RESEARCH REPORT

Future of manufacturing

Technology scenario: Employment implications of radical automation

SERIES Manufacturing employment outlook

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European Foundation for the Improvement of Living and Working Conditions

Contents

Executive summary

In this report, a global macrosectoral model is used to make a quantitative assessment of the potential employment impact of accelerated automation, primarily in light of digitisation. The model encompasses the major global regions but focuses mainly on the EU. It covers the whole economy but has particular relevance for the manufacturing sector. See Box 1 for a brief description of the applied E3ME model.

Since 2008, there have been many estimates of the possible employment implications of automation covering many countries and sectors. Typically, these examine the task content, which means what is actually done on the job, to assess susceptibility to automation. While often not reported as such, this will typically be well in excess of the likely rate of automation over time. In this study, the analysis extends previous studies to assess the impact on jobs by 2030. First, estimates are found from previous studies of the proportion of jobs in each sector and country that it would be technically feasible to automate. At least for manufacturing in Europe, rates are typically very high, approaching, and indeed sometimes exceeding, 50%. These are then set in relation to estimates of the investment required to automate these jobs and serve as an upper limit on the additional investment that is regarded plausible, as a percentage of GDP. This includes assumptions for the reduction in the cost of investment over time. The model applied also estimates the employment impact of changes in the supply chains to reflect the impact of digitisation on the material and transport intensity of production. These are applied to the model to find the economic consequences of the pass-through of lower unit costs, supply chain and income multiplier effects, distinguishing the initial assumptions for direct job losses due to automation from the final consequences for jobs once these wider economic transmission mechanisms are taken into account.

Because the future investment cost of automation is very uncertain, two cases are explored: a high-cost case, which implies slower uptake and hence fewer direct job losses, and a low-cost case in which uptake is faster and direct job losses are greater. Because the impact depends crucially on how the benefits of greater automation are distributed in society, a variant of the low-cost case in which workers enjoy a reduction in working hours, while maintaining pay, is also modelled. This mitigates some of the shift in the share of national income from wages to profits that would otherwise occur and that has been a driver of the increase in inequality experienced in many countries over the past three decades.

Capital equipment is substituted for labour, and the producers of capital equipment therefore see a substantial increase in demand. The additional value generated from the increase in labour productivity is shared among higher profits for firms, lower prices for consumers and higher wages for workers who retain their jobs. In the past, the large-scale introduction of labour-saving technological progress has displaced jobs in the short term, but in the longer term the income generated from lower production costs is spent on other goods and services – including products that did not previously exist – and new jobs are created elsewhere in the economy. In the scenarios modelled here, the job displacement effect still dominates results at the end of the forecasting period of 2030. There is a shift in the distribution of income from wages to profits and a related shift in final expenditure from consumer spending to investment. The negative impact on real household disposable income and spending of the loss of wage income outweighs the positive impact of lower consumer prices. Although not explicitly modelled, the shift in the income shares of labour and capital would increase the inequality of income distribution and depress consumer spending, because richer households spend a smaller proportion of their income. This shift is mitigated somewhat in the scenario that assumes that workers enjoy a pay-compensated reduction in working hours, although whether this could be achieved by regulation, as is assumed, is a matter of political judgement.

The scale of job loss expected in 2030, as a proportion of the jobs projected for 2030 in a baseline scenario with no acceleration in automation, is highest in the EU (10% in the high-cost scenario, 16% in the low-cost scenario). The corresponding numbers for the United States (US) are 9% and 14% respectively. The potential job loss is high in China and India as the rate of automation there is curbed by the very large scale of investment implied.

Within the EU, manufacturing, utilities, and transport and communications are the sectors with the largest proportional job losses in all three scenarios. Employment in manufacturing and utilities is expected to be 20% lower than the baseline in the high cost/low uptake case, rising to 30–35% in the low cost/high uptake case. All sectors see a significant improvement relative to the low-cost case if the benefits of automation are shared among workers by raising the hourly wage while reducing hours worked, particularly distribution, retail, hotels and catering, which is the sector most directly affected by household spending.

In contrast to the baseline – in which there are growth areas among many white-collar, non-manual occupations in the professional and associate professional categories as well as among a few blue-collar, manual occupations, including some less skilled occupations such as cleaners and labourers – all three technology scenarios paint a much more negative picture. Significant job losses are still projected for clerks and many skilled manual trades, as they are in the baseline, but these are now sharper and accompanied by significant declines for many other skilled, semi-skilled and unskilled occupations.

