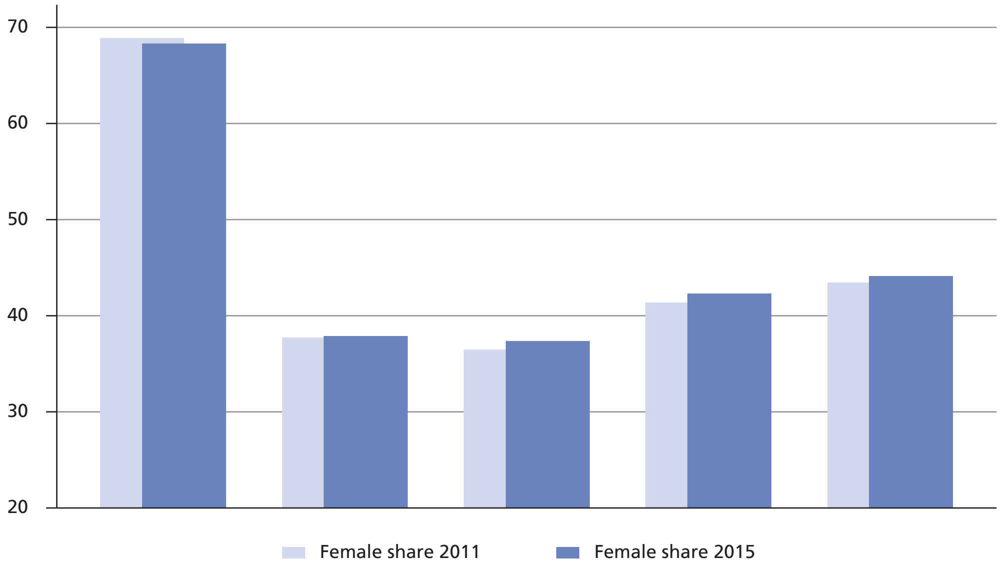
Source: EU-LFS, SES (authors' calculations).

In qualitative terms, over 2011–2015, the profile of female employment shifts involved upgrading, with employment polarisation more evident among men; during this period, women accounted for the majority of new well-paid jobs (top quintile). During the period of employment contraction (2011–2013), they were much less affected than men by the sharp employment declines in mid–low- and mid-paid jobs. During the subsequent upturn (2013–2015), male employment gains have been comparatively stronger in the bottom two quintiles, while female gains have been stronger in the top two quintiles. Lower paid service jobs – often in roles that tended to be dominated by women – have contributed considerably to recent employment growth among men.

The fastest growing job in 2013–2015 was that of personal service workers in the food and beverage sector (bottom quintile). Over 200,000 net new jobs were created in this role each year, which were more or less equally divided by gender.

An important qualification is that Figure 9 (alongside most figures in this chapter) describes marginal employment change over a given period. But male and female employment is not equally distributed across the wage distribution. Figure 10 shows that the proportion of workers who were women was only greater than 50% in the bottom quintile, was relatively low (less than 40%) in the middle quintiles and was just over 40% in the top two quintiles. The employment share of women in many countries reflects this distribution, confirming that there is a higher concentration of women in low-paid jobs and of men in low-mid and mid-paid employment.[9]

Figure 10: Female employment share (%) by job–wage quintile, EU, 2011 Q2 and 2015 Q2



Source: EU-LFS, SES (authors' calculations).

Changes that appear to be relatively significant in Figure 9 where they are characterised in terms of marginal change, only resulted in modest adjustments to the gender profile of workers over the period 2011–2015. There was a small decline in the proportion of women in the bottom quintile (-0.6 percentage points), but more than two out of three people employed in jobs in the bottom quintile are women (68%). Increases in the proportion of women in each of the top four quintiles ranged between +0.3 percentage points and +0.9 percentage points, but in each case the overall figure remained below the aggregate female employment share of 46%.

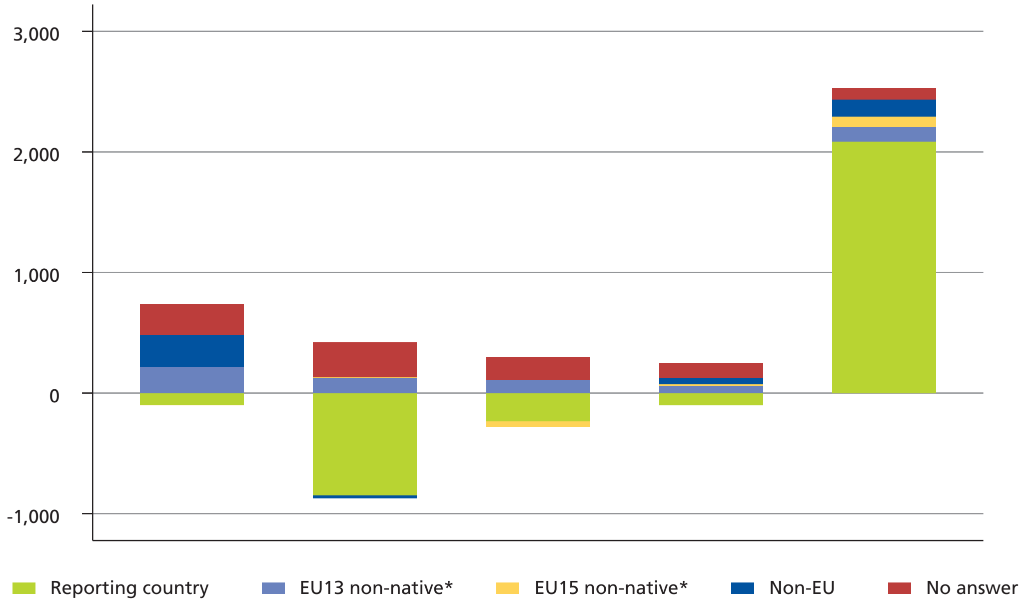
Non-native employment accounting for two out of three new jobs

Approximately 26 million workers in the EU (12% of total workers) were born in a different country to that in which they work. Despite the freedom of movement of EU citizens to work and settle in Member States other than that of their birth, the majority of this subgroup were born in non-EU

[9] Interesting exceptions are Finland, France, Germany and the Netherlands, where the top quintiles rather than the middle quintile have the lowest female share of employment.

countries. The migrant worker population increased by over two million between 2011 and 2015; by 2015 it accounted for around two-thirds of net employment growth over the preceding four years.[10]

Figure 11: Employment shifts by country of birth and job–wage quintile, EU, 2011 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).
Note: * For an explanation of these categories, please see last paragraph below.

Non-native employment growth was concentrated in the bottom two quintiles and the top quintile, while native employment only grew in well-paid jobs (Figure 11).

In each of the bottom four job–wage quintiles, net employment growth for non-native workers occurred alongside a decline in employment levels among native workers. It is important however to point out that this trend occurred at the quintile level rather than the job level. Of the 12 jobs recording the biggest employment losses overall, only two had different signs for native and non-native employment shifts: employment grew for skilled non-native workers (ISCO 61) and labourers (ISCO 91) in the agriculture/fishing sector.

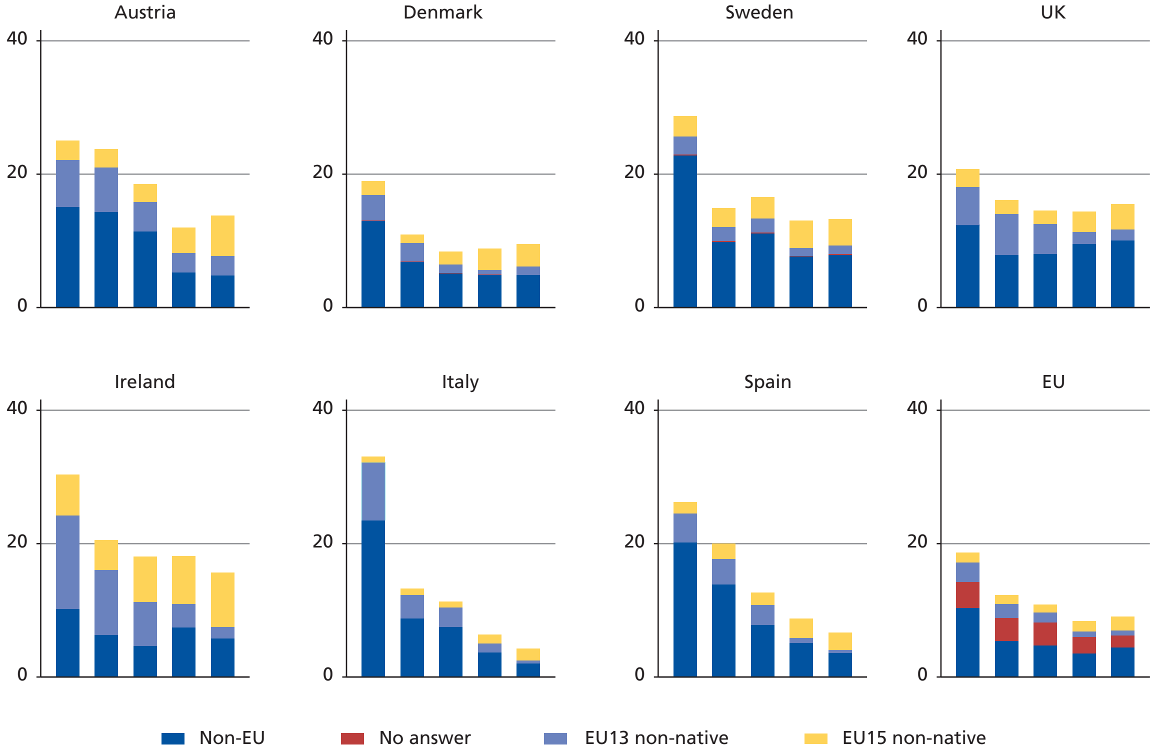
Around half of the growth of migrant employment occurred in Germany where, for historical reasons, the EU-LFS does not record the different categories of the country of birth variable but instead assigns all respondents not born in Germany to a 'no answer' category. The next biggest growth was in the category of EU13 non-natives (from the post-2004 accession countries) who now account for the majority of EU mobile workers. There was also growth of around half a million in the number of non-EU born workers – mainly in the bottom quintile – but with gains also occurring in well-paid, top quintile jobs. The number of mobile EU workers from other 'older' EU15 Member States was relatively stable with some very modest increases recorded in the top quintiles. As has been the case for over a decade, intra-EU labour mobility flow was predominantly east–west, from countries with lower GDP per head to countries with higher GDP per head.

[10] For historical reason, the German data record only two categories for the 'country of birth' variable in the LFS – 'reporting country' and 'no answer'. The authors' assumption is that the 'no answer' category refers almost exclusively to non-natives/anyone not born in Germany (the reporting country). This translates to non-native employment levels of 6,476,000 in 2015 Q2 and 5,548,000 in 2011 Q2.

The non-native working population tends to concentrate in older Member States, accounting for only a very marginal share (less than 4%) of the workforce in many of the post-2004 accession states – Bulgaria, Czech Republic, Hungary, Poland, Romania and Slovakia. But non-native workers account for over 15% of workers in Austria, Cyprus, Germany, Ireland, Luxembourg, Sweden and the UK. These workers tend to be largely concentrated in the lower wage quintiles, with their representation gradually falling in the higher wage quintiles. In some countries, for example, Italy and Spain, this trend is much more sharply defined than in others, such as the UK.

Figure 12 shows that by 2015 Q2, EU13 non-natives and, especially, non-EU born workers, were more likely to be in lower paid jobs, while the relative share of mobile EU15 non-natives is greater in well-paid employment in each of the selected countries.

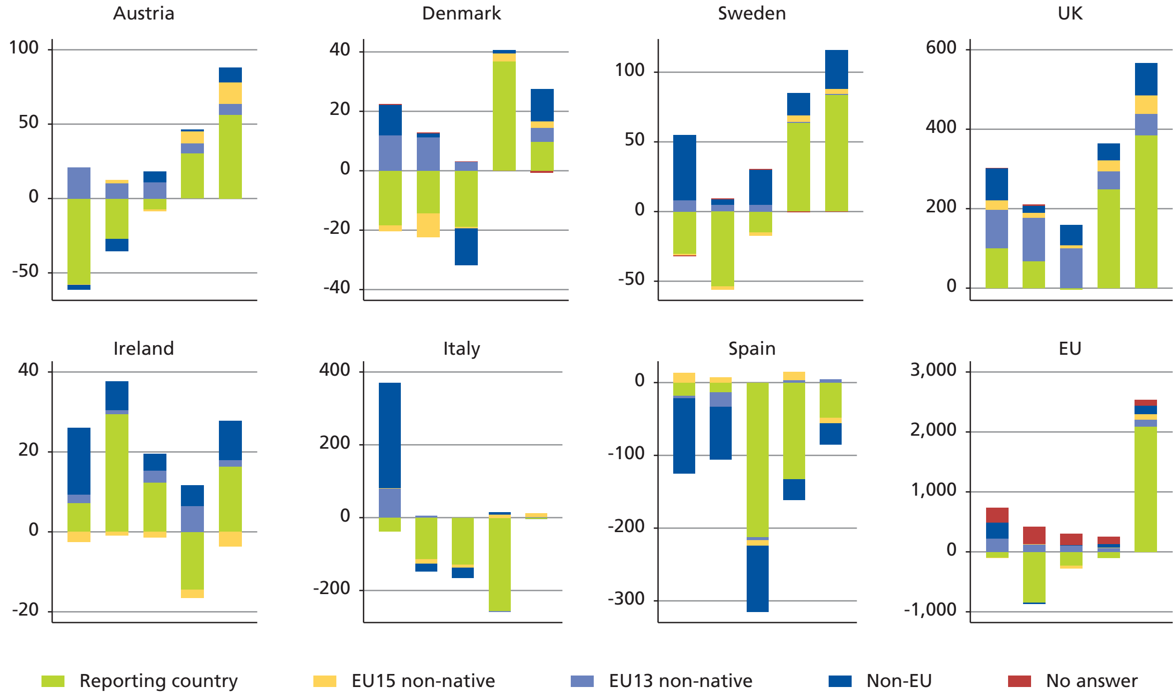
Figure 12: Distribution of non-native employment for selected Member States and EU (%), 2015 Q2



Source: EU-LFS, SES (authors' calculations).

There are clearly many factors at play in determining how non-native workers are integrated into labour markets. Notable ones include: the age, qualifications and legal entitlements of the migrant; the pull effects of existing migrant populations; demand for labour in general; and the specific demand for internationally mobile high-skilled workers. A relatively even distribution across the wage quintiles indicates that the employment opportunities for native and non-native workers are similar; this can be considered a proxy of non-segregation and non-discrimination in national labour markets, characteristics that are potentially attractive to those considering migration.

Figure 13: Employment shifts (in thousands) by country of birth for selected Member States and EU, 2011 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).

In all large host countries (except Spain), there has been an increase in non-native employment. As shown in Figure 13 (above), most of this increase has been concentrated in the lower three wage quintiles. In Austria, Denmark, Italy and Sweden, all net new employment in lower paid jobs is accounted for by non-natives. In countries with growing workforces – notably the UK – native workers tend to benefit from growth in well-paid employment. Overall, developments in native employment tend to be more upgrading, while those in non-native employment contribute more to employment polarisation by bolstering growth in low-paid work.

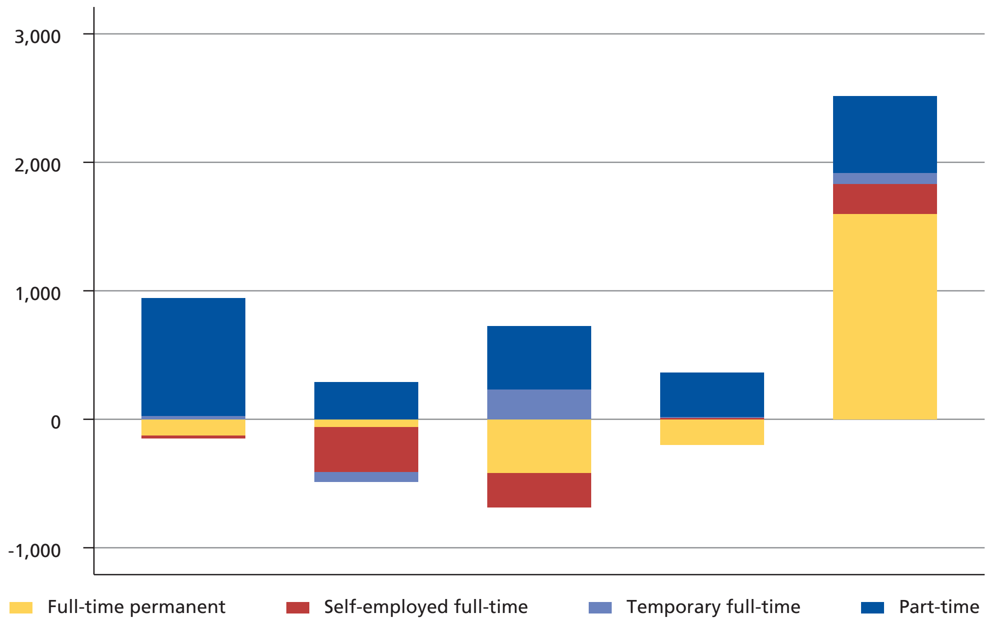
Atypical employment growing across the wage distribution

A decreasing proportion of European workers are in full-time, permanent employment, though this traditional employment status (henceforth described as 'core employment') still describes a majority of European workers. Over the last 20 years, the proportion of workers in this category has fallen by five percentage points (61.3% to 56.3% in EU15), mainly because of the growing share of part-time workers. From 2013 onwards, this figure stabilised as labour market performance began to improve.

There is wide variation across Member States regarding core employment. In 2015, only one in three workers in the Netherlands had this status – this is the country in which the 'part-time revolution' is most advanced. Over half of the Dutch workforce works part-time and an increasing share are self-employed. By contrast, in Bulgaria and the Baltic states, around four out of five workers have core employment status. The incidence of part-time work, in particular, tends to be much lower in eastern European Member States.

Figure 14 presents recent employment growth by quintile for core employment workers – those employees with full-time permanent work – and various, less typical workers, specifically part-time workers, those on full-time temporary contracts and those who are full-time self-employed. Core employment only increased in the top quintile; as a proportion of workers it either fell or remained the same across all other quintiles. At the same time, other forms of employment grew across all quintiles except mid–low paid jobs; their growth was particularly notable in the bottom and top quintiles, which meant they contributed to employment polarisation.

Figure 14: Employment shifts (in thousands) by job–wage quintile and employment status, EU, 2011 Q2–2015 Q2



Source: EU-LFS, SES (authors' calculations).

Employment growth outside of core employment has been dominated by a growing share of part-time workers, which occurred across the wage distribution in 2011–2015. In the same period, there was a very modest increase in full-time temporary employment, while the proportion of full-time self-employed workers fell. Developments in core employment reveal an emerging division between the top quintile and the others. There was no net addition of new core employment in the bottom four quintiles; the modest growth that did occur involved other forms of employment, particularly part-time work.[11]

In well-paid, top quintile jobs, employment increased more vigorously; two-thirds of this growth was in core employment. The remaining one-third relates mainly to increasing numbers of part-time professionals in the health and education sectors. In line with the overall gender share of employment in these sectors, the male–female ratio of these workers is 3:1. Teaching and health professionals in the education and health sectors, are among the top four jobs for net increases in self-employment, alongside the more typically private sector roles of legal professionals in legal/accounting activities

[11] There are no variables in the EU-LFS that would help assess the extent to which the 'gig economy' (for example, online work platforms and 'sharing economy' functions such as Airbnb landlords and Uber taxi drivers) is fuelling the growth of part-time work, though it seems probable that these emerging forms of very contingent work contribute to at least some of this recent growth.

and ICT professionals in computer programming, and there are eight retail sector sales assistants and six teaching professionals for every single ICT professional in the EU.

Figure 14 conveys some important messages. There was an ongoing destandardisation of employment in 2011–2015, mainly involving the replacement of full-time work with part-time work. This destandardisation occurred across the wage distribution and suggests that while core employment was the dominant mode of work, some degree of normalisation occurred regarding less typical work statuses. This core employment, with its greater contractual security, career advancement possibilities and full-time earning capacity, increasingly became a privileged position enjoyed by those in well-paid jobs.

Figure 15 shows how these trends manifested differently in four Member States with very divergent economic and labour market performances.

Figure 15: Employment shifts (in thousands) by job–wage quintile in (non-)standard forms of work in Germany, the UK, Spain and Greece, 2011 Q2–2015 Q2

Source: EU-LFS, SES (authors' calculations).

Part-time work grew in all four countries, particularly in Germany where by 2015, some 28% of workers were working part-time. But it has also grown in Greece and Spain despite large overall declines in the workforce of both these countries. These declines mainly affected core employment, with secondary impacts on the large shares of temporary workers in Spain and of self-employed workers in Greece. In the UK, a greater share of overall employment growth occurred in core employment, while self-employment grew at a similar rate to part-time work.

As temporary employment contracted, it appears that individual workers and employers began to opt for other forms of contingent employment – primarily part-time work, but also self-employment.

In conclusion, certain important factors boosted the growth of low-paid employment in 2011–2015. The strong growth of both part-time work and of non-native employment was concentrated in the lowest wage quintiles. The resumption of male employment growth in the lower half of the wage distribution was consistent with a shift down the wage distribution of those who lost their mid-paying construction and manufacturing jobs during the peak recession years. However, the strongest and most consistent feature of employment shifts in this period was the resilience of employment growth in well-paid, top quintile jobs. Together, these factors contributed to the aggregate shift pattern observed in EU employment data since 2011 – mildly polarised employment upgrading.

Summary conclusions

Increase in employment levels: During 2013–2015, employment levels in the EU enjoyed their first sustained increase since the global financial crisis, with approximately four million more people at work in 2015 Q2 than there were in 2013 Q2. Yet despite this, employment failed to return to pre-crisis levels during this period. The resumption of employment growth between 2013 and 2015 was reflected in increasing levels of employment in low-paid and mid-paid jobs, while the share of net new employment in 2013–2015 was relatively even across quintiles of the wage distribution; these were the same quintiles in which employment declines were sharpest following 2008.

Fastest growth in top wage quintile jobs: Since the late 1990s, the fastest employment growth occurred among jobs in the top wage quintile, relative to the rest of the wage distribution (this finding relates to both recessionary and non-recessionary periods). Jobs included ICT professionals in computer programming and business professionals in management consultancies. But these account for relatively modest shares of total employment and thus have had a limited impact in terms of the employment structure.

Major employment growth in service sector: The services sector accounted for nearly all net new employment up to 2015. Between 2013 and 2015, there was also a growth in new employment regarding LKIS such as food and beverages and residential care, as well as in manufacturing which grew by 800,000 jobs since 2013. There was also evidence of a recomposition of employment in this sector towards higher-paid jobs.