We do not model occupational or geographical frictions in the redeployment of workers made redundant, but past experience of industrial restructuring has shown that these can be significant with severe consequences for long-term unemployment, withdrawal from the labour force and social exclusion.

The results therefore highlight the importance of:

- a competitive market environment to promote full pass-through of productivity benefits to consumers
- an innovative and globally competitive production capability in Europe in the supply of automation and digitisation equipment and software, to capture the jobs stimulated by investment in the new technologies
- the social and political issues raised by the further projected shift in income from labour to capital and the possibility of mitigating this through regulation
- retraining and other active labour market policies to mitigate the impact of restructuring on those whose jobs are at risk

Box 1: The E3ME model

E3ME is a global macroeconometric model designed to address major economic and economy-environment policy challenges. Developed over the last 20 years by Cambridge Econometrics, it is one of the most advanced models of its type. Its strengths are listed below.

- **It offers a high level of disaggregation, enabling detailed analysis of sectoral and country-level effects from a wide range of scenarios. Social impacts are important model outcomes.**
- **Its econometric specification addresses concerns about conventional macroeconomic models and provides a strong empirical basis for analysis. It can fully assess both short- and long-term impacts and is not limited by many of the restrictive assumptions common to computable general equilibrium models.**
- **It enables integrated treatment of the world's economies, energy systems, emissions and material demands. This enables it to capture two-way links and feedback among these components.**

E3ME covers 59 global regions, with a detailed sectoral disaggregation in each one, and projects annually up to 2050. It is frequently applied at national level, in Europe and beyond, as well as for wider (European and global) policy analysis (Cambridge Econometrics, undated).

The baseline projection to which the projections in this report are compared incorporate the Eurostat population forecast available in 2017 and the short-term macroeconomic forecast produced by DG ECFIN in May 2017 (see Cedefop and Eurofound, 2018).

Introduction

Automation has a long historic association with human and economic development. Currently, most prominence is placed on digital information and communication-based technologies, not least robotics and, most recently, artificial intelligence (Eurofound, 2018). While these technologies can be applied even outside manufacturing, it is still arguably in material production that most of the productivity-enhancing potential will be realised. Thus, the subject matter of this report is an important part of the Future of Manufacturing in Europe pilot project as proposed by the European Parliament and delegated to Eurofound by the European Commission (DG GROW).

Much of the discussion and policy focus in manufacturing in Europe has been structured around the concept of Industry 4.0. This term was coined in Germany to capture ongoing and prospective automation in manufacturing. Chancellor Angela Merkel defined it as 'the comprehensive transformation of the whole sphere of industrial production through the merging of digital technology and the internet with conventional industry' (Davies, 2015, p. 10). McKinsey Global Institute defined Industry 4.0 as 'digitization of the manufacturing sector, with embedded sensors in virtually all product components and manufacturing equipment, ubiquitous cyber-physical systems, and analysis of all relevant data' (2017).

Public debate about automation has centred on the possibility of massive job loss. The typical approach followed in the literature has been to identify the tasks that are most vulnerable to automation and then identify the occupations in which workers spend a substantial proportion of their time doing those kinds of tasks. Several studies have attempted to estimate the impacts on jobs, typically focusing on the current technical feasibility of automating particular kinds of jobs rather than the likely actual rate of automation over time.

McKinsey Global Institute (2017) found that, for the big EU5 (France, Germany, Italy, Spain and the United Kingdom – UK), 54 million full-time equivalent jobs are associated with technically automatable activities and the potential impact due to automation is 46% of work activities. Building on Frey and Osborne's original work (Frey and Osborne, 2013), data from the World Bank suggest that in the OECD, on average 57% of jobs are susceptible to automation (Citi, 2016). A more conservative estimate was published by Arntz et al (2016) which reported that 9% of jobs across the 21 OECD countries were automatable. This estimate was revised upwards by Nedelkoska and Quintini (2018) who found that about 14% of jobs in 32 OECD countries were 'highly automatable': in the authors' view these are jobs that have a probability of automation of over 70%. But the figure varies considerably across countries, from 33% in Slovakia to just 6% in Norway. The same study reported that a further 32% of jobs have a probability of automation of between 50% and 70%. In these jobs, a significant share of regular tasks could be automated, but not all, which implies a substantial change in the skills requirements for these jobs.