Patterns of employment shift: During 2011 Q2–2015 Q2, most countries exhibited one of the two main patterns of employment shift – upgrading or polarisation – though some countries such as Hungary and Italy exhibited 'downgrading' shifts where relative employment growth was strongest in low-paid jobs.

Increase in part-time jobs: The proportion of part-time jobs in the EU increased rapidly in 2011–2015. This was the main component in the declining share of workers with core employment – full-time, permanent work. Growth of core employment status work was increasingly confined to top-quintile, well-paid jobs; in all other quintiles of the wage distribution, this category decreased and was largely replaced by other forms of employment.

Decrease in gender gap: The gender gap is closing (slowly) in terms of employment numbers and quality. The crisis had a disproportionate negative impact on men, largely due to the sectors that were hardest hit by the recession – manufacturing and construction. Recent employment growth was more evenly balanced by gender. While recent employment growth in higher paid jobs has tended to be greater for women than men, women continue to be under-represented in the top four quintiles of the job–wage distribution, while they account for over two-thirds of employment in the lowest quintile.

Part 2: What do you do at work and how? A framework for analysing tasks across occupations

Introduction

Until recently, the model of skills-biased technical change (SBTC) provided the canonical explanation for the observed changes in labour demand and wage inequality in advanced economies over the last few decades (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman, Bound and Machin, 1998; Machin and Van Reenen, 1998). In this model, technical change increases the relative productivity of high-skilled labour and therefore its relative demand; hence the observed expansion of wage inequality in most developed economies. The concept of skills that underlies this model is extremely simple: for understanding recent changes in labour demand and wage inequality, it is enough to characterise workers along a continuum of low to high skills (or even to classify them within a dichotomy of low and high skilled). As an explanation, it is also radically simplifying in the way it directly links the demand for skills to/changes in production technologies, without any discussion of how this takes place. The production process remains essentially a 'black box'.

At the turn of the century, the observation of non-linear changes in labour demand by skill level in the US and the UK (the phenomenon known as job polarisation; Autor, Katz and Kearney, 2006; Goos and Manning, 2007) led to a reformulation of this canonical model. The theory of routine-biased technical change (RBTC) argued that recent technological change is biased towards replacing labour in routine tasks (tasks that are easy to codify and automate). It claims that routine tasks are more frequent in the middle of the skills continuum, while non-routine are in the top and bottom, hence the polarising effect of recent technical change.

It is easy to see that underlying this alternative model is a richer concept of skills. It is non-linear and multidimensional: instead of a single continuum of skills, there are different axes (such as routine or cognitive task content) affecting the impact of technology on labour demand. But more importantly, this approach opens the 'black box of production' by differentiating tasks and skills – tasks are units of work activity that produce actual output, while skills refer to the human capability to perform tasks. This differentiation does not only allow a more detailed analysis of the effect of technology on labour demand (technology affects the production process and therefore tasks and such changes have an effect on the demand for skills), but also to introduce as a critical step in such an effect the mapping of tasks to skills, which can also change over time.

This alternative approach has sparked a growing literature, which has not only applied it to different periods and countries, but which has also discussed other types of task content beyond routine and cognitive (the ones proposed in the earlier RBTC literature; see Autor, Levy and Murnane, 2003). Indeed, it would seem that the task approach can potentially be expanded to a more comprehensive framework of measures, which can be used to characterise from a *material* perspective the nature of work activity across different occupations, countries and periods. But it appears that such a comprehensive framework has yet to be developed: most research focuses on the routine and cognitive dimensions, with the addition of some other aspects depending on the particular interest of each paper (such as manual, service or social interaction tasks). A more open and encompassing framework (including other types of task content besides cognitive and other types of task methods besides routine) could allow a better understanding of the impact of technology, trade and other explanatory factors on the nature of work and the structure of labour demand.

The aim of Part 2 is to contribute to the development of a more comprehensive, transparent and general-purpose set of task indices to be used for labour market analysis. Firstly, some background to the tasks-based approach is provided, including a discussion of the main concepts and what appears to be critical omissions. Secondly, the most important strands of the literature on the determinants of structural change in labour demand are briefly reviewed with the aim of gathering the implications of such literature for a conceptualisation and analysis of tasks. Thirdly, the framework for this analysis is presented, based on a critical evaluation of existing proposals. And finally, an application of this model of framework is briefly presented, using real data for European countries.

4 Understanding the tasks-based approach

According to the main proponent of the tasks-based approach in labour economics (David Autor), tasks can be simply defined as units of work activity that produce output (Autor, 2013). So the point of departure of this approach is a strictly technical view of production, seen as a mechanical process of transforming inputs into outputs. Work is an input in this process and tasks are more or less discrete units of work. Depending on the complexity of the production process, it may require the combination of more or less different types of tasks, in the same way as it may require different types of raw materials.

An important thing to note is the absence of any reference to human agency in the definition of tasks. This is intentional: one of the aims of the approach is to better understand the substitution of human workers by machines for the performance of some types of tasks. Work is therefore understood as any kind of active input into the production process, which can be performed by human beings or machines (or perhaps animals). Which factor will perform the task in a particular production process will depend on the principle of comparative advantage: 'comparative advantage in production means that the factor with the lowest economic cost of performing a task is assigned to that task. Economic cost in turn reflects both a factor's technological capability and its opportunity cost' (Autor, 2013, p. 5). In other words, depending on what is technologically feasible, a task will be performed by the most cost-effective factor.

But even in Autor's model, human labour has a certain primacy over machine input in the production process. Because it is intrinsically flexible and adaptable, human labour has historically preceded machine input in the performance of most types of tasks (Autor, 2013, p. 4). The typical historical sequence of automation would be one in which human workers first perfect and codify the performance of a particular task, which can then be taken up by machines once technology allows for it. This does not necessarily mean that all tasks will end up being carried out by machines: again, that will depend on the comparative advantage of capital over labour in each particular case.

From this perspective, skills are defined as the stock of (innate or acquired) human capabilities that allow human beings to perform tasks (Autor, 2013, p. 4). Different types of tasks require different types of skills, in quantitative and qualitative terms: some tasks require simple skills, some tasks require complex ones; some tasks require very specific skills and some tasks only generic skills. Human beings have the capacity to learn many different types of skills and, depending on the complexity of associated tasks, this may require a significant amount of time and effort. This results in specialisation, because it is simply more efficient for different workers to specialise in different tasks so that they can benefit from increased competence in such tasks over time.

As already discussed in the introduction, this approach provides the basis for a more nuanced and multidimensional understanding of the nature of labour demand than the traditional unidimensional concept of skills. It has clear foundations at the micro-level of production and seems particularly useful for understanding the process of automation of some types of jobs and in more general structural developments of labour demand. However, it has some problems too. To begin with, it strangely blurs the boundaries between the concepts of capital and labour by stating that work (and tasks) can be equally performed by both, depending on technology and relative costs. In a literal sense, it is true to say that machines can perform certain types of tasks. But a crucial difference is that machines have no real 'agency' as human workers do (at least, until a proper artificial intelligence comes into existence) and therefore there must always be human labour involved (for instance, designing, controlling or maintaining the machines). This is why even the most advanced industrial robots can be understood as very sophisticated tools: their main effect is to substantially increase the productivity of the few remaining industrial workers.

Perhaps the biggest problem of this approach, however, is that it neglects the social aspect of the production process, without which it cannot be properly understood.[12] As previously mentioned, what makes human labour a flexible and adaptable source of task input, is the fact that workers have real agency. But that also means that their input to the production process requires their cooperation. Ensuring such cooperation has historically been achieved by different means, including coercion and consent: the important point is that those means are themselves an important aspect of production, in at least two ways. Firstly, ensuring cooperation requires some labour input on its own, generating some specific tasks (such as supervisory, managerial and control tasks). Those tasks are not necessary for production in a *technical* sense and therefore cannot be explained with a technical framework such as the tasks-based approach being discussed here: they are necessary in a *social* sense, to ensure the cooperation of workers. Secondly, the need to secure cooperation will also (re) shape the contents and methods of labour input in production, in ways that cannot be explained with a strictly technical framework either. For instance, the level of routine involved in a job can be as much the result of social constraints as of technical ones. Taylorism used standardisation and routinisation of work as a tool for increasing the degree of managerial control over the labour process (Braverman, 1974).

Furthermore, tasks cannot exist in isolation, but have to be coherently bundled into jobs. One may think about tasks as units of labour input from the perspective of production, but jobs are the unit of labour demand from the perspective of firms and workers. And jobs are not only bundles of tasks, but also positions within the social structure of productive organisations, giving access to differential social power, resources and life chances. A tasks-based approach that does not take these issues into account, cannot advance its understanding of trends in work and labour demand, neither at the micro- nor at the macro-level.[13]

Finally, tasks are also socially embedded because the structures of production of any economy necessarily reflect the structures of consumption of society. The change in the contents and types of tasks in production will ultimately reflect how societies change in their tastes and preferences, in their institutions and organisational forms. This is why even within similarly developed capitalist economies, there can be significant differences in the prevalence of different types of tasks in their productive structures (and the associated occupational categories). Social democratic models, for instance, have tended to expand the public provision of social services and to reduce the weight of low-paid manual service occupations, while market-oriented models often moved in the opposite direction (Esping-Andersen, 1999). This is associated with different patterns of structural change in employment (job polarisation in the latter, structural upgrading in the former) and can be also reflected in a smaller weight of non-routine manual tasks in social democratic countries relative to market-oriented economies. This again would be a development driven by social rather than technical mechanisms and therefore cannot be fully understood within a strictly technical framework.

12 See Deming, 2015, for an alternative task model that emphasises the role of social skills within production.

13 In fact, the analyses from a tasks-based approach generally rely on data compiled at the level of jobs or occupations, because of the lack of statistical sources measuring tasks directly. But such a lack is not only the result of the limitations of existing statistics; it also reflects the fact that tasks are more a conceptual tool than a meaningful unit of analysis.

For those reasons, the following application of the tasks-based approach draws from existing proposals but makes the following qualifications:

- The structure and types of tasks in an economy do not only reflect the technical nature of the production process, but also its social organisation.
- The amount of labour input deployed across different types of tasks in an economy will not only reflect the methods and tools used in production, but also the structure of demand.
- The concept of tasks is only an analytical tool to understand better the structure and change of labour demand. Occupations (or jobs) are ultimately the unit of analysis, not tasks.

Review of the literature on the determinants of labour demand

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As previously discussed, the tasks framework is associated with a strand of academic literature discussing the implications of computerisation and technical change on the structure of labour demand. The following pages briefly review this literature, paying particular attention to the types of tasks that it identifies as most important, to feed later a proposed framework of task indices. This chapter also includes a review of other recent work on the determinants of labour demand that do not have an explicit tasks-based approach, but which also have potential interest for this purpose. In particular, focus will be placed on the literature on trade and organisational change as drivers of change in the structure of labour demand.[14]

Computerisation and technological change

As already discussed at some length, the RBTC hypothesis provides a more refined framework than the SBTC model for interpreting recent key trends in labour markets. First introduced by Autor, Levy and Murnane (2003), this theory identifies four broad categories of workplace tasks, which are classified along two main axes: routine (as opposed to non-routine) and cognitive (as opposed to manual). Routine tasks, which can be more easily automated, can be either cognitive (such as record-keeping or repetitive customer service) or manual (such as repetitive assembly).

Several influential papers defending the RBTC hypothesis and investigating job polarisation draw on the Autor, Levy and Murnane model (see for instance Goos and Manning, 2007; Autor, Katz and Kearney, 2006; Spitz-Oener, 2006; Goos, Manning and Salomons, 2010; Autor and Handel, 2013). However, only two of the above cited studies follow the original taxonomy (Goos and Manning, 2007; and Spitz-Oener, 2006); the others consider a three-fold classification of tasks by bringing together the two routine categories. More precisely, Autor, Katz and Kearney (2006) and Autor and Handel (2013) classify tasks into abstract, routine and manual, where the latter category refers to tasks that require physical effort and dexterity, with low cognitive demand but adaptability and flexibility. Goos, Manning and Salomons (2009, 2010) introduce instead the concept of service tasks – those that involve social interaction with clients – alongside abstract and routine ones. Both manual and service tasks tend to be in the non-cognitive (low-skilled) and non-routine quadrant, and therefore would grow in relative terms with computerisation.

The cognitive (abstract) axis is directly linked to the traditional concept of skills, since it refers to tasks that require intellectual effort (and therefore are complementary to information technologies) and that are often associated with formal educational requirements. The definition of what constitutes cognitive tasks is not precise in the papers reviewed, which can sometimes lead to somewhat contradictory measures. In the original formulation of Autor, Levy and Murnane (2003), they further differentiated between analytical (information-processing) and interactive (managerial) cognitive tasks. But this introduction of managerial responsibilities in the measurement of this task dimension implies the addition of a dimension of organisational power that does not seem warranted by the underlying technical framework.

The routine axis is the main focus of the model of RBTC and one of the most studied in recent literature. In the original formulation of Autor, Levy and Murnane (2003), routine tasks are defined

[14] Some studies also investigate the role of labour market institutions, such as minimum wages, trade unions and the regulation of employment contracts (see for instance DiNardo et al, 1996; Acemoglu et al, 2001; Card, 2001; Lemieux, 2007; Nellas and Olivieri, 2012). However, it is both conceptually and empirically difficult to link country-level institutional factors with micro-level task and occupational data, so it is not attempted here (for a discussion, see Eurofound, 2014).

as those that 'require methodical repetition of an unwavering procedure' (Autor, Levy and Murnane, 2003, p. 1,283). More recently, it has been more precisely defined as tasks, 'sufficiently well understood that can be fully specified as a series of instructions to be executed by a machine' (Acemoglu and Autor, 2011, p. 1,076). The problem with this concept is that it appears to conflate a very subjective meaning with a very technical one: whereas in human terms routine often means boring, the RBTC literature refers to repetitive, standardised and codifiable tasks that can be carried out by machines. Most repetitive, standard and codifiable tasks are likely to be felt as boring by human agents, but not all tasks that are boring are necessarily repetitive, standard and codifiable. A further problem is that the level of routine associated with a task depends on how that task is organised, rather than the content of the task itself. The routinisation of particular types of work is the historical result of social processes of division of labour and reorganisation of production under particular social conditions: for instance, the routinisation of manufacturing carried out by Taylor and Ford was explicitly aimed at reducing the degree of control craft workers had over the work process (Braverman, 1974). In any case, the RBTC model would argue that information technologies are substitutive of labour input in routine tasks and that it therefore tends to depress labour demand in those tasks.

Finally, at a more general level, a relevant conceptual problem in the RBCT theory is the considerable amount of overlap between the concepts of routine and cognitive tasks. Almost by definition, a task that is routine can be performed with little cognitive effort and vice versa: non-routine tasks will necessarily involve more active cognitive input (for a discussion, see Eurofound, 2014).

International trade

Over the last three decades, not only did the role of international trade grow considerably, with an increasing amount of final goods and services being exchanged in the global market, but its nature also changed, with an increasing international fragmentation of the value chain. Lower trade costs relating to policy barriers, transportation, and information and communication have increased opportunities for firms to offshore activities – to relocate part (or parts) of their production processes abroad. These relocations decisions have a clear impact on the distribution of the demand for skills. Still, the economic literature suggests that compared to technological change, international trade has only a minor role in explaining the demand shift towards skilled workers in advanced countries (for example, see Autor and Katz, 1999; Feenstra, 2010; Goldin and Katz, 2007; Acemoglu and Autor, 2011; Los et al, 2014; Michaels et al, 2014).

The 'new international trade', which involves a greater international division of labour and different countries adding value to global supply chains, has been described as 'trade in tasks', as opposed to trade in final goods (Grossman and Rossi-Hansberg, 2008). The literature identifies some types of tasks that are easier to trade than others. Such tasks: require codifiable rather than tacit information (Leamer and Storper, 2001); be can be summarised in deductive rules and are therefore more routine (Levy and Murnane, 2004); and do not require physical contact and geographic proximity (Blinder, 2006).

While earlier studies focused on the relationship between new forms of international trade and the composition of skills in the home economy, recent literature investigates the relationship between offshoring, as well the composition of onshore tasks. Offshoring is not only positively associated with the wage bill share of high-skilled workers, it also affects the type of tasks performed by workers. In particular, offshoring is associated with a statistically significant shift towards more non-routine tasks, which involve non-repetitive movements and procedures and interactive tasks, which require physical contact (Becker, Ekholm, and Muendler, 2013).

Another relevant point is that jobs that are more vulnerable to offshoring are not exclusively located at the bottom end of the employment distribution. According to Blinder (2009), more than one-fifth of US jobs that are potentially offshorable fall in the upper half of the occupational ranking. Impersonal services, which can be delivered electronically over long distance with little or no degradation in quality, do not only include low-end jobs such as telemarketers or telephone operators, but also high-skilled jobs such as computer system analysts or programmers. Within this context, Jensen and Pedersen (2012) explore the main drivers behind the offshorability of advanced tasks that are closer to a firm's core activities. In this regard, firms decide to offshore high-value business tasks to achieve international competitiveness and to access talented foreign workforce, rather than to save wages or other operational costs.

Organisational change

Although technological advances, together with international trade, have a prominent role in explaining recent changes in the employment structure, other recent studies have also highlighted the effects of modern organisational practices on the demand for labour market skills. From this perspective, the increasing relative demand for high-skilled labour is not only the result of a 'skill-biased' effect of information technology favouring employment at the top quintiles, but also of a skill-biased organisational change (SBOC) defined as 'the hypothesis that modern organisational changes are complementary to skilled workers' (Caroli and Van Reenen, 2001, p. 1,450).

Decentralisation of authority, delegation of responsibility and greater workers' autonomy are among recent trends in work organisation (see Caroli, 2001, and OECD, 1999, for a review). Indeed, trends in work organisation have been marked by a shift from mass production, 'Tayloristic' forms of organisations – characterised by centralised and bureaucratic control – towards 'just-in-time', flexible and less hierarchical ones. It is recognised that modern organisational practices lead to:

- increasing interaction, cooperation and exchange of information among workers (factors that require a greater ability to process, synthesise and communicate new pieces of knowledge);
- increasing workers' autonomy and responsibility, which entail higher self-planning and problem-solving skills;
- decreasing specialisation which run in parallel with a rising need for workers to perform multiple tasks.

Because high-skilled workers have a relative advantage with respect to these new skills requirements, recent changes in the organisational structure of firms and in workplace practices are expected to raise the demand for them, compared to unskilled workers.

While the majority of existing studies show that the effects of organisational change on the demand for skills is complementary and additional to technological advances (see for example, Bresnahan, Brynjolfsson and Hitt, 2002; Gale, Wojan and Olmsted, 2002; Greenan, 2003; Green, 2012), only a few argue that modern changes in work organisation have an independent effect on the employment structure (for example, Caroli and Van Reenen, 2001; Piva, Santarelli and Vivarelli, 2005). In most of these papers, skills are defined in terms of broad occupational classes. Although the use of occupational classification schemes to proxy skills is appealing, this approach disregards skills commonalities across occupations. More interesting results come from analyses that focus on specific sets of skills (Gale, Wojan and Olmsted, 2002, and Green, 2012). While technology has the largest impact on computer skills requirements, flexible work organisation practices have a greater effect on the demand for interpersonal and problem-solving skills (Gale, Wojan and Olmsted, 2002). Employee involvement is found to have a significant positive impact on skills such as literacy, external communication, influencing, self-planning, problem-solving and checking. Task discretion has a significant positive impact on self-planning skills (Green, 2012).

Evidence on the effects of organisational change on the demand for specific skills is limited; it appears that no study has specifically looked at tasks performed by workers. Further research would allow a clearer interpretation of the effects of organisational change on labour demand. The fact that such organisational changes, which explicitly aim at decentralising the decision-making process and reducing the number of hierarchical layers, has an impact on the structure of the workforce (and hence occupational structure) seems self-explanatory. Increasing availability of national survey data on skills and tasks required at the workplace makes such empirical analysis more feasible in the future.

6 Framework for measuring tasks across jobs

In Chapter 5, a review of the specialised literature allowed the identification of a number of task categories that seem relevant to understanding recent developments of labour demand and structural change in employment. The technological strand of the literature focused on cognitive and routine tasks as the main dimensions, although other secondary task categories were added, such as interactive (managerial), service and manual. The literature on the effects of trade on labour demand also gave a significant role to the routine dimension, although perhaps in this case social interaction is even more important. Finally, the organisational literature focused on autonomy, communication and cooperation (with colleagues rather than clients) and problem-solving.

Is it possible to classify each of those task dimensions identified in the literature within a more or less comprehensive conceptual framework? It appears that all of those categories could be classified on two axes that are conceptually different: one would refer to the content of tasks, while the other would refer to the methods and tools used for carrying out the tasks. The contents axis would refer to the object of work activity, understanding work as a transformative process, which is applied to things, ideas or social relations. The methods axis would refer to the ways in which work is organised and to the physical objects used for aiding the production process. The concepts previously reviewed – cognitive, manual and service tasks, for instance – would be classified within the contents axis. The concepts of routine or autonomy, on the other hand, would be classified within the methods axis.

In very simple terms, those two axes can be understood as the *what* and *how* of work activity. The content of tasks mostly depends on what is being produced (or rather, transformed in the production process); it therefore also depends on the structure of demand and needs that are satisfied by economic activity. It will tend to be associated, for instance, with the economic sector to which the work activity belongs: thus, interpersonal and service tasks are (obviously) more frequent in service sectors, while manual tasks are more frequent in goods-producing sectors such as agriculture and manufacturing. However, the complexity of contemporary production processes means that the link between the actual tasks performed by workers in each sector and the final output of the overall production process is significantly blurred: there are many intermediate and meta-tasks whose relation with the actual output is only indirect.

The methods of work are less dependent on what is being produced, relating more to the technology and social organisation of production. Therefore, they are more historically and institutionally contingent. For the production of the same goods or services, different societies or organisations can use significantly different methods and tools. It is important to note that, according to this framework, the level of routine of the task belongs under methods of work and not in the axis of task content. The level of routine involved in a task is the result of the unfolding of the division of labour and work organisation, not something given by what is being produced. According to this perspective, the replacement of labour input with capital for the performance of routine tasks would therefore only represent a further change in the division of labour and work organisation.

Table 2 (on next page) presents the full classification of tasks according to this proposed framework. All of the key task categories reviewed in the literature have been included in this framework, as well as some additional categories to fill gaps which seem implicit in the proposed model.

Table 2: Classification of tasks according to content and methods/tools

Content

1. **Physical tasks:** Tasks aimed at the physical manipulation and transformation of material things, which can be further differentiated into two subcategories.
   a. Strength: Tasks that primarily require the exertion of energy and strength.
   b. Dexterity: Tasks that primarily require a fine physical skill and coordination, particularly using hands.
2. **Intellectual tasks:** Tasks aimed at the manipulation and transformation of information and the active resolution of complex problems, which can be further differentiated into two sub categories.
   a. *Information-processing:* Manipulation and transformation of codified information, which can be further divided into:
      i. Literacy: Manipulation and transformation of verbal information.
      ii. Numeracy: Manipulation and transformation of numeric information.
   b. *Problem-solving:* Tasks that involve finding solutions to complex problems, which can be further divided into:
      i. Information-gathering and evaluation of complex information.
      ii. Creativity and resolution.
3. **Social tasks:** Tasks whose primary aim is the interaction with other people, which can be further differentiated into four subcategories.
   a. Serving/attending: Personally serving or attending customers, clients or patients.
   b. Teaching/training/coaching: Training and coaching others.
   c. Selling/influencing: Persuading and influencing others.
   d. Managing/coordinating: Supervising and coordinating others.

Methods and tools

4. **Methods:** The forms of work organisation used in performing the tasks, which can be further differentiated into three subcategories.
   a. Autonomy: The extent to which the worker is free to carry out the task as they need.
   b. Teamwork: The extent to which the task is carried out in direct cooperation with a small group of co-workers.
   c. Routine: The extent to which the task is repetitive and standardised.
5. **Tools:** The type of technology used at work, which can be further differentiated into two main types of technology.
   a. Machines (excluding ICT)
   b. Information and communication technologies.

The first broad category of this framework, physical tasks, encompasses the types of activities that the literature sometimes refers to as ‘manual’. This category is split into two categories. The first one, strength, refers to the pure exertion of muscular power. This is probably the category of labour input that has been most significantly replaced by technical change since the origins of human civilisation (even before machines, the domestication of animals enabled a very significant reduction in this kind of task input). Nonetheless, it remains a significant component of some types of work activity, so it is included in this framework. The second category of physical tasks is dexterity, which corresponds most directly with the concept of manual tasks. As with strength, over the centuries technical change has significantly reduced the amount of labour input of this kind, but it still represents a significant category of labour, even if it is clearly in secular decline.[15]

[15] In early versions of this framework, a third category was included, referring to the active physical observation of the environment. However, the decision was made to eliminate this category because it conceptually overlaps with some aspects of intellectual tasks (information-gathering and evaluation, in particular), and because the measures used did not behave as expected (they tended to correlate more with information-processing than with the other manual tasks, and they also had a very low variation across occupations).

The second broad category, intellectual tasks, refers to information-processing and problem-solving, and is similar to the concept of cognitive tasks found in the literature. Up until relatively recently in human history, intellectual tasks expanded as technical change reduced the amount of human labour necessary to carry out physical tasks. Particularly in the case of information-processing, advances over recent decades in computing allowed for a large-scale substitution of intellectual human input by machines. Following the framework of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), information-processing tasks were split into literacy and numeracy, referring respectively to the processing of verbal and numeric information. The richness of the PIAAC's Adult Skills Survey enabled the further differentiation of literacy into the processing of business, technical and humanities (verbal information), and numeracy into accounting and analytic mathematical tasks. The third category of PIAAC's framework (problem-solving in technology-rich environments) is considered as a separate category of intellectual tasks, kept at a higher level of generality by eliminating the direct reference to a technological environment. Problem-solving is further divided into the gathering and evaluation of information, and the creativity required for finding and/or implementing a solution.

The third broad dimension of the task content classification in this framework refers to social tasks, aimed at interaction with other people. Social tasks also grew over time, as technical progress reduced human input for physical tasks. But unlike information-processing, these types of tasks remain less directly affected by advances in computing and therefore seem likely to continue growing in the foreseeable future. Although this category of tasks is obviously linked to the service sector of the economy, it is important to note that they are by no means synonymous: the focus here is on the content of work as a transformative process; some types of services are actually aimed at the transformation of the physical environment (for instance, cleaning services) or the processing of information (such as business or legal services). Here the specific reference is work activity that is *directly* aimed at social interaction. The review of literature did not identify a finer breakdown of social interaction tasks that could fit this framework. For this reason and on the basis of an inspection of detailed occupational codes and a review of the areas covered by the different sources with task information, the following four subcategories were identified:

- serving/attending;
- teaching/training/coaching;
- selling/influencing;
- managing/coordinating.

It would have been preferable to include two extra categories of social tasks: caring and entertaining. Unfortunately, no sources were identified for these categories. The serving/attending subcategory (derived from the US Occupational Information Network dataset, ONET) does incorporate, to some extent, the dimension of caring, as shall be presented later.

The second part of this framework refers to the methods and tools of work. It is important to emphasise that these indices refer to how work is organised and which tools are used, rather than to the actual content of labour input, which is addressed in the first part of the framework. In this sense, the task content part of the framework is the more direct and more informative part; the methods and tools part should be considered as a secondary axis of information on some attributes of work activity, one that is necessary for a better understanding of labour input in the production process.

After all, work organisation and technology are key drivers (or determinants) of change in tasks rather than aspects of the change.

The methods category essentially refers to forms of work organisation. It has been broken down into three subcategories, drawing from the main dimensions identified in the specialised literature:

- autonomy, which refers to the degree of latitude of workers in their tasks;
- teamwork, which refers to whether or not workers work in direct collaboration with small groups of co-workers;
- routine, referring to the degree of repetitiveness and standardisation of work processes.

The inclusion of routine in this domain of the framework may seem surprising, since in previous papers it is often considered a type of task content (rather than a method), with a similar status as cognitive tasks. But as already argued, the degree of routine involved in a task is not an aspect of task content as such, but an aspect of how such a task is organised in a particular work process. The same type of task content (in terms of the object of the transformative process of work, as classified in the first half of the framework) can be carried out with a low or a high degree of routine. In this respect, the routinisation of a task can be understood in itself as part of the process of technical change, rather than as something given by the material nature of the production process.

Finally, this model includes two variables measuring the use of tools, one referring to machines and the other to ICT (which is further subdivided into basic IT and programming). In order to be exhaustive in this classification, a third category of non-mechanical tools could have been added here, but such tools are so pervasive that it would be useless for the purposes of this framework.

It is important to note that the proposed classification of tasks is aimed as a tool to be used for later analysis of jobs or occupations. In quantitative approaches to labour market analysis, tasks are never directly observed, measured or classified. A proper task analysis and classification would require a very different approach, probably similar to what Taylor called 'scientific management' nearly a century ago. This involved studying, in detail, a particular work process in order to break it down into its smallest possible units, which could then be classified. No statistical source measures and classifies tasks in such a way and it is quite likely that such a source will never exist. So the task approach, in this sense, is just a framework for analysing occupations or jobs from a material perspective, focusing the analysis on the types of labour input into the production process that the different jobs or occupations typically involve.

Nonetheless, it is possible to conceive this proposed task classification as a set of (more or less) exhaustive categories that could be used to classify tasks if they could be measured. Those categories can then be used to characterise jobs or occupations by using variables drawn from different statistical sources, and as an approximation – a way of measuring the extent to which a particular job or occupation involves a particular type of task.

In the next chapter, each of the categories in this classification of tasks will be converted into a job-level index, measuring the extent to which a job involves a particular task.

7 Application of the model to EU-level occupational analysis

This chapter presents a specific application of the proposal for Europe, building a set of indices for occupations and sectors, combined at the two-digit level, that match the classification of tasks presented in Chapter 6.

Sources

There are two main options for measuring the task content of different types of jobs: aggregating the answers of individual workers to surveys on skills and working conditions; and drawing from occupational databases based on the assessment of experts. At present, there is no international source of either of those categories that can be used for constructing the full set of task indices set out in Table 1. Therefore, it is proposed that information is drawn from different sources, summarised below.

Workers' surveys: The data contained in these sources are generally measured at the level of individual workers and contain responses to questions on what the respondents do at work, among other issues. Two sources fit this category: the European Working Conditions Survey (EWCS) and the OECD's Survey of Adult Skills (PIAAC). Using workers' surveys to infer the task content of jobs and occupations has advantages and disadvantages. It enables the study of variability in task content within each occupation or job type. But gathering information on tasks from workers introduces a potential bias in measurement, since workers' answers may be subjectively biased or just wrong (dissatisfied workers may exaggerate the amount of routine in their jobs, or new recruits may not be able to answer). Furthermore, there can be inconsistencies in the classification of workers across occupational levels and sectors, which can be negative for the purposes of this study (every misclassified worker would bias the occupation-level task scores).

Occupational databases: These datasets, which contain information from both jobholders and occupational analysts, include a range of variables measuring factors such as task content, skill requirements and job characteristics. Two main sources were identified in this category, both from the US: The Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network dataset (ONET).[16] These sources are generally quite detailed in their measure of task content. Their conceptual framework is closer than that of the workers' surveys to the framework being proposed here. However, certain problems make it necessary to use them as a complementary source only, despite their greater relevance to the task model being proposed here. Firstly, they are only available for the US and although the task content of occupations should (in principle) be roughly the same across similarly developed economies, as discussed earlier certain institutional and socioeconomic factors differ across countries, which could have an impact even at the level of task content. A second problem is that these databases do not allow for the study of variation in task content and methods that may exist within each occupation. Finally, while the conceptual framework of ONET is closer to this proposed framework than other sources, it is obviously not identical to it so for this reason, it is still useful to triangulate its information with other sources.

Table 3 (on next page) shows the sources used for the construction of indices for each category of task in this proposed framework. As can be seen, ONET can provide a more exhaustive coverage of all the elements in the model presented here. ONET has a modular structure, with different datasets providing information on job attributes from different perspectives. Elements have been taken

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16 In fact, ONET also partly uses workers' own assessment through a dedicated survey, although this is complemented by experts. For more details, see Eurofound (forthcoming).

from four of those datasets (work activities, abilities, skills and context), in some cases providing information on the same element from a different angle. In practice, those different modules of ONET have been used as though they were different sources, for instance, systematically comparing the scores given by those different modules for the same element in this model when possible.

Table 3: Mapping sources to elements in the task model

	EWCS	PIAAC	ONET			Available In x sources
			Work activities	Abilities	Skills	
In terms of the object of work/task:						
1. Physical: Manipulation and transformation of things	x			x		[2]
a. Strength	x			x		2
b. Dexterity				x		1
2. Intellectual: Manipulation and transformation of ideas	x	x		x		[3]
a. Information-processing: Processing of codified information		x		x		[2]
i. Literacy: Processing of verbal information		x		x		2
- Business		x				1
- Technical		x				1
- Humanities		x				1
ii. Numeracy: Processing of numerical information		x		x		2
- Accounting		x				1
- Analytic		x				1
b. Problem-solving: Finding solutions to complex/new issues	x	x		x		[3]
i. Information-gathering and evaluation	x	x		x		3
ii. Creativity: finding a solution	x			x		2
3. Social: Interacting with other people		x	x		x	[2]
- Serving/attending			x			1
- Selling/persuading		x	x		x	2
- Teaching/coaching		x	x		x	2
- Managing/coordinating		x	x			2
In terms of the methods and tools used in the work/task						
1. Work organisation						
a. Autonomy: Self-direction and latitude	x	x				2
b. Teamwork: Working in small groups	x					1
c. Routine: Repetitiveness and standardisation of the task	x					1
i. Repetitiveness	x					1
ii. Standardisation	x					1
2. Technology						
a. Operation of mechanical machinery and tools (non-ICT)	x		x		x	2
b. Operation of ICT	x	x	x			3
- Basic IT		x				1
- Programming		x			x	2

Source: EWCS 2010, PIAAC and ONET data.
Note: The total number of sources used for the construction of the higher-level indices is in brackets.

Table 3 also shows that the value of different sources depends on the area in question. For instance, the EWCS is very detailed in terms of work organisation, whereas PIAAC has excellent coverage of intellectual tasks and ONET has good coverage of all the task content categories. As shown in the last column of Table 3, some elements are only covered in one of the sources, but in most cases the indices have been constructed by combining information from two or three sources. As most of the variables used are just partial proxies of the concepts of the proposed framework, this redundancy can increase the consistency and robustness of the measure. Having different measures of the same concept is also very useful for testing the validity of this framework, as will be shown later.

It is important to highlight that although the three sources refer to the employed population, they refer to different geographic areas. ONET bases its measurement on US workers, while the EWCS is a European survey and the PIAAC covers different OECD countries (many but not all in Europe). To keep a certain degree of consistency, the EWCS sample has been restricted to EU15 and the PIAAC sample to the available EU15 countries, as well as the US. ONET obviously remains restricted to the US. This way, the set of task measures will refer to advanced western economies, a group of countries with broadly similar levels of economic development and comparable socioeconomic structures.

Construction of the indices

The indices were constructed by aggregating information from different variables from the indicated sources. Each of the variables was standardised in a 0–1 normative scale, reflecting the intensity of each type of task content in each job. Then, the average scores of those variables were extracted for each occupation-sector combination in each source, as well as some information on their dispersion for later inspection. Following this, all these variables were combined in a single dataset and compared using the EU15 LFS distribution of employment by sector and occupation in 2012 as weights. After the final selection of variables for each component of the model, they were aggregated following the nested structure of this framework (starting from the more detailed level and continuing the aggregation upwards).[17]

Consistency across sources and variables

In order to evaluate the consistency of the indicators across the original sources and variables used, a separate principal components factor analysis was conducted on all the original variables used for the construction of the indices. The first seven factors identified by the principal components analysis were extracted as variables; these were all the factors with an eigenvalue higher than one, accounting for more than 82% of the total variance for all the 43 original indicators included in the analysis. These variables were then correlated with each of the components and subcomponents of the index, to compare the results of the normative aggregation with the statistical aggregation performed by the principal components analysis (which is entirely based on the observed correlations in task intensity across occupations and sectors). The results are summarised in Table 4 (on next page).

Factor 1 is positively correlated with general cognitive tasks related to information-processing in literacy domains (business literacy in particular) and information-gathering, and basic IT tasks. It is instead negatively correlated with physical tasks, (non ICT) machinery and routine methods.

Factor 2 can be seen as an indicator of social interaction tasks, very strongly correlated with the social interaction domain, particularly with the teaching and managing components, as well as with problem-solving and some of the literacy subcomponents (mostly humanities).

Factor 3 identifies routine industrial tasks, with a positive correlation with the indices of routine, machine operation and physical tasks, and a negative correlation with social interaction tasks.

[17] For more details on the methodology of the construction of the indices, see Eurofound (forthcoming).

Table 4: Summary statistics on consistency across sources

	Cronbach's Alpha for all source variables within domain	Correlation of indices with factors extracted by principal components from all the original variables from original sources					
		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
In terms of the object of work/task:							
1. Physical: manipulation and transformation of things	0.8	-0.76	-0.16	0.45	-0.15	-0.23	-0.12
a. Strength		-0.80	-0.13	0.33	-0.16	-0.31	-0.12
b. Dexterity		-0.62	-0.18	0.54	-0.12	-0.10	-0.11
2. Intellectual: manipulation and transformation of ideas	0.91	0.62	0.65	0.04	0.29	0.19	0.19
a. Information-processing: processing of codified information		0.67	0.53	-0.02	0.45	0.20	0.10
i. Literacy: processing of verbal information		0.72	0.61	-0.09	0.22	0.09	0.08
- Business		0.82	0.30	-0.13	0.35	0.04	0.14
- Technical		0.60	0.55	0.25	0.16	-0.00	-0.09
- Humanities		0.60	0.64	-0.11	0.06	-0.06	0.19
ii. Numeracy: processing of numerical information		0.56	0.40	0.06	0.62	0.29	0.10
- Accounting		0.46	0.14	-0.01	0.81	0.09	0.10
- Analytic		0.59	0.42	0.21	0.34	0.25	0.17
b. Problem-solving: finding solutions to complex/new issues		0.49	0.73	0.10	0.09	0.16	0.27
i. Information-gathering and evaluation		0.58	0.63	0.22	0.10	0.14	0.07
ii. Creativity: finding a solution		0.32	0.72	-0.05	0.07	0.16	0.46
3. Social: interacting with other people	0.82	0.21	0.79	-0.38	0.36	-0.14	0.03
- Serving/attending		-0.12	0.36	-0.71	0.18	-0.31	-0.10
- Selling/persuading		0.27	0.53	-0.35	0.62	-0.02	0.03
- Teaching		0.30	0.86	-0.10	0.01	-0.05	-0.02
- Managing		0.20	0.78	-0.01	0.33	-0.06	0.22
In terms of the methods and tools used in the work/task							
1. Work organisation	0.43						
a. Autonomy: self-direction and latitude		0.45	0.22	-0.09	0.24	0.10	0.76
b. Teamwork: working in small groups		0.20	0.40	0.18	-0.31	0.02	-0.39
c. Routine: Repetitiveness and standardisation of the task		-0.21	-0.14	0.62	0.21	0.02	-0.35
i. Repetitiveness		-0.44	-0.43	0.25	0.12	-0.02	-0.31
ii. Standardisation		0.09	0.18	0.67	0.19	0.05	-0.22
2. Technology	0.82						
a. Operation of mechanical machinery and tools (non-ICT)		-0.45	-0.15	0.79	-0.03	-0.00	-0.12
b. Operation of ICT		0.84	0.29	-0.11	0.19	0.32	0.11
- Basic IT		0.81	0.30	-0.06	0.20	0.08	0.26
- Programming		0.36	0.18	0.22	0.03	0.74	0.14
	Variance explained:	51%	8%	7%	4%	4%	3%

Source: EWCS 2010, PIAAC, ONET data (2012 EU15 LFS weights), authors' elaboration.

Factor 4 picks up on accounting and business literacy as well as selling social interaction tasks, thus referring to business-oriented administrative and office tasks. It is interesting to note that this factor is slightly positive in its correlation with the routine component of the index.

Factor 5 picks up specifically on ICT analytic tasks: programming, some numeric analytic tasks and problem-solving, with a negative correlation with the social tasks domain.

Finally, Factor 6 is correlated with autonomy and creativity (and negatively with routine tasks) and can therefore be interpreted as an indicator of creative tasks.

Overall, this initial analysis of the internal consistency of these measures seems reasonably reassuring. While the factors obtained by principal components factor analysis are not identical to the variables constructed following the theoretical framework, they are quite consistent with them – in fact, some of them are extremely similar.

An important observation that can also be made from this analysis is that although the correlations were highest among items that are linked in the framework, there were also some significant correlations between different domains. In fact, there is a significant overlap in the task content indices, which means that (as will be shown later) if the raw scores of all the indices for a particular occupation at any level of the framework were added together, the result would often be much higher than one. This highlights an important aspect of the task measures that are being presented here: each of the indicators of this framework presents an assessment of a particular attribute of the task content of a particular job, rather than a breakdown of total labour input for that job into a series of distinct and mutually exclusive categories of tasks. In other words, the same work activity can involve different types of task content simultaneously. For instance, the act of teaching obviously involves a large amount of task content in the category of 'teaching' (a subcomponent of the social tasks domain), but it also involves a significant degree of information-processing, problem-solving and even other types of social task content such as managing or influencing (which is part of the 'selling' component'). These secondary types of task input are not activities separate from teaching, but rather secondary types of labour input that are also required by the act of teaching itself. That is why there is a significant amount of overlap between the different types of task content and why it cannot be assumed that the different task indicators should add up to one. This is a strength – not a weakness – of this framework, as it will allow a richer characterisation of the task input of different occupations.

One aspect of the principal components factor analysis that is not included in Table 4 (for reasons of space), is the fact that in most cases the factors combine information from variables measuring the same concept across the three sources used, which implies that there is a high degree of consistency across them.[18] What is included is an indicator of inter-item covariance and scale reliability, Cronbach's Alpha, computed for all the original variables used for each of the main components of this framework. The values are reassuringly high for all components except work organisation, which was to be expected as this component includes indicators that measure different forms of work organisation, rather than different aspects of the same underlying factor. In fact, in the approach used here, only higher-level aggregates of the task content domains are provided (physical, intellectual and social), as they are supposed to be internally consistent vectors of indicators measuring different aspects of the same reality; the domains of task methods and tools shown at the bottom of the table are not aggregated at the higher level because they measure different forms of work organisation

[18] The full table is available in Eurofound (forthcoming).

and technology use at work. The fact that the ‘tools’ indicators (machines and ICT) also display a high Cronbach’s Alpha value reflects the fact that they are empirically correlated in reverse (those using analogue machines are less likely to use digital ones and vice versa), something which was not necessarily an assumption of the framework.

Distribution of task content and methods across occupations in Europe

This section discusses the distribution of the different indicators of task contents, methods and tools for European workers. Since this paper is more an initial presentation of a new set of indices than an actual analysis of the distribution of tasks across Europe (which is left for a subsequent study), this discussion is restricted to a broad evaluation of the scores across the two-digit occupations for the EU15 as a whole. The aim is to evaluate the plausibility of these indices, rather than to carry out a substantive analysis of those results.

The results shown in Table 5 (p. 48 and p. 49) reflect the raw scores of the indices, which are expressed in percentages, on a task intensity scale that has been applied to the original sources, as previously explained. Scores for the broad task indices are summarised below.

Physical task indices: As could be expected, the highest scores are for agricultural and industrial occupations, with very low values for managers and professionals. Since the raw scores are shown, the values can be understood as a direct approximation to the intensity of physical task content. In this sense, the measures reflect the fact that even in the most ‘physical’ occupations, the intensity of actual physical tasks is not very high: in comparison, the intensity of intellectual tasks in the most ‘intellectual’ occupations is much higher. In advanced economies, this is to be expected as a result of the general development of technologies that reduce the need of physical task input even in the most manual work activities.

Intellectual task indices: The scores within this domain are very strongly linked to the skill level of occupations (which underlies the ISCO code ranking), as was to be expected. The variation across the occupational hierarchy of these indices is relatively high: managerial and professional occupations receive scores above 60%, while the less skilled occupations receive scores below 30%. Within information-processing tasks, the highest scores are for the business literacy tasks (a rather broad category that includes measures of tasks such as reading and writing letters and financial statements), as well as for accounting numeracy tasks, which are very high (above 70% or even 80%) for managerial occupations and business and related professions. The lowest values overall are for analytic numeracy tasks (involving statistical and mathematic operations) and for humanities literacy tasks, except for those occupations that could be expected to have high values in those areas (such as engineers and teachers). Problem-solving, on the other hand, shows more uniformly high values (with very few occupations below 40%), although managerial and professional occupations do stand out from the rest.

Social task indices: These are generally linked to skill level as well, although with less variability and more exceptions. The values of the ‘serving and attending’ component, which measure task content that involves a direct personal contact with the public, shows highest values for hospitality and retail managers, health professionals, associate professionals and sales workers; and low values for agricultural and manufacturing occupations, as well as ICT professionals. The other components of social tasks look also plausible: selling/influencing tasks are more frequent in managerial occupations and for sales workers; teaching and training is highest for teachers, managers and professionals; and managing is highest for managers. Overall, the social domain assigns high scores to managers, moderately high scores to sales and personal care workers, as well as some professionals, and low scores to industrial and low-skilled service occupations such as cleaning or food preparation assistants.

Work organisation indices: These indices are the least linked to the skill level of occupations, with a significant amount of diversity across the three subindices. Autonomy is perhaps the component most linked to skill level, but there are some interesting exceptions (such as the high autonomy of some agricultural and low-skilled service occupations, or the low autonomy of health workers). Teamwork is high among professionals and managers, but also among construction and manufacturing labourers and personal care workers. Routine is negatively correlated with the skill level of occupations, although it is quite high in some mid-level occupations such as clerks.[19]

Technology indices: The use of machines and ICT equipment strongly differentiates agricultural and industrial non-professional occupations from the rest. Agricultural and industrial occupations use machinery to a significant extent (approximately 40% of 'intensity') and use ICT to a much lower extent (less than 20%). For most of the other occupations, the use of machinery is below 20% (with a few exceptions) and the use of ICT is higher (above 40% or even 50%). PIAAC allows a further differentiation between basic IT and more advanced programming ICT tasks at work: the latter is extremely rare except for very specific occupations, while the former is very high in managerial, professional, administrative and service occupations.

[19] See Eurofound 2014 for a more detailed discussion of the link between routine and skills.

Table 5: Task indices scores for two-digit occupations

Occupation (ISCO08 – two-digit codes)	1.Physical	1.a.Strength	1.b.Dexterity	2.Intellectual	2.a.Information-processing	2.a.i.Literacy	2.a.i.i.Business	2.a.i.ii.Technical	2.a.i.iii.Humanities	2.a.ii.Numeracy	2.a.ii.i.Accounting	2.a.ii.ii.Analysis	2.b.Problem-solving	2.b.i.Information	2.b.ii.Solving	3.Social	3.a.Serving	3.b.Selling	3.c.Teaching	3.d.Managing	4.WO.Autonomy	4.WO.Teamwork	4.WO.Routine	4.WO.Routine.Repet	4.WO.Routine.Stand	5.Tools.Machines	5.Tools.ICT	5.Tools.ICT.Basic IT	5.Tools.ICT.Program	Empl.Share (EU15, 2012)
Chief executives, senior officials and legislators	16.6	11.5	21.6	65.1	57.6	63.4	87.6	54.2	50.4	51.8	75.5	34.0	72.6	72.0	74.5	60.7	53.8	73.6	52.0	61.9	79.5	60.0	39.7	24.1	55.4	13.5	63.1	85.1	9.0	1%
Administrative and commercial managers	11.2	7.1	15.3	64.5	59.2	62.4	87.1	58.0	46.1	56.0	80.8	47.7	69.7	69.6	70.6	55.3	47.4	64.7	52.5	56.5	77.5	55.7	48.3	29.5	67.1	8.9	66.9	91.3	12.7	2%
Production and specialised services managers	16.6	13.8	19.4	63.5	57.0	62.0	84.4	62.5	43.8	52.1	73.7	41.1	69.9	68.2	71.7	60.9	58.9	63.3	56.0	65.3	73.5	56.0	53.0	29.5	76.6	16.9	61.5	85.0	12.2	2%
Hospitality, retail and other services managers	28.8	25.7	32.0	58.6	52.5	56.2	79.7	51.8	36.3	48.7	81.3	27.1	64.7	59.7	69.8	62.5	70.4	68.7	50.6	61.2	73.1	40.6	49.4	38.0	60.8	17.8	50.4	73.3	8.3	2%
Science and engineering professionals	17.5	10.0	25.0	65.4	59.4	62.1	76.1	61.5	41.3	56.8	66.8	51.1	71.4	72.0	71.4	42.3	35.5	48.1	43.7	41.8	71.2	56.6	49.8	31.2	68.4	19.1	68.1	85.5	22.5	3%
Health professionals	35.8	29.0	42.6	58.9	49.0	60.0	63.8	63.5	43.0	38.1	46.0	26.7	68.8	73.3	64.3	54.3	66.2	53.1	52.5	45.9	58.0	58.5	48.4	35.4	61.4	15.0	45.9	63.2	5.8	3%
Teaching professionals	16.1	17.3	14.9	58.1	49.4	62.0	65.2	60.1	52.8	36.8	42.8	33.1	66.8	65.1	68.5	55.0	53.2	48.9	72.9	44.8	56.4	56.0	39.9	24.5	55.2	5.9	48.7	74.1	7.3	5%
Business and administration professionals	9.9	6.1	13.8	61.6	55.8	60.5	84.6	55.6	42.9	51.2	70.1	40.4	67.4	68.6	66.1	44.1	37.1	56.2	45.0	37.7	73.0	51.4	45.9	30.3	61.6	6.6	67.1	88.3	12.8	3%
Information and communications techn. professionals	16.9	4.3	29.5	63.5	53.6	58.6	74.0	59.9	40.4	48.6	52.7	44.0	73.3	74.4	72.0	36.1	23.4	43.8	42.5	33.1	74.8	54.8	44.1	29.9	58.2	12.9	84.7	89.9	60.5	2%
Legal, social and cultural professionals	14.3	12.0	16.7	56.5	45.3	59.5	74.9	48.0	47.6	31.1	43.0	17.8	67.8	67.4	68.3	48.1	58.3	52.8	45.0	36.8	70.5	47.9	38.9	25.0	52.8	6.5	54.6	77.2	7.9	3%
Science and engineering associate professionals	31.2	22.4	40.0	56.1	47.9	52.2	60.5	63.1	27.2	43.7	55.1	34.5	64.3	67.8	60.4	39.2	33.6	41.5	41.9	39.6	59.9	56.7	56.9	38.3	75.6	30.1	48.9	68.5	14.0	4%
Health associate professionals	37.4	32.3	42.5	50.2	41.3	51.0	57.1	57.4	31.7	31.6	37.4	20.9	59.0	62.8	55.3	43.3	58.1	44.8	38.0	33.1	52.2	64.2	45.1	34.1	56.1	17.5	40.4	55.8	7.2	3%
Business and administration associate professionals	14.1	8.9	19.3	55.2	50.6	56.3	82.1	55.1	33.5	44.9	71.1	28.1	59.9	62.3	57.4	42.2	45.1	53.4	35.6	34.8	66.5	43.5	44.0	33.0	55.0	7.9	62.0	81.8	9.5	7%
Legal, social, cultural and related associate professionals	25.6	23.0	28.2	49.9	37.3	49.0	59.2	44.2	33.0	25.7	36.0	12.9	62.5	60.4	64.6	44.8	53.2	48.0	43.2	35.3	63.2	62.1	38.6	30.8	46.3	9.6	40.5	62.5	5.1	2%
Information and communications technicians	26.0	13.6	38.4	57.4	46.0	54.5	71.7	56.9	33.7	37.5	47.2	26.6	68.8	72.0	64.5	33.7	28.1	41.1	37.6	27.7	66.5	54.0	45.8	35.3	56.3	21.2	75.8	78.3	36.9	1%
General and keyboard clerks	14.6	6.8	22.5	47.8	42.7	51.1	79.7	44.6	25.5	34.3	55.1	22.1	52.8	56.6	48.9	32.8	44.7	35.5	26.1	24.9	60.8	44.1	45.1	40.6	49.6	8.4	62.0	77.9	6.5	3%
Customer services clerks	18.2	12.0	24.4	48.0	43.3	50.5	75.9	51.3	25.5	36.0	61.0	17.2	52.7	55.8	49.3	42.1	58.6	52.0	32.1	26.5	49.5	47.7	51.7	47.4	56.0	10.3	56.0	70.3	8.3	2%
Numerical and material recording clerks	19.7	14.5	24.9	49.8	46.5	49.8	76.1	46.5	22.6	43.3	66.2	27.1	53.0	55.9	49.8	34.7	38.6	38.5	30.4	31.5	58.4	44.4	50.3	39.1	61.5	11.7	55.9	74.1	8.9	4%
Other clerical support workers	26.6	22.2	31.0	43.7	37.7	46.1	65.8	45.3	22.5	29.3	42.4	16.9	49.6	51.3	47.3	32.7	43.3	36.4	27.5	25.2	57.3	50.4	48.4	50.5	46.2	12.5	47.7	67.7	7.1	2%
Personal service workers	35.4	32.5	38.3	40.7	31.3	36.8	36.1	31.2	18.7	25.9	44.1	9.3	50.1	48.2	52.0	40.5	58.7	44.7	30.5	28.3	53.0	46.2	50.0	50.4	49.5	13.2	17.8	38.6	3.2	5%

Table 5: (continued)

Occupation (ISCO08 – two-digit codes)	1.Physical	1.a.Strength	1.b.Dexterity	2.Intellectual	2.a.Information-processing	2.a.i.Literacy	2.a.i.i.Business	2.a.i.ii.Technical	2.a.i.iii.Humanities	2.a.ii.Numeracy	2.a.ii.i.Accounting	2.a.ii.ii.Analysis	2.b.Problem-solving	2.b.i.Information	2.b.ii.Solving	3.Social	3.a.Serving	3.b.Selling	3.c.Teaching	3.d.Managing	4.WO.Autonomy	4.WO.Teamwork	4.WO.Routine	4.WO.Routine.Repet	4.WO.Routine.Stand	5.Tools.Machines	5.Tools.ICT	5.Tools.ICT.Basic IT	5.Tools.ICT.Program	Empl.Share (EU15, 2012)
Sales workers	31.0	29.2	32.9	45.6	39.7	42.8	47.9	38.4	18.8	36.6	63.5	12.3	51.6	50.3	52.7	46.4	61.2	60.2	33.3	31.0	53.6	38.6	45.4	44.5	46.4	12.9	30.2	42.0	4.9	7%
Personal care workers	37.3	37.4	37.2	43.5	31.8	42.1	38.4	40.8	24.8	21.4	20.1	9.2	55.3	54.1	56.4	39.4	50.4	38.3	36.6	32.4	51.3	57.6	40.5	35.7	45.3	11.3	22.1	38.2	4.2	4%
Protective services workers	32.5	31.0	33.9	45.0	34.1	50.2	54.3	63.8	32.4	18.0	18.4	10.1	56.0	59.6	52.5	43.6	59.9	43.0	40.9	31.1	44.3	59.5	41.2	33.2	49.3	16.9	38.7	60.9	5.7	1%
Market-oriented skilled agricultural workers	42.5	40.3	44.6	41.2	29.9	38.0	45.1	31.1	25.8	21.9	43.9	11.8	52.4	51.0	54.1	28.1	27.5	31.1	24.5	29.4	70.8	28.0	50.8	42.8	58.7	36.6	21.0	47.9	3.9	2%
Market-oriented skilled forest., fish. and hunt. workers	43.3	44.7	41.9	37.1	26.4	30.6	25.4	21.2	14.6	22.2	27.2	5.1	47.9	48.8	46.1	29.8	31.8	35.1	24.2	27.8	48.3	46.6	58.7	57.5	60.0	35.1	17.4	53.3	2.5	0%
Building and related trades workers, excl. electricians	43.2	44.0	42.4	43.3	31.6	35.2	32.6	38.7	14.1	28.1	39.7	15.6	55.1	55.6	54.5	34.9	38.7	36.5	31.6	33.3	55.2	47.9	61.9	56.1	67.6	34.4	12.2	48.6	3.7	4%
Metal, machinery and related trades workers	42.8	38.6	46.9	45.2	35.0	40.1	34.3	53.3	18.4	29.9	43.2	17.6	55.3	59.6	50.7	30.4	29.1	34.1	31.4	27.6	50.2	49.8	62.2	49.8	74.6	46.8	22.3	38.5	9.5	4%
Handicraft and printing workers	39.9	31.5	48.3	45.5	36.0	41.1	46.8	44.6	19.9	30.9	47.2	16.8	55.0	53.6	56.7	32.0	40.8	34.8	27.7	27.1	57.2	39.5	60.9	48.1	73.7	40.3	29.9	47.0	11.6	1%
Electrical and electronic trades workers	41.1	35.3	46.8	50.7	39.6	46.6	49.3	61.0	21.5	32.7	41.9	21.0	61.8	63.5	59.3	37.3	44.5	41.9	34.2	30.5	60.8	55.7	54.0	38.9	69.1	41.1	34.8	55.2	13.4	2%
Food processing, wood, garment and related trades	40.2	36.8	43.6	39.6	29.9	34.4	36.7	32.5	13.7	25.3	39.4	11.8	49.3	50.2	48.2	28.3	27.7	33.3	26.7	25.7	51.0	42.6	65.1	56.6	73.5	35.0	17.5	45.0	5.7	2%
Stationary plant and machine operators	42.3	40.2	44.4	36.7	27.9	32.9	23.6	38.4	9.7	22.9	30.1	11.7	45.5	48.8	41.1	23.3	15.5	24.5	28.4	24.2	38.8	55.4	72.3	61.7	82.9	51.0	17.8	28.3	5.0	2%
Assemblers	42.2	35.3	49.2	35.3	24.6	30.3	16.6	33.8	6.2	18.8	22.3	9.0	46.0	49.4	42.6	20.7	18.6	20.9	24.6	19.4	37.8	53.8	70.4	60.8	80.0	49.0	20.3	18.6	5.9	1%
Drivers and mobile plant operators	33.5	28.7	38.3	38.2	30.4	37.9	32.7	45.6	15.9	22.8	28.9	8.5	46.0	43.7	48.4	31.8	43.3	32.4	27.1	25.0	44.7	30.9	50.8	48.0	53.5	34.0	15.5	27.9	2.2	4%
Cleaners and helpers	34.9	37.3	32.5	24.8	14.8	22.4	14.8	14.2	5.9	7.2	9.7	1.4	34.9	30.5	39.3	26.7	48.6	19.0	18.6	20.8	56.1	30.5	48.4	56.9	39.9	17.5	7.3	35.9	0.9	4%
Agricultural, forestry and fishery labourers	42.7	42.6	42.7	33.0	22.4	26.8	9.6	10.8	6.7	18.1	21.8	5.1	43.6	41.0	46.2	28.7	35.4	26.0	25.7	27.6	51.9	44.8	52.4	56.8	48.0	36.6	9.1	18.1	1.7	1%
Labourers in mining, construction, manuf. and transport	42.8	44.1	41.4	34.2	25.6	30.3	23.7	30.1	7.3	21.0	25.8	7.1	42.7	45.1	40.5	30.9	38.5	28.5	29.3	28.2	40.0	55.5	62.4	58.4	66.4	37.6	17.8	30.5	2.7	3%
Food preparation assistants	37.1	35.6	38.7	29.1	18.9	23.4	14.2	17.9	5.2	14.5	18.2	3.5	39.3	41.9	36.7	27.5	42.0	28.3	22.4	17.8	41.3	51.5	51.7	47.5	55.9	18.2	7.5	14.6	1.2	1%
Street and related sales and service workers	16.5	26.5	6.5	37.2	27.5	29.9	20.6	5.5	7.8	25.1	52.8	3.8	46.8	37.0	57.4	39.6	62.8	58.0	24.0	17.4	62.0	0	17.5	20.0	15.0	3.0	17.2	37.6	5.0	0%
Refuse workers and other elementary workers	35.2	33.7	36.7	34.1	24.6	31.1	27.9	27.6	12.1	18.1	23.7	6.4	43.6	40.1	44.4	28.9	49.4	28.6	22.6	20.3	49.2	40.8	44.6	45.8	43.4	26.3	15.3	32.3	5.3	1%

Note: The blue scale represents low task intensity; white represents medium and the orange scale represents high task intensity.
Source: EWCS 2010, PIAAC, ONET data (2012 EU15 LFS weights), authors' elaboration.

8 Conclusions

This report has tried to contribute to the development of a comprehensive, transparent and general-purpose set of task indices to be used for analysing European occupational structure, drawing on different international databases – most importantly, the Programme for the International Assessment of Adult Competencies (PIAAC), the European Working Conditions Survey (EWCS) and the Occupational Information Network dataset (ONET). The first part provided some background to the tasks-based approach, discussed the main concepts and identified critical omissions. The second part briefly reviewed the most important strands of the literature on the determinants of structural change in labour demand, in order to identify the implications of this literature for a conceptualisation and analysis of tasks. The third part presented a new framework, based on a critical evaluation of existing proposals and related literature. Finally, a brief application of this new model was presented, using real data for European countries.

The results of the last exercise appear reasonable and are reassuring, with some exceptions already indicated that may require further consideration. Overall, the constructed variables seem to paint a plausible picture of the distribution of the different types of task input in the EU economy: intellectual and social tasks are the most pervasive, while physical tasks play a secondary role; autonomy and ICT use are more widespread than routine task methods and analogue machinery use. In subsequent analysis, these indicators will be used to analyse, in greater detail, the distribution of tasks across Europe, their association with other attributes of jobs such as wages, education and job quality, and the role they have played in the recent structural evolution of European labour markets.

Without dedicated sources for measuring the task content of occupations in Europe, the best option is to draw from different existing sources in an attempt to provide a fairly complete picture, as was the aim of this report. This approach is, inevitably, incomplete and unavoidably involves bias in its measurements. While not ideal, however, the model presented here can provide a unique perspective on European labour market structures, which, it is hoped, may be useful.

Part 3: What do Europeans do at work? The distribution and evolution of task content, methods and tools in Europe

Introduction

Part 2 of this report introduced a framework of task indices for occupational analysis that should provide a fresh perspective on European employment structures. This part puts that framework to work, linking the newly created task indices to the employment and job quality data compiled over the years for the European Jobs Monitor. The most obvious goal of this exercise is to try to better understand recent structural change in European labour markets. Other goals are to improve understanding of: how task content, methods and tools are bundled in existing jobs, using Europe as an example; and whether such bundling is consistent across individuals, countries and over time. The potential use of a comprehensive task framework for employment and training policies in Europe will also be discussed.

This part of the report is divided into three chapters – 9 to 11. Chapter 9 describes the overall distribution of tasks across European job categories, in an attempt to identify how the different domains of task content, methods and tools are bundled into existing jobs. Chapter 10 shifts to the individual level distribution of tasks in order to evaluate whether or not jobs (specific combinations of occupations and sectors) are meaningful units of analysis: in other words, whether there is more heterogeneity within or across jobs in terms of task contents and methods. Chapter 11 explores the relationship between the task indices and other attributes of jobs, with particular attention placed on job quality. The task framework is used to compare the employment structures of different European economies; how those task structures have changed in recent years will be evaluated. It concludes with a brief discussion on the policy implications of the findings.

9 Distribution and bundling of tasks across European jobs

The task indices introduced in Part 2 consist of a vector of scores for each occupation and sector combination (jobs). The values of each index in the framework can range from zero to one, reflecting the intensity with which each job involves carrying out work in each of the task categories. Figure 16 (on next page) shows the individual raw scores in all the lower-level task indices for the nine largest jobs in the sample (the occupation-by-sector combinations that employ the largest number of people in Europe). This serves as an illustration of the framework and as a first approximation of the data that underlie the rest of the analysis of Part 2.[20]

The nine jobs are split into three groups. The top chart shows the task scores for three administrative service occupations: sales workers in the retail sector, clerks in public administration and office and building cleaners. Sales workers in retail is the single occupation-sector combination that employs the most people in EU15, according to the 2014 EU-LFS data (5% of total employment), whereas the other two jobs account for roughly 1% of employment. The task profiles of these three service jobs are rather different. Office cleaners carry out mostly physical tasks (requiring more strength than dexterity), with very limited intellectual tasks (except for some problem-solving) or social tasks (except for some serving). While in terms of methods and tools, the most salient result is a high degree of repetitiveness (though not standardisation, which is the other half of the measure of routine). Public administration clerks, on the other hand, have extremely low physical task content, rather high intellectual tasks (particularly business literacy and information-gathering and evaluation), relatively low social tasks and very high use of ICT tools. Sales workers in retail have relatively high levels of physical tasks, low literacy but high numeracy intellectual tasks; the most salient aspect of their task profile is their very high level of social tasks, particularly in the categories of serving and selling. Their use of machines or ICT tools is almost as low as that of cleaners.

The middle chart shows three high-skilled professional jobs: teacher, doctor and nurse.[21] Teacher is the second largest job in the database, making up more than 4% of total European employment, whereas the jobs of doctor and nurse make up around 2%. The task profiles of these three jobs are much more similar than in the previous case, as could be expected. But there are some very significant differences: doctors and nurses have much higher values in physical tasks, particularly in the category of dexterity, whereas teachers have higher scores for humanities literacy, solving and teaching. Despite the extreme similarity of their task profiles, there are also very telling differences between doctors and nurses: doctors have generally higher levels of literacy (particularly technical) and numeracy tasks, and higher levels of problem-solving and social tasks in general (especially managing and teaching). It is interesting to note that these three categories of highly-skilled professional jobs have relatively similar profiles in terms of tools and methods: in particular, they have low levels of repetitiveness but high levels of standardisation, the exact opposite to office cleaners.

The bottom chart shows the task profiles of waiters, building trade workers in construction and drivers (each of them accounting for less than 2% of overall employment). Building trades in construction involve very high levels of physical tasks, but also some degree of technical literacy and basic numeracy, as well as relatively high levels of problem-solving. They involve low levels of social tasks, high autonomy, high levels of routine (both in terms of repetitiveness and standardisation)

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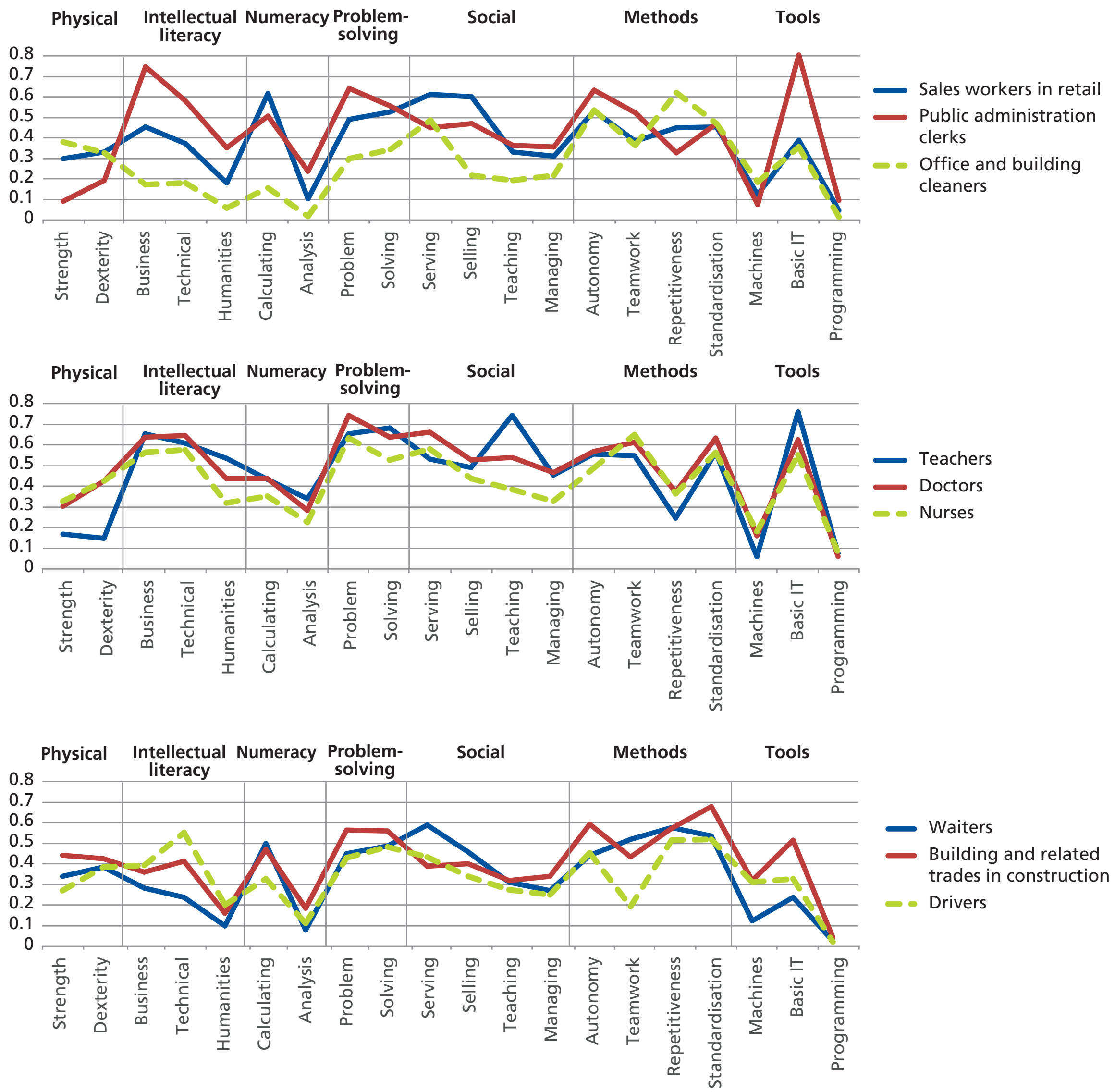
[20] See the previous part of the report for a detailed account of the construction of these indices.

[21] The occupation title used to describe these jobs refers specifically to teachers in education and doctors and nurses in the health sector. In these cases there is a very close match between occupation and sector, so the sector information is almost irrelevant.

and high levels of machine use. Waiters also carry out high levels of physical tasks, with very low literacy activity (though with some basic calculating numeracy), some degree of problem-solving, a significant extent of serving and selling, high repetitiveness and low use of machines and ICT. Finally, the job of driver involves relatively high levels of manual dexterity, technical literacy and machine use, with below average values in all the other categories.

Figure 16: Task profile of nine significant jobs



Source: EWCS 2010, PIAAC, ONET data (2014 EU15 LFS weights), authors' elaboration.

This exercise shows that the different jobs in the database have significantly different task profiles and that the observed differences seem perfectly plausible according to what is common knowledge about those jobs. It also shows that in order to characterise a job in terms of task content and methods, it is necessary (or at least, very useful) to look at the whole profile rather than at individual task categories. In other words, any single category of tasks does not provide enough information to characterise the job adequately. For instance, physical tasks are generally associated with low-skilled jobs, but doctors and nurses perform a rather significant amount of physical tasks despite being highly skilled occupations. The task profiles in Figure 16 show that they also involve a high degree of intellectual and social tasks, with low levels of repetitiveness (thus differing from other jobs with high degree of physical tasks, such as office cleaners). Finally, this has shown some surprising similarities across jobs for some task categories. Some types of tasks tend to show relatively high values across many very different jobs (such as problem-solving), whereas others seem to be more occupation-specific (physical tasks, which are very low in most cases). As already mentioned in Part 2, this is an outcome of the normalisation strategy that was used in the construction of the task indices, where efforts were made to preserve the original intensity scales as much as possible. The underlying assumption is that the scales for the task measures used in constructing the dataset, provide a useful evaluation of actual intensity in the performance of each task category in each job. If this assumption is correct, the fact that the problem-solving scores are generally high reflects something real: most jobs, including those with low levels of 'cognitive' tasks (information-processing in the framework) involve a significant amount of problem-solving, which is an important type of cognitive or intellectual task.

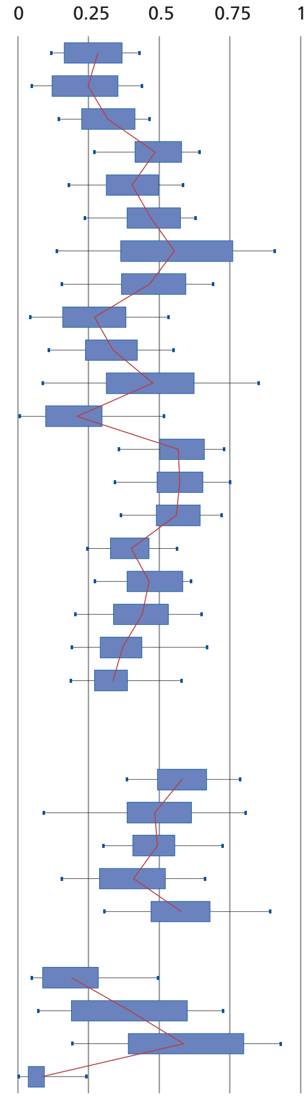
But the results shown so far concern specific occupations. What about the average task profile for the whole of the European workforce? That can be analysed by calculating the average task scores for all jobs in the economy, making the contribution of each job to the overall average correspond to its share of total employment in 2014 (the most recent available year). The result can be understood as a tasks profile of the average job in the EU and is shown in Figure 17 (on next page). On top of the average values of each of the task indices at all levels of the framework, some statistics of dispersion are also included (standard deviation and the coefficient of variation), as well as a graphical representation of the distribution using percentiles.

According to this approximation, the average European job would involve a high level of intellectual tasks (particularly the processing of business–administrative information and problem-solving), a mid-high level of social tasks (serving and selling), and a low level of physical tasks. In terms of the task methods and tools, they would involve relatively high levels of autonomy, some degree of routine (particularly in terms of standardisation), and more ICT (basic office applications) than machinery use. The most widespread task categories are problem-solving, serving and selling, autonomy and routine. All of these indices have relatively high average scores and a low dispersion – most types of jobs involve these tasks to some degree. On the other hand, business-related task content (business information-processing, accounting, ICT and basic IT) have high average values, but also a high dispersion, which means that their distribution is more polarised: high levels of these categories are involved for some jobs, low levels for others. Finally, strength-related physical tasks, humanities literacy tasks, analytic numeracy tasks, machinery use and programming have low average values and a high dispersion, meaning that the majority of jobs involve very little of these types of task, with only a small minority of jobs doing them.

Figure 17: Average task scores for EU15, 2014 (EU-LFS weights)

Task indices	Summary statistics		
In terms of the object of work/task:	**Mean**	**Std dev**	**CV**
1. Physical	0,28	0,11	0,39
a. Strength	0,25	0,13	0,52
b. Dexterity	0,32	0,10	0,33
2. Intellectual	0,49	0,11	0,22
a. Information-processing	0,40	0,12	0,30
i. Literacy	0,47	0,12	0,26
- Business	0,55	0,24	0,44
- Technical	0,47	0,16	0,35
- Humanities	0,27	0,15	0,56
ii. Numeracy	0,34	0,13	0,39
- Accounting	0,48	0,23	0,47
- Analytic	0,21	0,16	0,74
b. Problem-solving	0,57	0,11	0,20
i. Information-gathering and evaluation	0,57	0,12	0,22
ii. Creativity	0,56	0,11	0,19
3. Social	0,40	0,10	0,26
- Serving/attending	0,46	0,12	0,26
- Selling/persuading	0,44	0,14	0,32
- Teaching	0,37	0,13	0,36
- Managing	0,34	0,11	0,33
In terms of the methods and tools used			
1. Work organisation			
a. Autonomy	0,58	0,12	0,21
b. Teamwork	0,48	0,20	0,41
c. Routine	0,49	0,13	0,25
i. Repetitiveness	0,41	0,16	0,39
ii. Standardisation	0,58	0,17	0,30
2. Technology			
a. Machines	0,19	0,14	0,71
b. ICT	0,39	0,22	0,55
- Basic IT	0,59	0,24	0,41
- Programming	0,08	0,10	1,20

Distribution (percentiles 5, 25, 75, 95)
(lines link average values)



Source: EWCS 2010, PIAAC, ONET data (2014 EU15 LFS weights), authors' elaboration.
Note: Std dev = Standard deviation. CV = Coefficient of variation

One of the key advantages of using a comprehensive framework rather than a piecemeal approach to task analysis is that it is possible to evaluate how different types of task content and methods interact with each other. An initial assessment of the raw task scores for individual jobs showed that the different task categories seemed to be associated in particular ways: such task interactions can be as important for characterising jobs as the individual task scores themselves, so they merit specific analysis.

Table 6 (on next page) shows the bivariate correlations between all the indices in the framework, at all levels. It shows that physical and intellectual tasks are quite consistent internally. In the case of physical tasks, which have just two components (strength and dexterity), they have a correlation of 0.81, which means that in most cases, jobs that require manual dexterity also require high levels of physical exertion and stamina (referred to in the index as 'strength'). The much more detailed set of indicators of intellectual tasks also show quite high levels of consistency, with most bivariate correlations above 0.7. So the different types of intellectual tasks measured in the framework tend to bundle together in the same jobs, with the partial exception of accounting/basic numeracy tasks (which displays generally lower correlations with other intellectual task categories). Social task content, on the other hand, is less internally consistent, except in the categories of teaching and managing (which often coexist in the same jobs). Consequently, even though all the categories of tasks included within the social domain are conceptually related, they are generally not bundled together in the same jobs (again, except teaching and managing).

Table 6 (on next page) also shows the correlation between indices of different domains. Physical and intellectual tasks display a strong and quite consistent negative correlation. Jobs that involve a significant amount of physical tasks tend to involve less intellectual task activity and vice versa. There are some partial exceptions: technical literacy tasks and information-gathering are not so negatively correlated with physical tasks, suggesting that some physically intensive jobs require technical literacy and some degree of problem-solving as well.[22] On the other hand, social tasks tend to show a negative correlation with physical tasks and a positive correlation with intellectual tasks. In fact, the correlations between the detailed social and intellectual task indices are often higher than among the different social task indices, which, as previously mentioned, are not very high. The main exception in this pattern is the category of serving social tasks, which shows a much milder negative correlation with physical tasks and a very weak positive correlation with intellectual tasks.[23]

The correlation between the task content and the task methods and tools domains also reveals some interesting patterns. Physical tasks tend to be associated with less autonomy, more routine (particularly in terms of repetitiveness) and less ICT use, while the opposite happens to intellectual tasks. The exceptions are technical literacy and accounting-basic numeracy tasks, which are less negatively correlated with routine work methods.[24] Social tasks tend to be similar to intellectual tasks in this respect, with the exception of serving, which lies somewhere between physical and intellectual (less autonomy and more repetitiveness, but less use of machinery).[25]

A factor analysis of all the lower level task indices in the framework provides an alternative way of looking at how the different task categories tend to bundle together in existing jobs. Table 7 (p. 59) shows the main output of such a factor analysis: the rotated factor loadings, the uniqueness score for each index and the total variance explained by each factor.

22 Specific jobs that combine high levels of physical (dexterity in most cases) and technical tasks are health professionals and associates, engineering associate professionals and metal industrial workers.

23 The jobs that combine physical and social serving tasks are a peculiar mix, if a relatively common one. They include personal service workers, personal care workers, waiters and health professionals.

24 Some examples of jobs combining basic numeracy tasks and routine repetitive methods are administrative associate professionals and customer service clerks.

25 Some of the correlations between the indices for methods and tools (not shown here) are also interesting. Autonomy is negatively correlated with machinery but not with ICT. The relationship between routine and tools is different for the two routine components: repetitiveness is positively correlated with machinery and negatively with ICT, while standardisation is positively correlated with both machinery and ICT. This could suggest that the use of technology in general requires some degree of standardisation in the organisation of work, while only mechanical tools involve repetitive work patterns (while ICT allows for more flexibility).

Table 6: Bivariate correlations between different task indices

	1.Physical	1.a.Strength	1.b.Dexterity	2.Intellectual	2.a.InfoProc	2.a.i.Literacy	2.a.i.LitBus	2.a.i.LitTec	2.a.i.LitHum	2.a.ii.Numeracy	2.a.ii.NumAcc	2.a.ii.NumAna	2.b.ProbSolv	2.b.i.ProbInfo	2.b.ii.ProbCreativ	3.Social	3.SocServing	3.SocSelling	3.SocTeaching	3.SocManaging
In terms of the content:																				
1. Physical																				
a. Strength	0.96																			
b. Dexterity	0.94	0.81																		
2. Intellectual	-0.65	-0.69	-0.53																	
a. Information-processing	-0.71	-0.75	-0.59	0.94																
i. Literacy	-0.73	-0.75	-0.62	0.93	0.94															
- Business	-0.78	-0.80	-0.67	0.83	0.89	0.90														
- Technical	-0.40	-0.47	-0.28	0.77	0.78	0.83	0.67													
- Humanities	-0.62	-0.60	-0.57	0.81	0.78	0.89	0.74	0.67												
ii. Numeracy	-0.63	-0.68	-0.51	0.86	0.95	0.80	0.79	0.65	0.61											
- Accounting	-0.52	-0.55	-0.43	0.68	0.80	0.62	0.71	0.46	0.44	0.89										
- Analytic	-0.56	-0.60	-0.46	0.80	0.85	0.74	0.68	0.66	0.64	0.87	0.64									
b. Problem-solving	-0.51	-0.55	-0.41	0.93	0.76	0.79	0.65	0.67	0.73	0.66	0.45	0.64								
i. Info. gathering and evaluation	-0.46	-0.53	-0.33	0.89	0.75	0.77	0.65	0.72	0.69	0.65	0.45	0.63	0.94							
ii. Creativity	-0.49	-0.49	-0.44	0.85	0.70	0.74	0.58	0.54	0.71	0.60	0.40	0.59	0.92	0.71						
3. Social	-0.47	-0.41	-0.50	0.68	0.68	0.72	0.57	0.52	0.68	0.57	0.49	0.45	0.60	0.52	0.66					
- Serving/attending	-0.15	-0.07	-0.24	0.11	0.11	0.20	0.16	0.04	0.22	0.01	0.09	-0.11	0.09	0.00	0.18	0.66				
- Selling/persuading	-0.50	-0.48	-0.48	0.69	0.72	0.68	0.64	0.48	0.59	0.69	0.71	0.44	0.57	0.51	0.57	0.85	0.51			
- Teaching	-0.44	-0.38	-0.47	0.68	0.63	0.71	0.47	0.59	0.74	0.49	0.29	0.53	0.65	0.59	0.67	0.82	0.28	0.55		
- Managing	-0.39	-0.36	-0.38	0.67	0.66	0.66	0.52	0.53	0.62	0.59	0.45	0.55	0.60	0.52	0.67	0.84	0.29	0.61	0.74	
In terms of the methods and tools:																				
1. Work organisation																				
a. Autonomy	-0.55	-0.56	-0.48	0.62	0.60	0.57	0.63	0.32	0.56	0.56	0.50	0.53	0.58	0.46	0.66	0.39	0.03	0.47	0.29	0.46
b. Teamwork	-0.03	-0.04	-0.02	0.23	0.16	0.21	0.11	0.24	0.19	0.10	-0.05	0.16	0.28	0.34	0.17	0.17	0.01	0.07	0.28	0.19
c. Routine	0.38	0.35	0.38	-0.20	-0.18	-0.28	-0.27	-0.08	-0.33	-0.08	-0.04	-0.06	-0.20	-0.09	-0.29	-0.31	-0.36	-0.26	-0.22	-0.13
i. Repetitiveness	0.51	0.52	0.44	-0.56	-0.51	-0.58	-0.50	-0.42	-0.56	-0.40	-0.26	-0.39	-0.55	-0.47	-0.56	-0.46	-0.19	-0.38	-0.47	-0.40
ii. Standardisation	0.09	0.04	0.14	0.22	0.20	0.13	0.08	0.27	0.04	0.25	0.18	0.27	0.21	0.30	0.09	-0.03	-0.35	-0.02	0.12	0.18
2. Technology																				
a. Machines	0.70	0.63	0.72	-0.39	-0.42	-0.48	-0.53	-0.15	-0.47	-0.31	-0.29	-0.24	-0.31	-0.22	-0.36	-0.52	-0.55	-0.49	-0.34	-0.25
b. ICT	-0.83	-0.88	-0.67	0.83	0.86	0.86	0.89	0.64	0.70	0.78	0.61	0.72	0.68	0.69	0.60	0.48	0.02	0.54	0.47	0.46
- Basic IT	-0.76	-0.77	-0.66	0.79	0.81	0.82	0.87	0.61	0.73	0.72	0.58	0.71	0.67	0.65	0.61	0.49	0.04	0.51	0.49	0.51
- Programming	-0.34	-0.44	-0.18	0.49	0.47	0.41	0.36	0.38	0.33	0.48	0.28	0.52	0.45	0.44	0.41	0.10	-0.30	0.17	0.22	0.19

Note: Some interesting combinations of tasks are highlighted.

Table 7 could also be understood as an alternative way of generating aggregate task indices. As explained in Part 2, the strategy for aggregating low-level task indicators into high-level indices was shaped by a theory-driven conceptualisation and classification of tasks. An alternative approach would have been to construct aggregate indices based on the observed patterns of correlation between the low-level indices, which is essentially what the principal components factor analysis does. But the intention here is different: since the factors constructed by the principal components procedure summarise the observed patterns of correlation among all the variables introduced in the analysis, it should reveal more clearly how tasks tend to bundle together in real jobs.

Table 7: Principal components factor analysis of low-level task indices

Domain	Indicator	Rotated factor loadings: Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Physical	Strength	-0.26	-0.80	-0.32	-0.12	0.17
	Dexterity	-0.20	-0.78	-0.23	0.17	0.28
Intellectual	Business	0.45	0.60	0.53	0.03	0.15
	Technical	0.74	0.17	0.32	0.15	0.31
	Humanities	0.71	0.49	0.23	-0.09	0.20
	Accounting	0.21	0.26	0.86	0.01	0.16
	Analytic	0.57	0.35	0.48	0.31	0.22
	Info. gathering	0.78	0.27	0.26	0.19	0.21
	Creativity	0.70	0.39	0.23	-0.05	0.31
Social	Serving	0.13	0.12	0.05	-0.89	0.17
	Selling	0.44	0.26	0.60	-0.46	0.16
	Teaching	0.83	0.20	0.10	-0.24	0.21
	Managing	0.72	0.11	0.41	-0.24	0.25
Methods	Autonomy	0.25	0.60	0.43	0.09	0.39
	Teamwork	0.61	-0.09	-0.38	0.07	0.47
	Repetitiveness	-0.46	-0.59	0.03	0.11	0.44
	Standardisation	0.36	-0.47	0.31	0.45	0.35
Tools	Machines	-0.10	-0.78	-0.05	0.47	0.17
	Basic IT	0.48	0.64	0.41	0.16	0.17
	Programming	0.33	0.36	0.14	0.58	0.41
	Variance explained:	**26.7%**	**22.5%**	**14.2%**	**10.7%**	

Notes: Task 1 combines intellectual and social
Task 2 reflects the strong correlation between machines, physical and routine tasks - and the contraposition with ICT, autonomy and non-technical intellectual tasks and the contraposition with ICT, autonomy and non-technical intellectual tasks
Task 3 combines accounting, selling and business literacy tasks
Task 4 combines programming, machines, standardisation, analytical maths
The task indices that are less well defined by the factor analysis are the methods.
Source: EWCS 2010, PIAAC, ONET data (2014 EU15 LFS weights), authors' elaboration.

Table 7 shows that, as already argued, intellectual and social tasks tend to bundle together. The analysis constructs a first factor that accounts for more than one-quarter of all the variance of the low-level task indices, and combines information from the social indicators of teaching and managing, the intellectual indicators of problem-solving, technical and humanities literacy, as well as teamwork. The second factor seems to contrast manual industrial versus administrative/clerical work: the factor loadings are high and positive for ICT office applications, autonomy and business literacy, and high and negative for strength, dexterity, use of machinery and routine work methods. The third factor is mostly derived from the task indicators of accounting-basic numeracy, social-selling tasks and business literacy: it can be therefore interpreted as a bundle of task content typically associated with business service activities. Finally, the fourth factor seems to capture advanced technical tasks – programming, use of computers and standardisation, with a very negative correlation with social interaction tasks. These four variables alone can explain nearly three-quarters of all the variability present in the list of 20 low-level task variables.

This exercise enables the following conclusions to be drawn:

- the different categories of tasks in the framework tend to bundle together in systematic ways;
- intellectual and social tasks tend to go together, with some exceptions (such as serving and calculating tasks);
- physical tasks tend to be opposed to intellectual tasks, again with some exceptions (for instance, dexterity often goes together with technical literacy; and problem-solving is relatively high even for physically demanding jobs);
- physical tasks tend to be associated with the use of machines and routine task methods (both in terms of routine and standardisation), whereas intellectual literacy and numeracy tasks tend to be associated with use of ICT and a relatively high degree of standardisation (not repetitiveness).

Is it therefore necessary to do away with the nested index structure and use the four factors shown in Table 7 instead? After all, these factors provide a more efficient way of presenting the data (with one-fifth of the variables, three-quarters of the information is retained). But more efficient does not necessarily mean more useful: the structure of the framework makes intuitive sense and links directly to the debate on the changing employment structures in advanced economies. Furthermore, even if the different task categories tend to bundle together in particular ways, the effects of underlying change factors such as technology or regulation are likely to affect them at the individual level, which suggests a value in keeping the analysis at the most disaggregated level that is manageable.

In other words, the point is *not* that only task bundling matters. It is perfectly valid to focus the analysis on particular categories of tasks (such as routine task methods, or cognitive literacy tasks) if, for instance, the goal is to understand how a technical innovation affects some particular types of work activity (such as whether computerisation replaces routine tasks). The individual task level also matters, even if tasks tend to bundle together. That said, however, it is certainly important to have such bundling in mind when analysing tasks and the way in which they change over time, because otherwise important aspects of the phenomena being studied may be missed. For instance, if (intellectual) information-processing tasks tend to go together with social tasks, an innovation that allows (intellectual) information-processing task input to be replaced by computers, may not have short and medium term effects in the observed levels of labour input because of the associated social tasks that cannot be replaced by machines. In the long run, the effect is likely to be felt anyway (the task bundling associated with different types of jobs will eventually change), but it may take a while to change the training and occupational structures that underlie such bundling. In contrast, if a particular task category is less bundled with other task content (and if it is associated with particular occupations), the effect on employment of an innovation affecting this task may be much more immediate.

10 Diversity of task content and methods in Europe

As explained at length in Part 2, the task indices were constructed at the level of jobs (defined as the detailed combination of occupation and sector), not individual workers. Jobs also form the main level of analysis for this part. The underlying assumption is that the detailed occupation is the level at which tasks are coherently bundled and organised, which means that even if tasks are a useful analytic and measurement concept, they cannot be the actual unit of analysis; jobs serve this function instead. Furthermore, the task categories being discussed here are attributes of jobs, not of the individual workers performing them. It is the job that forms part of the productive structure of the firm and has to be filled by a person with the necessary skills and competences. If a person conducting a particular job is replaced, the task bundle remains – this is an assumption behind the approach taken here. But is it empirically accurate? In other words, is most of the observed variation in the distribution of tasks across the working population linked to the different occupational positions? Are the workers within the same detailed occupation performing similar sets of tasks? Or is the distribution of tasks independent of the jobs workers have?

Unfortunately, individual-level data are not available for the full set of variables in this task framework. One of the three sources used for constructing the indices (ONET) is only measured at the occupational level, so it is not possible to explore the variation that exists within jobs for the derived indices. However, the two other sources used for constructing the indices, do measure task content and methods at the level of individual workers. They can therefore be used to test for consistency in the distribution of tasks across jobs for a selection of indices within the framework.[26]

Table 8 (on next page) shows the result of this analysis using a multivariate decomposition of variance. With this technique, the observed variation at the individual level of each index available in each source (for instance, *1.Physical-a.Strength* in the EWCS) is split into two components: the variation that can be attributed to the differences between the mean values across jobs; and the variation that results from differences in the values of different workers within the same jobs. If, for instance, all the observed variation in the index of physical strength resulted from a different requirement in each occupation, there would be no variation in the score of physical strength *within* each job, and the variance *explained* by the job would be 100%. If, on the other hand, the job was totally irrelevant regarding the amount of physical strength that each individual had to do at work, there would be no significant differences in the average level of strength required by the different jobs; all the variation in the scores of this variable would take place within jobs, in which case, the variance explained by the job would be 0%.

The variable of occupation (ISCO at the two-digit level) can be used to explain just under 30% of the total variance of physical strength, according to EWCS data as shown in Table 8. If the combination of occupation and sector is used ('job', which is the preferred unit for this analysis, and which results from combining NACE and ISCO at the two-digit level), this increases by roughly 4% (so that the variance explained by between-jobs differences is around 34% of the total in this case). In other words, around one-third of the total variance observed at the individual level in physical strength tasks is associated with differences across jobs, with the remaining two-thirds being attributed to differences within jobs (for workers in the same occupation and sector combinations).

[26] With this approach, only the variance of each individual index across jobs can be analysed, without taking into account the actual combination or bundling of tasks for each occupation, as discussed in the previous part of the report. This is because it is not possible to combine information at the individual worker level across sources; only two subsamples of variables from the framework can be analysed separately (not enough to evaluate the variance in the bundling across task categories). Subsequent work aims to evaluate the individual and job-level variation in the bundling of tasks.

A country variable was added to the variance decomposition analysis to evaluate the extent to which this factor explains some of the variance in task content. In the case of physical strength, the importance of the country variable is very limited: on its own, it accounts for 4% of the total variance, and if added to the model with 'job' (shown in column 3 of the EWCS section of Table 8), it adds even less (around 3% of more variance explained). So in this case, country matters very little, definitely much less than the occupation and sector variables that are used to define the basic unit of analysis.

Table 8: Decomposition of variance at job and country level

	EWCS				PIAAC			
	ISCO	ISCOx NACE	ISCOx NACE Country	Country	ISCO	ISCOx NACE	ISCOx NACE Country	Country
In terms of the object of work								
1. Physical								
a. Strength	29.8%	33.8%	36.9%	4.0%				
b. Dexterity					8.2%	11.2%	18.0%	6.9%
2. Intellectual								
a. Information-processing					35.8%	38.5%	40.9%	3.9%
i. Literacy					38.9%	41.2%	43.3%	4.2%
- *Business*					39.6%	40.7%	41.8%	2.6%
- *Technical*					23.7%	28.0%	32.6%	6.3%
- *Humanities*					31.8%	35.2%	36.1%	2.0%
ii. Numeracy					27.1%	31.1%	33.2%	2.7%
- *Accounting*					24.9%	29.2%	31.2%	2.4%
- *Analytic*					24.4%	28.3%	29.7%	2.0%
b. Problem-solving								
i. Information-gathering and evaluation	20.2%	24.6%	26.4%	3.4%	8.2%	13.3%	15.1%	2.4%
ii. Creativity	12.4%	15.4%	17.0%	2.2%				
3. Social								
- *Serving/attending*								
- *Selling/persuading*					22.3%	26.8%	28.4%	3.0%
- *Teaching*					28.6%	29.9%	33.5%	5.8%
- *Managing*					19.4%	36.2%	37.2%	2.5%
In terms of the methods and tools used								
1. Work organisation								
a. Autonomy	16.2%	20.9%	24.1%	3.5%	17.8%	17.8%	17.8%	0.8%
b. Teamwork	5.3%	11.5%	13.1%	2.5%				
c. Routine								
i. Repetitiveness	12.0%	14.6%	18.6%	4.4%				
ii. Standardisation	7.9%	11.6%	13.5%	2.2%				
2. Technology								
a. Machines	26.4%	30.2%	30.4%	0.4%				
b. ICT	45.8%	49.8%	52.0%	2.4%	51.3%	53.1%	53.6%	1.8%
- *Basic IT*					36.6%	39.9%	40.0%	0.3%
- *Programming*					17.0%	21.9%	22.4%	0.4%

Source: EWCS 2010 and PIAAC surveys (2014 EU15 LFS weights), authors' elaboration.

The amount of individual-level variance explained by the occupation–sector combination varies considerably across the different components of the task framework. In most of the task content variables, the between-job variation explains between 30% and 40% of the total. The exceptions are problem-solving (15%–25% of whose variation takes place across jobs) and dexterity (less than 15%). It was already shown that the problem-solving indices have high values for most jobs and a low degree of variation, so it is not very surprising that a larger share of variation takes place within jobs in this case. It seems reasonable to think that problem-solving tasks are more transversal types of requirement, less affected by the specific job performed than by other variables (such as seniority or even psychological traits). The case of dexterity (an index derived from PIAAC data exclusively) seems more surprising, because it would seem a requirement more specific of particular types of jobs. But with these exceptions, it seems that task content is considerably job-specific.

The indices of task methods display a much smaller between-job variation. The combination of occupation and sector can only explain between 10% and 20% of the total individual-level variance observed for these indices. In other words, task methods (work organisation) are much less job-specific than task content. This makes perfect sense: the variables of occupation and sector classify workers according to the position they occupy in the division of labour and therefore reflects how the production process is subdivided into tasks. So occupation and sector directly determine what kinds of tasks workers carry out, while how those tasks are organised is more contingent. Or, to be more precise, it is more affected by other factors such as the social organisation of production (power relations in the workplace and in the labour market, for instance). Workers with scarce skills may bargain a higher degree of autonomy at the workplace, while even the stronger bargaining positions would find it difficult to substantially change the amount of physical effort required in a particular job (although this may also be possible: the negotiation of occupational definitions may alter task content, though, in any case, to a smaller extent than task methods because they are more directly affected by the material attributes of the production process).

It is particularly interesting to note that the index of routine task methods shows a very low between-job variation, with most of the variance taking place within jobs. In the specialised literature, the concept of routine tasks has occupied a central position and in the majority of studies has been analysed at the level of jobs, and not individuals. But if routine task methods are particularly heterogeneous within jobs, this approach seems particularly problematic. Even more than in other cases, evaluating the role played by routine task methods in recent labour market developments while ignoring the within-job variation can lead to misleading results. For instance, it will be argued later that the extent of routine tasks has decreased from a compositional perspective (the most routine-intensive jobs shrank in recent years), but it has expanded if looked at from an individual perspective (because many jobs have become more routine). This sheds an entirely different light on the discussion about the link between computerisation, routine tasks and employment. Computerisation may replace highly routine tasks, while making all jobs more routine. Yet this development is completely concealed from view if the within-job variation in task methods is ignored, which is (arguably) particularly strong in this case.

The variables measuring the use of technology at work are much more strongly linked to job classification. The between-job differences account for around 30% of the variance in machine use and for a very large 50% of the variance in ICT use (the latter finding is very robust, since it is confirmed independently by the two sources used). In some ways, this is an expected result: the use of tools is obviously an important part of the technical organisation of production and it should be much less contingent on other factors. But particularly in the case of ICT, it is somewhat surprising too because of the common assumption that it has become a widespread requirement in most types of jobs nowadays. Later, the trend in ICT use at the individual level will be evaluated, but it can already be said that it is very strongly determined by the job category that workers are in, rather than evenly spread across the working population.

So what is the final assessment regarding the heterogeneity of task content and methods within job categories? To begin with, it must be acknowledged that most of the observed variation in task content and methods takes place *within* rather than *between* jobs, for most of the components of this framework. This on its own suggests that within-job variation in task contents should play a more important role in the debate on structural change in employment and job quality. Of course, the fact that this aspect of the distribution of tasks is largely absent from the literature is not the result of an oversight but of limitations in the available data. But as more data on tasks become available, within-job variation in tasks should be more carefully studied.

That said, the results shown in Table 8 do seem to support the use of an occupational approach for task analysis. It must be kept in mind that the sources used here are subject to a significant amount of measurement error and that measurement error is necessarily conflated with within-job variation in the decomposition analysis. In both of the sources used, it would probably be impossible to find any classification variable that could account for more than 70%–80% of the total variance in any case. That means that the estimation of the variance accounted for by job classification is likely to be a rather conservative one.

There are reasons to expect sources of within-job variation in task contents and methods that would not invalidate the assumption that the job is the most appropriate unit of analysis. For instance, seniority rules can alter the distribution of tasks between workers for the same job; for example, more experienced workers can take over more problem-solving tasks, whereas new entrants can carry out (initially) more repetitive tasks. Within-job variation in competences can also slightly reshuffle the actual allocation of tasks: within a job requiring the processing of complex numeric information, some workers can be more gifted in performing more advanced analytic tasks, while others can take over the more basic calculations. Within certain parameters given by the particular job being carried out, it is perfectly reasonable to expect that differences in the specific skills, competences and even psychological traits of different workers would give rise to small differences in the actual bundle of tasks being performed. This would not invalidate the assumption that the job is the most appropriate unit of analysis for research on tasks and related issues.

In conclusion, the distribution of tasks across the working population is largely structured by the division of labour across occupations and sectors, as measured by the international standardised classifications used in this and other studies. Between-job differences account for roughly 30%–40% of the observed variance in task content (except for problem-solving, which has more within-job variation) and for 30%–50% of the variance in the use of machines and ICT tools at work. These percentages provide support for the use of detailed occupation (or the combination of occupation and sector) as the unit of analysis, although they also suggest that within-job variations should be more systematically taken into account, since they can also be an important part of the story. In the particular case of task methods (including the extent to which routine is present in the job), these results suggest that within-job variation is even more important. It is especially necessary to take this into account before deriving any conclusions from an analysis of between-job differences since they are comparatively small.

Cross-country differences in task variables

Figure 5 showed that the variation in task scores across countries is minimal compared to the variation across jobs. This provides some support for a methodological decision that was in fact forced on the research because of data limitations: the use of a single set of indices for all European countries included in this study. The data used for constructing the indices do not enable the construction of the indices separately for each country, which means that cross-country variation is missing. At least it has been shown that this means no more than 4%–5% of the total variance observed at the individual level is missing. But could it be that this 4%–5% is still important? Could that small cross-country variation in task content and methods have significant implications?

Figure 18: Cross-country variation in task indices

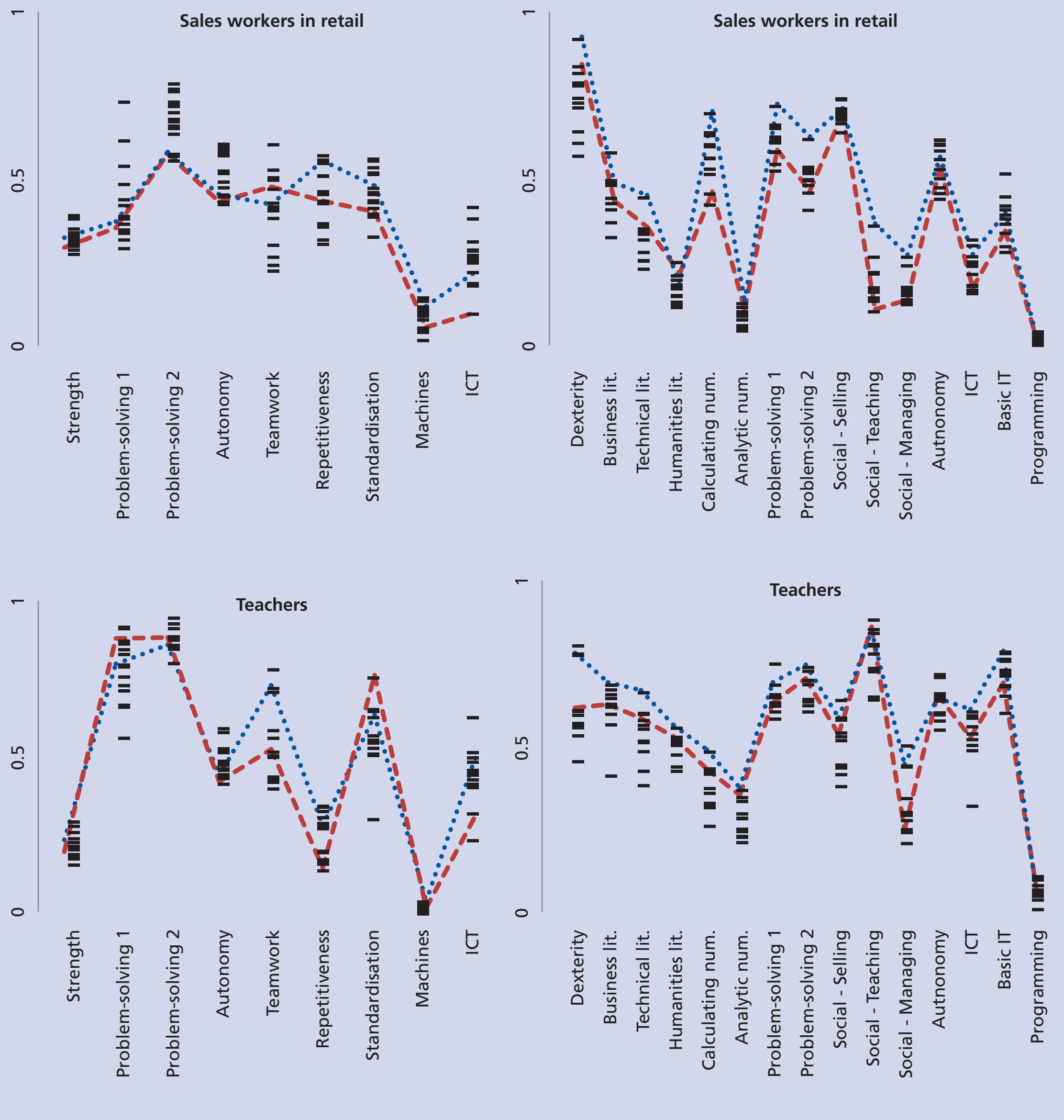
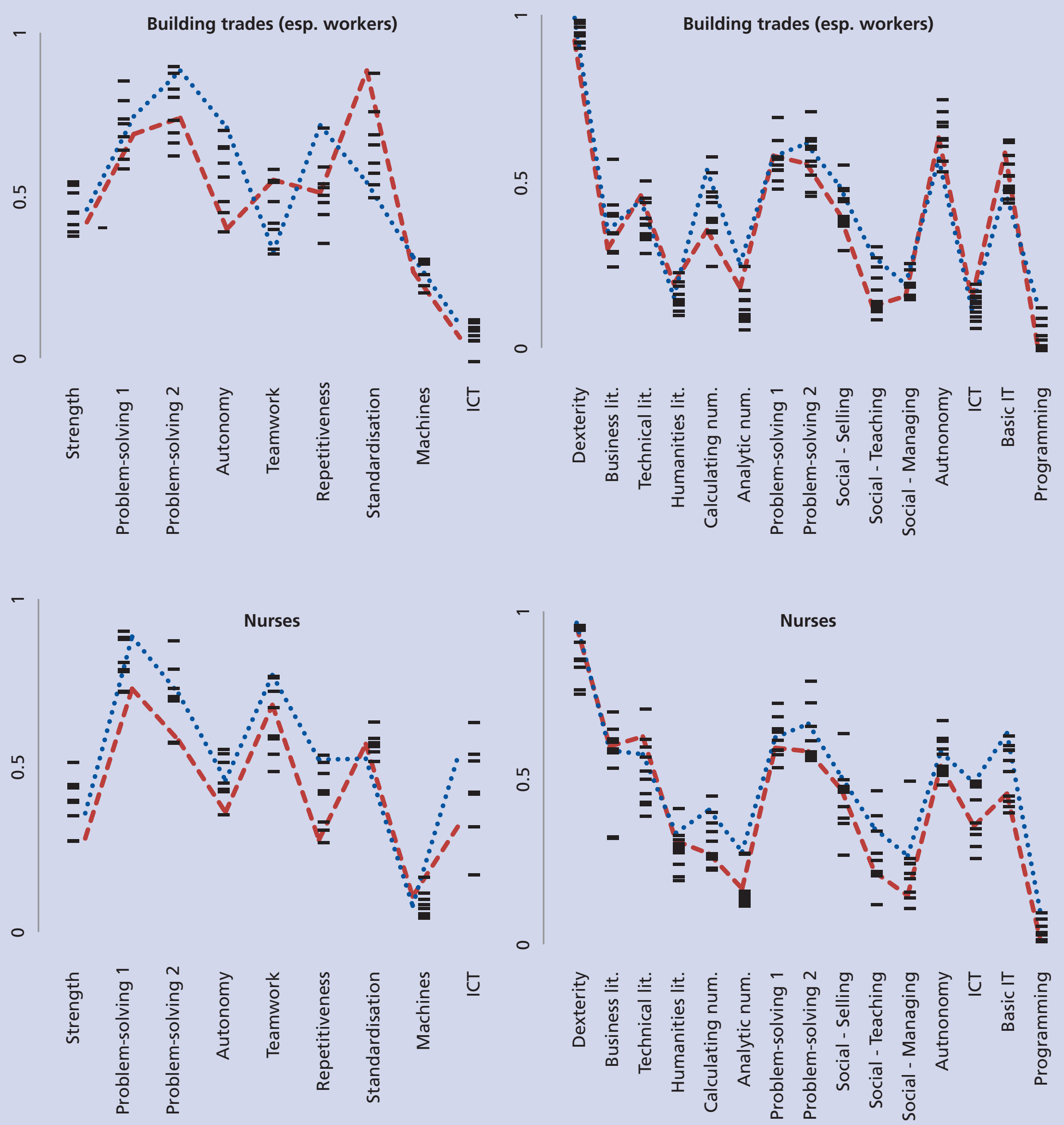


Figure 18 (continued)



Note: UK and US indicated with dotted line, Germany indicated with dashed line.
Source: EWCS (left) and PIAAC (right) (2014 LFS weights), authors' elaboration.

Although it is not possible to construct a national version of the entire framework of indices for the whole set of jobs in the economy, it is possible for a subsample of some common jobs. The occupation-by-sector combinations that employ a larger share of employment do involve enough people to allow a country-level analysis. The cross-national average in the task scores of those common jobs has been looked at in Figure 16. Figure 18 (starting on page 65) shows, for the same jobs, the cross-country variation in task content and methods according to the EWCS and PIAAC databases.

As expected, the results show a significant degree of consistency across countries. In addition to the average value of the scores in each country and index, Figure 18 includes a line linking all the scores for two countries, Germany and the UK for the EWCS, and Germany and the US for PIAAC, the aim being to choose two countries as dissimilar to each other as possible. In addition to the dispersion in the country averages for each index, it is possible to get an idea of the similarity of the entire task profile for the same jobs across different countries. This exercise further confirms the level of consistency across countries: in nearly all cases, the profiles represented by the lines are very similar in Germany and the UK or US (although the lines are not entirely overlapping, they are very similar in shape and rarely cross). Perhaps the single exception is the occupation of building trades specialist workers, where there is some inconsistency in the lines representing Germany and the UK, suggesting some difference in the overall task profile of this job in both countries. However, even in these cases, most of the discrepancy tends to concentrate in the indicators of task methods, which, as already seen in Part 2, are less well defined by the occupational boundaries. Content and tools are generally more consistent across countries (as indicated by the smaller dispersion of the country lines in Figure 18), with perhaps the exception of problem-solving, which was also indicated previously.

The characteristics of two of the sources used to construct the task indices have enabled a discussion on the heterogeneity of task content and methods within jobs at a given point in time. But what about heterogeneity over time? In this approach, the task variables are measured only at a particular point in time (this is also the case for most previous studies on this issue). This is entirely imposed by limitations in the data available for measuring tasks, which are generally only measured at a particular point in time; if they are available in more than one point, they cannot be compared because of changes in the underlying classifications or variables. But even if it is a methodological decision imposed by data restrictions, it is important to be aware of its potential repercussions: essentially, using a fixed set of task indices only makes sense if the distribution of tasks across jobs does not change much in the short–medium term (or at least, over the time period that is being analysed, generally ranging one or two decades). Is it possible to evaluate the empirical validity of such an assumption?

As before, a small set of variables from the framework can be used to provide at least a partial exploration of this issue, this time using data from the EWCS, which has been conducted several times using a more or less consistent questionnaire. For most of the task indices derived from the EWCS, it is possible to generate consistent estimates of the average scores for the period 2000–2010, and therefore to evaluate the change in those scores over a period of a decade. The results of this exercise are summarised in Table 9 (on next page).

Table 9: Individual and compositional change in task indices

	Change in index at the individual level			Change in the composition		Statistically significant change in two-digit ISCO occupations		
	2000	2010	Change	2000 mean with 2010 emp.	Change			
Physical: Strength	0.269	0.248	-0.021 **	0.262	-0.007	Nurses (-21%), other associated professionals (-22%), office clerks (+24%), personal and protective (-18%)	-8%	-3%
Intellectual: Problem-solving; info-gathering and evaluation	0.637	0.631	-0.006	0.641	0.003	None	-1%	1%
Intellectual: Problem-solving, creativity	0.827	0.829	0.002	0.833	0.007	None	0%	1%
Methods: Autonomy	0.645	0.634	-0.011 *	0.654	0.009	Corporate managers (-9%), doctors (-10%), engineers (-8%), other associated professionals (-6%)	-2%	1%
Methods: Routine, repetitiveness	0.394	0.412	0.018 **	0.385	-0.009	Teachers (+33%), office clerks (+13%), salespersons (+21%)	5%	-2%
Methods: Routine, standardisation	0.499	0.576	0.077 **	0.483	-0.016	Generalised increases for managers, professionals and clerks, sales and metal workers	15%	-3%
Tools: Machines	0.175	0.162	-0.013 **	0.153	-0.023	Engineers (+123%), doctors (+201%), other assoc. prof. (-36%), office clerks (+38%)	-7%	-13%
Tools: ICT	0.290	0.417	0.127 **	0.294	0.004	Generalised increases for all except agricultural, manufacturing and low-skilled service occupations	44%	1%

Note: * p<0.1, ** p<0.05.
Source: European Working Conditions Survey (EWCS), 2000 and 2010, EU15.

The numbers on the left-hand side of Table 9 show the simple average in the scores of each of the indices available from the EWCS in 2000 and 2010. The third column shows the change in that score, with asterisks indicating whether this change is statistically significant. According to the EWCS, between 2000 and 2010 there was a significant decline in the indices of physical strength tasks, autonomy and use of machinery at work (the biggest declines in relative terms, around 8%, are those of strength and use of machines). During the same period there was a statistically significant increase in the use of ICT at work, and in the extent of task standardisation and repetitiveness. The increase in the use of ICT in this period was really impressive, going from an average of 0.29 to nearly 0.42 (an increase of 44% in 10 years). The increase in the average score of task methods standardisation was also very substantial, from 0.5 to 0.58 (more than 15% higher). On the other hand, the two problem-solving indices show no significant change between 2000 and 2010.

From an occupational perspective, these changes in the average levels of the indices can be the result of two different developments: a change in the averages within occupations; and a change in the shares of employment across occupations. In the first case, changes in task content and methods would be the result of developments independent from the occupational structure (for instance, trends that affect all occupations simultaneously). In the second case, the changes in the task content and methods would be the indirect result of changes in the occupational structure.

One way to identify the nature of the occupational dynamics behind the change in the averages shown in Table 9, is to calculate a counterfactual score using the average values for each occupation in 2000 and the occupational shares in 2010. If all of the observed change in the individual-level scores is the result of changes in the structure of employment across occupations, that counterfactual should provide a very similar result to the observed result. If the counterfactual result is very different from the observed result, it is possible to infer that occupational change was not the main factor behind the observed changes. The results of this exercise are presented in the fourth and fifth columns of Table 9. It is thereby possible to evaluate the occupational component of the observed changes in task content and methods by comparing the figures in columns 5 and 3 of Table 9.

In the cases of strength and machines, the signs of the counterfactual and the actually observed change coefficients are the same, meaning that occupational change went in the same direction as within-job changes. In fact, the counterfactual change in the use of machines is larger than the observed change, which implies that the most machine-using occupations shrank significantly in the 2000–2010 period and that this was partially offset by a small increase in machine use within some occupational categories. Looking at the individual occupational categories, there was a statistically significant change in each index, which is summarised in the last column of Table 9. There was a very significant increase in the use of machinery for engineers, doctors and office clerks; in fact most of the within-occupation increase in machine use took place in job categories where the extent of machine use was relatively small.

A more surprising result is the counterfactual value for ICT use. In spite of the fact that the distribution of this variable was strongly affected by the occupational structure, as shown in Table 8 earlier, the overall large increase in the use of ICT at work is almost entirely explained by within-job developments. In other words, the massive increase in ICT use is not due to an increase in the share of ICT-intensive occupations (this effect does exist, but is comparatively tiny), but rather to an increase in ICT use generalised in most service occupations. Looking at the specific occupational level (in the last column of Table 9), all except agricultural, manufacturing and low-skilled service occupations experienced a significant increase in ICT use. This means that an approach entirely based on an analysis of the occupational composition of employment (with fixed values for task content, methods and tools) is likely to miss the most important developments in ICT use.

But the most noteworthy results are those of the two routine task indices. In this case, compositional and within-job changes go in the opposite direction. The shift–share analysis confirms what has already been established by the literature: occupations that are routine-intensive have been shrinking in recent years. The reduction is small, but significant: the index of repetitiveness shrinks by about 2%, and the index of standardisation by about 3%, when the change is due only to the composition being considered. But the change at the individual level is positive and also significant: an increase of 5% for repetitiveness and 15% for standardisation. The increase in the degree of routine tends to concentrate in occupations that may not have been traditionally considered routine, in particular in the case of standardisation. Managers, professionals and clerks are among the occupational levels that experienced the largest increase in the index of routine task methods between 2000 and 2010.

This puts the whole debate of routine-biased technical change (RBTC) in a different light. The most frequent argument in the literature is that routine-intensive occupations have been structurally shrinking in recent years because advances in computing have allowed machines to perform routine tasks at a comparatively lower cost. According to this, computerisation would structurally decrease the amount of routine task labour input involved in a job. And according to analysis of the

EWCS data, that may be true in compositional terms; however, a much larger effect taking place within occupations (particularly in professional, clerical and managerial ones) goes in the opposite direction. Of course, it is impossible to know whether this increase in routine task content within occupations is the result of computerisation, but the argument could be as plausible as the opposite one. The increasing use of computers at work could require an increasing degree of standardisation in labour input. It is even possible to conjecture that the use of computers could routinise work by allowing a tighter control and monitoring of the labour process (Sewell and Barker, 2012; West and Bowman, 2014). And perhaps increasing standardisation of the labour process in many highly skilled occupations can increase the chances of these occupations being replaced by machines in a not so distant future. A generalised routinisation of work could lead to later rounds of RBTC also affecting the highest layers of employment, until now relatively protected. Again, all these potential developments are concealed if the analysis does not allow for within-job changes in the degree of routine task intensity.

11 Distribution and change of task content and methods in Europe: A structural approach

Can the task indices constructed for this report provide new insights into the structural differences between European labour markets and about the patterns of structural change observed in recent years? Some partial answers to that question have already been provided, but only indirectly. This part of the report explicitly compares the structural composition of employment across countries from a task perspective, evaluating its change over time and its implications for job quality.

Figure 19 (on next page) shows a comparison of the average intensity score for each of the high-level task indices across European countries in 2014. For instance, in Romania the average intensity of physical tasks of all jobs is 0.35, whereas it is only 0.23 in Luxembourg (the largest and smallest values for that index). It is important to remember that the same job receives the same task score in each country: only the share of employment in different jobs (the structure of employment) varies in Figure 19. In other words, Figure 19 shows that the occupational–sectoral structure has a higher concentration of jobs requiring physical tasks in Romania. However Figure 19 cannot show whether Romanian jobs are more physical than Luxembourgish jobs, because the task content of jobs is constant across countries. But since it has been shown that the cross-country variation in task content is tiny compared to the between-job variation (see previous part), this should be a reasonable if probably conservative estimation of the actual amount of cross-country differences in tasks.

The structural differences in task content and methods across Europe, according to this approximation, are rather small, as can be seen clearly in Figure 19. The dispersion is not the same in all the task categories of the framework: it is largest in the indicators of machine and ICT use, as well as in the indicator of physical task content, and smallest in the routine methods indicator. The use of technology at work is probably the aspect most directly linked to the degree of economic development in the different countries, so the fact that the related indicators are the most diverse across Europe is not surprising. In fact, an inspection of the ranking of countries in terms of each of the task categories reveals a high degree of consistency, which again seems linked to broadly defined economic development. There are, however, some countries whose position in a particular task indicator is less consistent: for instance, the extent of routine tasks in Germany seems comparatively high; the Czech Republic has comparatively high values of intellectual tasks and ICT use while the opposite happens in Spain; and Greece and Portugal have lower levels of routine than would be expected looking at their overall task composition.

The differences in the task intensity scores across countries, although significant, are small, so it is worth finding an alternative way of representing them, one that focuses on the differences and represents the whole task profile. Rather than showing the actual values of each country, Figure 20 (p. 73) presents the difference between each country and the EU average for each task indicator. It only shows nine countries, representing the different European regions and different stages of economic development.

The three countries represented in the first graph of Figure 20 are highly developed northern European economies (the Netherlands, Sweden and the UK), which stand out from the rest by having more labour input in intellectual and social tasks, fewer physical tasks, more ICT and less machine use and less repetitive work methods. But there are some differences within this group too: the intensity of basic numeracy tasks and serving social tasks are lower in Sweden, whereas the UK has higher levels of business literacy, serving and selling social task content.

Figure 19: Structural comparison of task content and methods in Europe, 2014

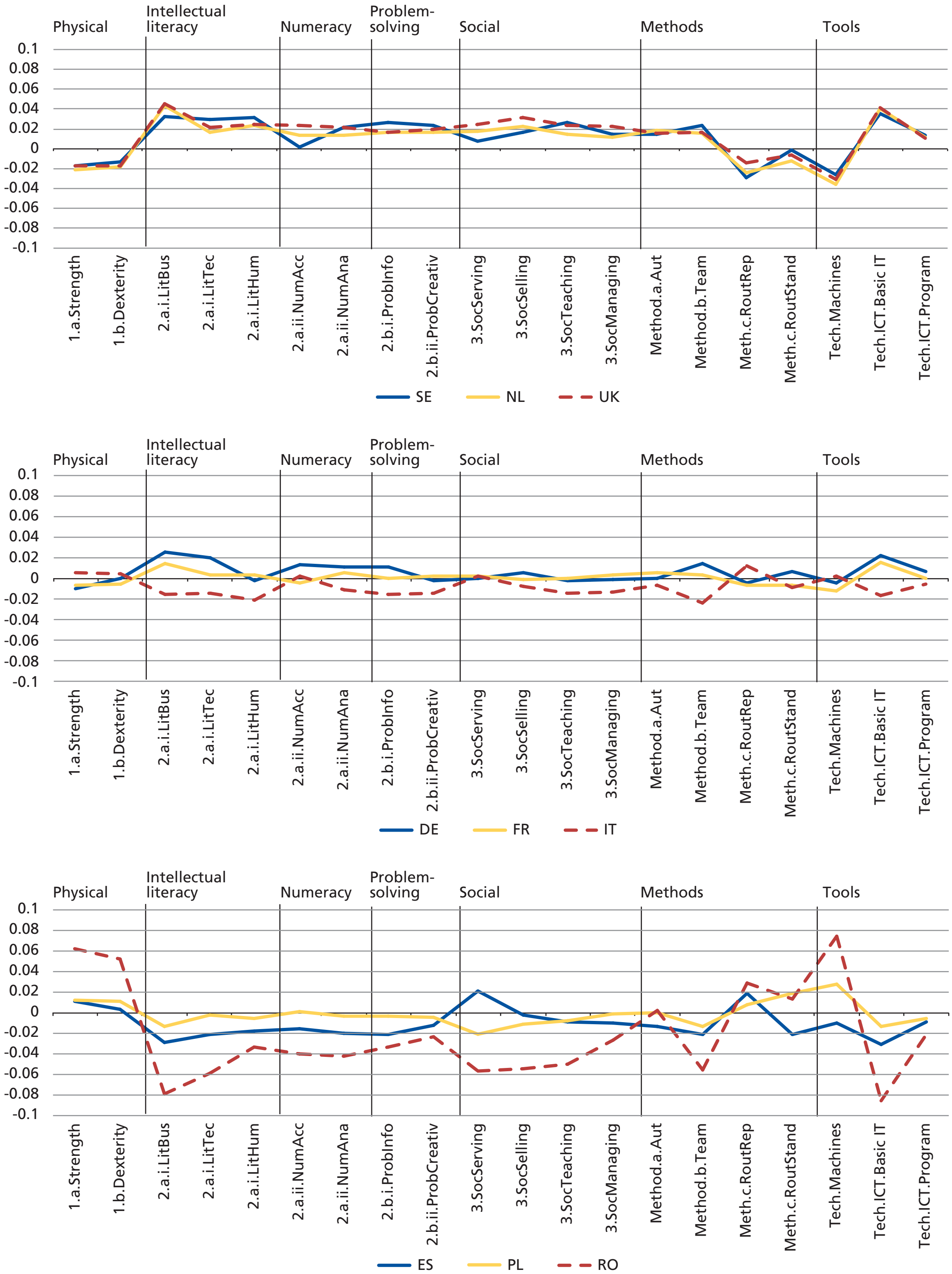
Physical tasks		Intellectual tasks		Social tasks		Routine methods		Machine tools		ICT tools	
RO	0.35	LU	0.52	UK	0.42	CZ	0.52	RO	0.28	LU	0.48
SK	0.31	SE	0.50	NL	0.41	RO	0.52	SK	0.24	UK	0.42
BG	0.30	UK	0.50	SE	0.41	SK	0.52	CZ	0.23	NL	0.42
GR	0.30	NL	0.50	MT	0.41	HU	0.51	PL	0.23	SE	0.42
HU	0.30	FI	0.49	LU	0.41	PL	0.51	HU	0.23	BE	0.41
PL	0.30	BE	0.49	IE	0.41	EE	0.51	BG	0.23	DE	0.41
HR	0.30	IE	0.49	BE	0.41	SI	0.51	SI	0.22	IE	0.40
CZ	0.30	DE	0.49	DK	0.40	HR	0.51	EE	0.22	MT	0.40
PT	0.30	DK	0.49	EE	0.40	BG	0.51	HR	0.22	FI	0.40
ES	0.30	MT	0.49	LT	0.40	LT	0.50	LT	0.22	DK	0.39
IT	0.29	SI	0.49	FR	0.40	IT	0.50	LV	0.21	FR	0.39
EE	0.29	EE	0.49	DE	0.40	DE	0.50	PT	0.21	AT	0.39
SI	0.29	LT	0.49	FI	0.40	PT	0.50	IT	0.20	SI	0.39
LT	0.29	AT	0.48	ES	0.40	ES	0.50	GR	0.20	EE	0.38
LV	0.29	FR	0.48	LV	0.40	AT	0.50	DE	0.20	CZ	0.38
AT	0.29	CZ	0.48	SI	0.40	MT	0.50	AT	0.20	LT	0.37
FI	0.29	PL	0.48	CY	0.40	GR	0.49	FI	0.19	CY	0.37
IE	0.28	LV	0.48	AT	0.40	LV	0.49	ES	0.19	LV	0.37
DE	0.28	HR	0.47	GR	0.39	IE	0.49	FR	0.19	IT	0.37
FR	0.28	HU	0.47	BG	0.39	FR	0.49	IE	0.18	HR	0.36
CY	0.28	IT	0.47	IT	0.39	BE	0.49	MT	0.18	HU	0.36
MT	0.28	GR	0.47	HR	0.39	FI	0.49	BE	0.18	PL	0.36
DK	0.28	BG	0.47	CZ	0.39	UK	0.49	CY	0.18	ES	0.36
SE	0.27	CY	0.47	PL	0.39	CY	0.49	SE	0.18	GR	0.35
BE	0.27	ES	0.47	HU	0.38	SE	0.48	DK	0.18	BG	0.35
UK	0.27	SK	0.46	PT	0.38	DK	0.48	UK	0.17	SK	0.35
NL	0.27	PT	0.46	SK	0.38	NL	0.48	NL	0.17	PT	0.34
LU	0.23	RO	0.45	RO	0.35	LU	0.47	LU	0.15	RO	0.29

Source: EWCS 2010, PIAAC and ONET data (2014 LFS as weights), authors' calculations.

The second graph of Figure 20 shows three large core European countries, whose values are very close to the average, again with some interesting details. The profile of Germany is slightly higher in terms of technical literacy, accounting, teamwork and standardisation, whereas Italy's profile reflects a less advanced economic structure with slightly higher levels of physical tasks, lower literacy levels and problem-solving and less use of ICT.

But the largest differences appear in the third graph of Figure 20, representing Spain, Poland and Romania. The Romanian profile diverges the most from the EU average, with much higher levels of physical intensity, machine use and routine methods, lower literacy levels (particularly business and technical) and considerably lower levels of social task content, teamwork and ICT use. The pattern for Spain is smoother and similar to Italy, though it has a higher intensity of serving tasks, higher repetitiveness levels and lower standardisation. By contrast, the task profile of Poland is closer to the European average than Italy or Spain, with the exception of a lower level of serving social tasks and a significantly higher use of machines and standardised work methods.

Figure 20: Structural comparison of the task profiles of nine European countries, 2014



Source: EWCS 2010, PIAAC and ONET data (2014 LFS as weights), authors' calculations.

The task profiles seem to reflect the degree of general economic development of each country, but also some country-specific and structural peculiarities linked to history, economic specialisation or other factors. The task profile of Spain reflects its reliance on tourism and personal services (serving tasks, which tend to be repetitive and involve low intellectual demands) and a certain amount of limitation in productive structures with respect to its level of GDP. Poland's profile suggests a degree of modernity in productive structures, probably linked to a specialisation in relatively advanced manufacturing activities (this is also the case for the Czech Republic, not shown here).

This kind of comparison may have interesting implications for educational and training policies. Certain types of task content appear to be strongly linked to economic development; it therefore seems reasonable to orient educational systems towards them. Literacy and problem-solving, social interaction, teamwork and ICT use are the types of tasks that most consistently differentiate European countries by stage of economic development. But at the same time, the specificities indicated also suggest that there is no single inexorable path. It may also be strategically sensible to orient the skill base towards other types of task contents such as machine use, standardisation or manual dexterity, in order to profit from international trade; or even towards serving social tasks to benefit from a specialisation in leisure and touristic services.

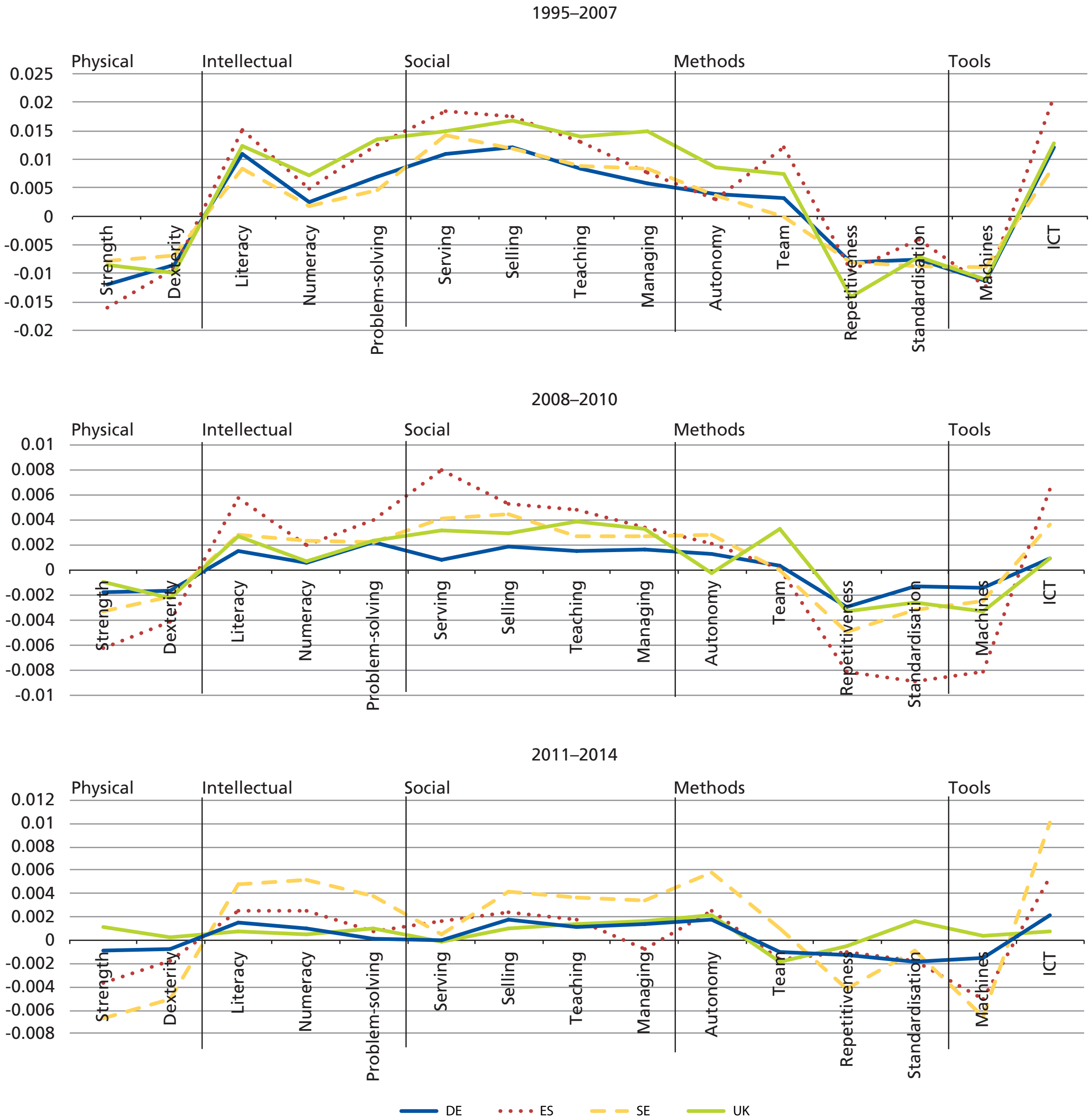
Comparing countries with different levels of economic development can provide some clues about how the employment structure may evolve in the future in terms of tasks content and methods. But there is a more direct means of using recent trends to try to forecast future developments. By linking the task indices to the data that have been compiled over the years by the European Jobs Monitor, it is possible to evaluate how, in recent decades, structural change has altered the task profile of European economies. This is shown in Figure 21 (on next page), where representation is restricted to four countries for which there are detailed employment data available from 1995: Germany, Spain, Sweden and the UK.[27]

Despite initial differences in economic structures, these countries share quite similar and more or less consistent patterns of change in the task composition of the labour markets over the period depicted (1995–2014). In the period 1995–2007, the four selected countries significantly expanded the level of labour input in social tasks (particularly selling and serving), literacy tasks and ICT use. During the same period, they significantly reduced labour input into routine task methods, machine use and physical task content. The shift towards social tasks was particularly strong in Spain and the UK, which experienced faster structural change from a task perspective during this period. The two subsequent periods – 2008–2010 and 2011–2014 – are imposed by breaks in the time series, but they also coincide with the first and second stages of the economic crisis. For these periods, Figure 21 shows a very similar profile, although it is less obvious because of the shorter time involved. (Note: the scales of the three charts differ in the interest of clarity) Again, it shows a shift of labour input away from routine, machine and physical tasks and towards social and literacy task content. In the period 2008–2010, Spain experienced much faster structural change than the other countries shown, with a very large shift towards serving social tasks and literacy. In the period 2011–2014, the fastest changing country was Sweden, which shifted towards numeracy and literacy tasks in particular.

The implications of these results are rather similar to those discussed earlier. There is a more or less universal shift in the task profile of European economies: away from routine task methods (particularly regarding repetitive tasks; less so for standardisation), machine use and physical task content and towards social tasks (particularly serving and selling), literacy task content and ICT use. It is interesting to note that although numeracy task content also expanded in recent years, it did so to a much lower degree than literacy. A similar development occurred with problem-solving tasks.

27 Other countries are available on request.

Figure 21: Structural change in task profiles in four European countries



Source: EWCS 2010, PIAAC and ONET data (LFS as weights), authors' calculations.

In addition to these more or less general trends, some interesting peculiarities can be seen in the patterns of change at country level. For instance, Spain experienced the fastest structural change from a task perspective, which may reflect some kind of catch-up process; at the start of the period being examined, Spain had the least developed economy of the four countries. But structural shifts in Spain seem to be comparatively biased towards serving social task content. In contrast, Sweden also experienced fast structural change over the whole period (particularly during the crisis) with much lower growth in serving social tasks, and greater growth in numeracy and problem-solving tasks.

The focus of the European Jobs Monitor is the qualitative aspect of structural change in employment. In other words, the aim is to evaluate how recent patterns of change in the occupational structure of different countries impact job quality. Over the years, it has identified two dominating patterns of structural change in Europe: one of job polarisation and one of structural upgrading. In the first case, the jobs with lower and higher wage levels expanded relative to those in the middle. This pattern was found in most continental European economies during the period 1995–2007 and became almost pervasive around Europe in the first stage of the economic crisis (falling later as the economy regained steam). The pattern of structural upgrading, by contrast, involves an expansion of jobs with higher wage levels with respect to those in the middle and bottom levels, with some linearity in the relationship between employment growth and job quality. This pattern was generalised in the Nordic economies, especially during periods of economic growth. Southern European countries experienced a flatter expansion of mid–high-paid jobs among those at the bottom level during the pre-crisis period and job polarisation during the crisis.

The four countries shown in Figure 21 are good representatives of those different patterns of structural change from 1995 to 2014: Germany experienced more or less consistent job polarisation throughout; Spain experienced upgrading with growth in mid-level jobs in 1995-2007, followed by sharp polarisation during the crisis; Sweden experienced consistent structural upgrading; and the UK experienced strong upgrading with some polarisation in 1995–2007, followed by a short period of structural downgrading during the first stage of the crisis. Are these different patterns of structural change in terms of wage levels linked to different patterns of structural change in terms of task contents? Figure 21 does not suggest so. For instance, the change in the task profiles of Germany and Sweden between 1995 and 2007 are strikingly similar, despite being total opposite cases of job polarisation and structural upgrading, as shown earlier. In other words, the change in the task profile of the different economies does not seem to be linked to the observed patterns of job polarisation and upgrading in any obvious way.

In order to understand this better, it is useful to look at how the job quality indices are routinely used to evaluate the implications of structural change, related to the new task content and methods variables presented here. Figure 22 shows the bivariate correlation coefficients between the three job quality indicators of the European Jobs Monitor and each of the task indicators of this framework.

The European Jobs Monitor has three indices for measuring the quality of jobs in each country: ‘wage’ is based on the average hourly wage of each job; ‘education’ is based on the average educational level of workers in each job; and ‘amenities’ is based on the average score in a multidimensional index of non-pecuniary job attributes (intrinsic job quality, employment quality, health and safety and work–life balance). These indices were constructed by aggregating information from different European datasets, most importantly the European Survey on Income and Living Conditions (EU-SILC), EU-LFS, EWCS and Structural Business Statistics.[28] The scores of these indices are expressed as the average percentile of workers in each job according to each of the attributes. Figure 22 also shows the average value of each task index across job–wage quintiles constructed for the EU15 in 2014: each of those quintiles represent 20% of employment, ranked by the average wage of jobs, from lowest to highest.

The different indices from the task framework have very distinctive correlations with the job quality attributes of jobs, according to Figure 22. Physical task content has a clear negative correlation with the three indices of job quality, whereas intellectual task content has an even stronger positive correlation. The negative association between physical tasks and job quality is particularly strong for amenities and strength, whereas the positive association between intellectual tasks and job quality is strongest for education, literacy and humanities. Social task content also has a positive correlation with the three indicators of job quality, but it is much weaker than for intellectual tasks.

[28] For more details, see Eurofound, 2013.

Figure 22: Correlations between job quality and task indices, 2014 (EU15)

	Correlations with job quality indices			Values for wage quintiles				
In terms of the object of work/task:	**Wage**	**Education**	**Amenities**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
1. Physical	-0.59	-0.76	-0.83	0.35	0.36	0.31	0.24	0.18
a. Strength	-0.62	-0.77	-0.83	0.34	0.34	0.27	0.19	0.14
b. Dexterity	-0.49	-0.67	-0.74	0.36	0.39	0.35	0.30	0.22
2. Intellectual	0.80	0.85	0.76	0.38	0.42	0.46	0.54	0.61
a. Information-processing	0.77	0.83	0.75	0.29	0.33	0.38	0.47	0.54
i. Literacy	0.79	0.88	0.79	0.34	0.39	0.44	0.54	0.61
- Business	0.67	0.78	0.77	0.32	0.45	0.52	0.69	0.75
- Technical	0.73	0.66	0.53	0.28	0.38	0.48	0.56	0.60
- Humanities	0.70	0.81	0.74	0.14	0.20	0.22	0.33	0.46
ii. Numeracy	0.67	0.69	0.64	0.24	0.26	0.31	0.39	0.46
- Accounting	0.43	0.48	0.51	0.37	0.41	0.45	0.55	0.59
- Analytic	0.72	0.67	0.61	0.08	0.13	0.18	0.27	0.38
b. Problem-solving	0.72	0.76	0.67	0.47	0.51	0.54	0.62	0.69
i. Information-gathering & evaluation	0.73	0.73	0.63	0.45	0.52	0.55	0.64	0.69
ii. Creativity	0.65	0.72	0.70	0.49	0.51	0.52	0.59	0.68
3. Social	0.49	0.66	0.58	0.37	0.33	0.36	0.42	0.50
- Serving/attending	-0.04	0.28	0.22	0.53	0.40	0.42	0.45	0.49
- Selling/persuading	0.42	0.60	0.55	0.41	0.36	0.39	0.48	0.54
- Teaching	0.63	0.70	0.57	0.29	0.29	0.32	0.40	0.54
- Managing	0.59	0.56	0.52	0.27	0.29	0.30	0.36	0.46
1. Work organisation								
a. Autonomy	0.45	0.50	0.60	0.52	0.56	0.54	0.62	0.67
b. Teamwork	0.24	0.24	0.12	0.43	0.43	0.48	0.51	0.56
c. Routine	-0.08	-0.34	-0.42	0.48	0.54	0.53	0.49	0.46
i. Repetitiveness	-0.46	-0.58	-0.62	0.49	0.47	0.46	0.35	0.29
ii. Standardisation	0.30	0.03	-0.05	0.47	0.60	0.60	0.62	0.63
2. Technology								
a. Machines	-0.18	-0.60	-0.65	0.16	0.28	0.26	0.18	0.12
b. ICT	0.73	0.84	0.80	0.19	0.26	0.35	0.52	0.60
- Basic IT	0.69	0.77	0.75	0.35	0.48	0.53	0.71	0.81
- Programming	0.44	0.40	0.37	0.03	0.05	0.07	0.11	0.15

Source: EWCS 2010, PIAAC and ONET data (2014 EU15 LFS as weights), authors' calculations.

At the detailed task level, some interesting variations can be seen. Serving tasks are only marginally correlated with education and amenities and are uncorrelated with wages, whereas the other three social task categories show a clearer positive correlation. The average scores across wage quintiles reveal a non-linear pattern of association between serving tasks and wage levels: serving task content is most frequent at the top and at the bottom of the wage distribution (as shown at the beginning of this part of the report, serving social tasks are relatively high for some highly skilled service occupations such as doctors and nurses). To a smaller extent, this also happens with the selling task component.

Figure 22 also shows the results for the methods and tools indicators. Autonomy is positively correlated with the three job quality indices (particularly with amenities), while routine is negatively correlated with amenities and education (not with wages). The detailed routine subcomponents also reveal interesting variations: repetitiveness has a moderate negative correlation with the three job quality indices, while standardisation has a mild positive association with wages and no correlation with education or amenities.

The results by wage quintiles show a non-linear association with the routine task index, as predicted by the literature: routine task methods are more frequent in the middle of the wage structure. Looking at the two subcomponents, it is apparent that this non-linearity comes from the aggregation of two more or less linear but contradictory patterns of repetitiveness and standardisation (repetitiveness negatively and standardisation positively linked to wages). A similar non-linear pattern is found for machine use, which is most frequent in the middle of the wage structure, having a negative correlation overall with the three job quality indices (particularly amenities and education). The indicators of ICT use show a clear and linear positive correlation with the three job quality indices.

It is interesting to note that the highest correlations in Figure 22 are those between the task indices and the average education level of each job, while the lowest are between the task indices and average wages. This suggests that, as hinted at in previous publications (Eurofound, 2013), the indices of education and amenities are more directly linked to the division of labour and the technical structure of the production process, while wages are more affected by institutional factors such as industrial relations systems, minimum wages or employment regulation. This may also suggest a possible reason for the contrast between the changes in the task profiles of the different countries and the patterns of polarisation and structural upgrading. Job polarisation, in fact, is only apparent when jobs are characterised by their average wages: when the average educational level of jobholders or non-pecuniary job attributes are used, the nature of structural change in European labour markets in recent years is unambiguously upgrading in nearly all cases (Eurofound, 2013). This is one of the reasons why Eurofound has often argued that the observed cases of polarisation seem more driven by institutional than technological factors.[29] If that is the case, then the task variables, which characterise jobs according to their contribution to the production process from a primarily technical perspective, would not be associated to job polarisation, at least not to a significant extent. Future work will aim to empirically test this possibility.

[29] Other reasons include the association between polarisation and labour market deregulation, and the clear demarcation between patterns across different European institutional families; see Eurofound, 2014 and Fernández-Macías, 2012 for more details.

Conclusions 12

The tasks framework introduced in Part 2 was used in Part 3 to analyse the distribution of tasks content and methods across Europe. The most important findings from this approximation are summarised here.

Task bundling: The different types of task input are combined in particular ways in existing jobs, such as intellectual and social tasks tend to go together, whereas physical task content tends to be negatively correlated with intellectual tasks. This 'task bundling' affects not only broad domains, but also very specific subdomains in the framework, associated with particular types of jobs. For instance, despite the generally negative association between physical and intellectual tasks, there is a significant association between physical dexterity and technical literacy for some particular types of jobs, such as health professionals and associate professionals, engineering associate professionals and metal industrial workers. What this means is that even if tasks were the smallest unit of labour input in the production process or if technical change tended to affect specific types of task content, the different types of tasks cannot be understood in isolation.

Task distribution: The distribution of tasks input across the working population is fundamentally structured by occupation and (to a lesser extent) sector of activity. Since occupation and sector are variables that classify workers in terms of division of labour, this was to be expected. An estimated 30%–40% of the total variance in task input is explained by occupation and sector, which could be probably be expanded to a bit more than 50% of total variance if analysis adjusted for measurement problems. This leaves about 50% of the total variation in task input taking place within each of the job categories (defined here as the combination of two-digit occupations and sectors). The sources of these within-job variations in task content and their potential implications are yet to be understood. This issue merits more attention.

Changes in task categories: The ongoing (if sporadic) European Working Conditions Survey (EWCS) enables a partial evaluation of a very important aspect of within-job heterogeneity: whether the overall change in particular task categories was the result of structural or intrinsic change (in other words, whether the change occurred in the distribution of employment across different types of jobs, or in the task profile of each job over time). Using the limited set of task indices available for this exercise, some instances in which structural change was consistent with intrinsic change emerged, which would justify a structural approach to task analysis. However, there were also some instances in which this was not observed; the most striking case referred to the variables of routine task methods (repetitiveness and standardisation). Reflecting the research literature, it was found that these types of task input are *structurally decreasing* (in other words, the most routine jobs are shrinking in employment), while at the same time *intrinsically increasing* to a much larger extent (all jobs are becoming routinised). This puts the whole debate on routine-biased technical change (RBTC) in a different light and highlights the importance of taking within-job variation in tasks much more seriously.

Changes in task profile: The new tasks framework also enabled a comparison of employment structures across Europe and over time from a new perspective. It was possible to identify a more or less typical sequence of change in the task profile of economies as they grow: routine task methods (especially regarding repetitiveness; less so for standardisation), machine use and physical task content tended to decrease, while serving and selling social tasks, literacy task content and ICT use tended to increase. However, some variations around this general pattern also emerged, seemingly linked to economic specialisation: for instance, in some countries (such as Spain and the UK), serving and selling social task content grew, whereas in others (such as Germany and Poland), technical literacy and standardisation task methods expanded.

Link to job polarisation: In an initial analysis, no obvious link was found between structural change in the task profiles of the countries and the observed pattern of job–wage polarisation. This may reinforce what has already been suggested in previous publications: that the observed patterns of polarisation in some countries is specific to wage distribution and likely to be more affected by institutional differences and developments, than by technological or organisational factors. However, more research is needed to fully answer this question.

The findings presented here seem to show that identifying the effect of technology, or trade, or any other factor on a particular type of task input in production, is not enough to predict occupational change in the near future. This is because the jobs affected by technical change in some particular types of task input do other tasks as well; and those other types of task input may be much more resilient – it may even be the case that technical change has a positive effect on the demand of those other types of task input. Furthermore, the combination of one type of task with another may alter the effect of technical change on any one of the tasks. But this analysis has also identified significant changes in the composition of tasks within occupations over time: an external factor reducing the amount of demand for a particular type of task input can simply be accommodated by a recombination of the task bundle of occupations, having no final effects on the occupational structure.

In this sense, it may be that the key factor for the resilience of particular occupations to technical change is not so much the types of task content that they do, but the variety of tasks they typically involve. The typical examples of jobs wiped out by technical progress, such as lift operators, tend to be cases of super-specialisation in a single, very specific type of task input. If that is the case, the vast majority of existing occupations would be relatively protected against that kind of technological replacement, since most occupations involve the combination of many different types of tasks across different domains.

The fact that tasks do not exist in isolation, but are specifically and consistently combined, or bundled, into particular jobs, has very important implications for our understanding of structural change in general and the effect of technology in particular. If task input could be actually bought and sold in the labour market, the effect of an innovation affecting a particular type of task input could be almost immediate (requiring just the time necessary to adapt existing productive structures). But tasks are put into bundles, which are then advertised as jobs, for which workers who have been trained for those bundles must be hired in order for them to be carried out within an organisational structure. This all means that the effects of technical change are mediated by a multitude of factors; inevitably, there will be a very significant degree of inertia in terms of structural change.

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Annexes

Annex 1: Knowledge-based services aggregation: breakdown by NACE two-digit sector

Title	Codes NACE Rev.2 two-digits
Private knowledge intensive services	50 to 51 Water transport, air transport
	69 to 71 Legal and accounting activities, activities of head offices; management consultancy
	activities, Architectural and engineering activities; technical testing and analysis
	73 to 74 Advertising and market research, other professional, scientific and technical activities
	78 Employment activities
	80 Security and investigation activities
	59 to 63 Motion picture, video and television programme production, sound recording and music
	publishing activities, programming and broadcasting activities, telecommunications, computer
	programming, consultancy and related activities, information service activities
	72 Scientific research and development
	64 to 66 Financial and insurance activities (section K)
	58 Publishing activities
	75 Veterinary activities
	90 to 93 Arts, entertainment and recreation (section R)
Public knowledge intensive services	84 Public administration and defence, compulsory social security (section O),
	85 Education (section P),
	86 to 88 Human health and social work activities (section Q)
Less knowledge intensive services	45 to 47 Wholesale and retail trade; repair of motor vehicles and motorcycles (section G)
	49 Land transport and transport via pipelines
	52 Warehousing and support activities for transportation
	55 to 56 Accommodation and food service activities (Section I)
	68 Real estate activities
	77 Rental and leasing activities
	79 Travel agency, tour operator reservation service and related activities
	81 Services to buildings and landscape activities
	82 Office administrative, office support and other business support activities
	95 Repair of computers and personal and household goods
	53 Postal and courier activities
	94 Activities of membership organisations
	96 Other personal service activities
	97 to 99 Activities of households as employers of domestic personnel; Undifferentiated goods- and
	services-producing activities of private households for own use (section T), Activities of
	extraterritorial organisations and bodies (section U)

Source: Eurostat.

Annex 2: Dealing with major breaks in classification or data

Country	Nature of break	Year/Q	Impact	Solution
Germany	ISCO occupational classification break	2012 Q1	Significant reassignment of employment across ISCO categories, at one and two-digit level of detail.	Use 2012 Q2–2015 Q2 data for all German charts, omitting the first year.
The Netherlands and Slovakia	ISCO occupational classification break	2013 Q1	Some reassignment of employment across ISCO categories. Mainly obvious at two-digit level.	Use 2013 Q2–2015 Q2 data for all Dutch charts, omitting the first two years.
France	ISCO occupational classification break	2013 Q1	Some reassignment of employment across ISCO categories. Mainly obvious at two-digit level.	Aggregate ISCO two-digit to one-digit for ISCO 2d categories 10-54.

Source: EU-LFS.

Other breaks are identified by Eurostat for other Member States in different quarters, for the core variables (ISCO and NACE) as well as for employment estimates. However, adjustments were only made in the above cases as they involved obviously artificial and large shifts in employment share by occupation. Luxembourg was dropped in the analysis due to very significant variation in job employment share estimates from year to year.

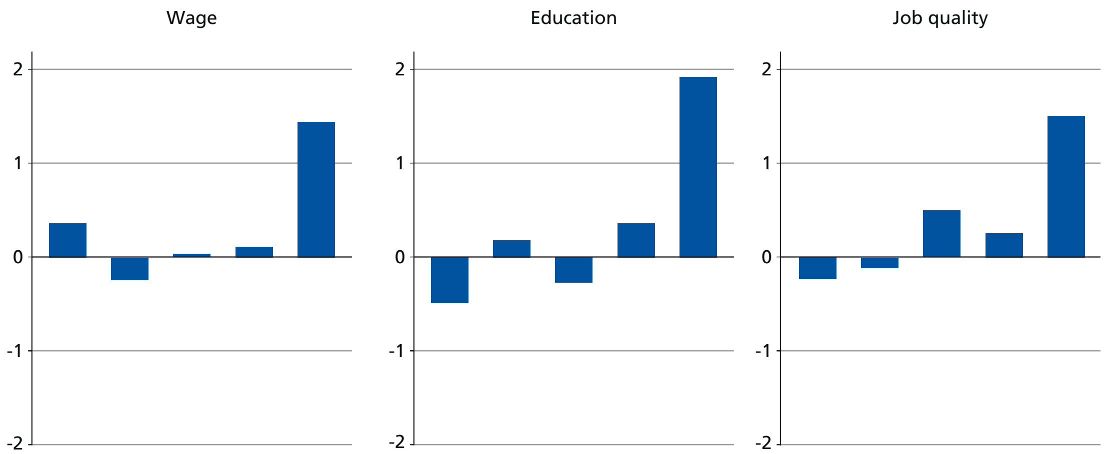
For the EU28 aggregate figures for 2011 Q2, the missing data for Germany, the Netherlands and Slovakia are accounted for by backcasting from 2012 Q2 (or 2013 Q2 in the case of the Netherlands and Slovakia) to 2011 Q2 using the aggregate employment shift observed – preserving the structure of employment observed in 2012 in Germany, and 2013 in the Netherlands and Slovakia. The assumption, therefore, is that the composition of employment by jobs did not change in Germany in 2011–2012, nor in the Netherlands and Slovakia in 2011–2013; only the levels of employment changed. For the EU28 aggregates in the breakdown charts (such as gender, full-time/part-time), the missing data for Germany, the Netherlands and Slovakia are generated using a similar backcasting, but also taking into account observed changes in employment for the categories of the breakdown variable(s).

Annex 3: Comparing employment shifts, 2011 Q2-2015 Q2, using different job quality measures

As pointed out in previous European Jobs Monitor annual reports (see for example, Eurofound, 2014, pp. 29, 41), the shape of the observed employment shifts depends on the particular job quality criterion used to rank jobs. In most of the analysis in this and related previous work (Eurofound, 2008, 2011, 2013, 2014, 2015), focus has been placed on job wage as a primary ranking criterion. Wages are only one dimension of job quality, but they tend to be an important one, highly correlated with other relevant aspects of job quality. The use of mean or median job (or occupation) wage as the basic ranking criterion has also been the common approach of much of the employment polarisation literature (see for example, Goos and Manning, 2007), even if there is, on occasion, the confusing presentation of employment shifts in terms of 'skill percentiles' when relating results based on a wage-based ranking of jobs (see for example, Autor, 2010).

As Figure 23 highlights, using job–wage to rank jobs and assign them to quintiles tends to generate more polarised patterns of employment change (greater relative growth at the edges, less in the middle) than other ranking criteria, such as the average educational attainment level of jobholders in a specific job. Recently, Salvatori (2015) noted something similar based on UK data.

Figure 23: Employment change, 2011 Q2–2015 Q2 (yearly %) by wage, education and job quality quintile



Note: EU27 (excluding Luxembourg). Q2 data in each year. Data adjusted for breaks in France, Germany, the Netherlands and Slovakia as indicated in Annex 2.
Source: EU-LFS, SES, 5EWCS (authors' calculations).

Figure 23 compares a job–wage ranking, an education-based ranking and a non-pecuniary job quality ranking, regarding observed employment shifts in the EU during 2011 Q2–2015 Q2. The education-based ranking is based on the average educational level of jobholders (using the ISCED-based *hatlev1d* variable in the EU-LFS). The job quality ranking is based on a multidimensional non-pecuniary job quality indicator, based on answers to 38 questions in the 2010 EWCS.

There are some points of similarity between the three charts, reflecting the high correlation (r>0.7) between the different measures of job quality used to rank jobs. The top quintile is growing regardless of the ranking criterion and job destruction is concentrated in the lower quintiles – quintile two and three for the wage-based ranking, and quintile one for the education-based and job quality-based ranking. Both in terms of education and non-pecuniary job quality, the pattern has been one of occupational upgrading in this period, with greatest relative gains in the top quintile and greatest relative declines in the bottom quintile. Only the wage-based ranking presents a more polarised employment shift, with relative loss in the middle quintiles, though again the single most obvious feature of the wage-based chart is strong growth at the top, reflecting a clear upward-skewed, asymmetrical polarisation.

The reason for the (modest) differences between the three measures is that an important proportion of jobs in the middle of the wage distribution have a relative wage premium (a higher relative position in terms of wages than education or non-pecuniary job quality attributes) and that these jobs have been responsible for a large share of overall job destruction during and after the global financial crisis. An illustrative example is the job of building and related trade worker in the construction of homes sector (see Table 1); in the third quintile as measured by wages, but in the bottom quintile as measured by educational attainment.

So anxieties about the 'shrinking middle' relate mainly to employment shifts when categorised using one measure of job quality – wages. Other important ranking measures tend to show shifts in a more upgrading light, consistent with the predictions of SBTC. This recalls Oesch's conclusion, based on a jobs-based analysis of the pre-crisis period (1990–2008) for five European countries: 'the employment drop in the lower-middle and middle quintiles concerns comparatively well-paid working-class jobs' (Oesch, 2013). The jobs disproportionately affected by employment loss during and after the crisis were mid-paying jobs that do not require high levels of formal education.