Some studies have attempted to go further and to gauge the likely extent of automation over a given time horizon. McKinsey Global Institute (2018) estimated that artificial intelligence will reduce the share of job profiles characterised by repetitive activities or that require a low level of digital skills in total employment to around 30% by 2030, and will increase the share of jobs characterised by non-repetitive activities and requiring high digital skills from roughly 40% to more than 50% over the same period. The World Economic Forum (undated) suggested that automation and technological advancements could lead to a net employment impact of more than 5.1 million jobs lost to disruptive labour market changes between 2015 and 2020. This net figure was made up of a loss of 7.1 million jobs, two-thirds of which are concentrated in the office and administrative job family, and a gain of 2 million jobs in several smaller job families (in 15 major developed and emerging economies). In Germany, the Institute for Employment Research (IAB, 2016) found that 1.5 million jobs compared to their no digitisation baseline will be eliminated by 2025 in a digitised world and, at the same time, Economy 4.0 will create 1.5 million new jobs due to structural changes towards the expansion of the services sector.

There is huge uncertainty associated with the type of scenario modelled in this report. The range of estimates of job loss that could potentially occur in the initial substitution of workers by machines testifies to uncertainty even in this first basic step. The next step is to explore how potentially automatable tasks pan out in terms of actual job loss. This is not just about how the technological frontier will shift over time. It is fundamentally about the introduction of economics into an analysis that, thus far, is purely technical. At the microeconomic level, it is hardly the case that all that is technologically feasible will be economically rational for the firm. Most obviously, the price of the automation technology relative to labour must be taken into consideration, but also the rationale of automating specific tasks in the context of the overall organisation of work. Moreover, from the macroeconomic perspective, the scale of investment required to replace workers with machines, especially to the extent predicted by some of the estimates presented above, may just be unrealistic in terms of the share of GDP of such investment. Then there are the effects along the supply chain from the increased demand for these new technologies by firms. Many other economic interactions also need to be accounted for. The most important issues are probably how the productivity gains affect consumer demand and how the competitive position of European companies evolves compared to companies around the world.

What these economic complexities, together with other social and political developments in a global economy, actually mean for employment in Europe is thus highly uncertain. Compared to the two scenarios previously conducted in Eurofound's Future of Manufacturing in Europe project, on the employment implications of a possible global trade war (Eurofound, forthcoming) and the implementation of the Paris Climate Agreement (Eurofound, 2019), this technological scenario could be viewed as highly speculative. However, we consider the value of this report to be twofold. First, it outlines many of the factors that should be considered when evaluating the final effects of a large initial displacement of employees by technological change and makes an attempt to both quantify and model them. Second, it indicates that the somewhat cataclysmic assumptions of potential job loss from the mass introduction of digital technologies are somewhat mitigated when a fuller economic analysis comes into play. However, as with past experiences of radical technological change, the more positive effects derived from the income generated from lower production costs and spending on other goods and services are dwarfed by the initial job displacement effect; they still dominate the model results at the end of the forecasting period of 2030.

1 Scenario design

This section starts with a qualitative description that summarises the approach taken. It then proceeds with a detailed description of the modelling assumptions, comprising the automation rates determined on the basis of technological potential and automation rates taking into account economic feasibility. Some focus is then placed on the treatment of digitisation of the supply chain and investment changes. Finally, there is a description of how a scenario was developed to explore the impact of reduced working hours alongside automation.

Qualitative description

The purpose of this study is to synthesise the insights from the literature to produce quantified global scenarios and to compare the potential impacts on the EU with those of other major global blocs. The E3ME model is a global model that distinguishes countries (including each of the EU Member States) and global regions in considerable sectoral detail, allowing the introduction of different scales of impact by country and industry (Cambridge Econometrics, undated). We draw on the task-based approach outlined above and translate it into an approach that can be applied to jobs classified by sector.

Because the future investment cost of automation is very uncertain, we model a high-cost case, which implies slower uptake and hence fewer direct job losses, and a low-cost case in which uptake is faster and direct job losses are larger. Because the impacts depend greatly on how the benefits of greater automation are distributed in society, we also model a variant of the low-cost case in which workers enjoy a higher hourly rate of pay and a reduction in working hours: this mitigates some of the shift in the share of national income from wages to profits that would otherwise occur and that has been a driver of the increase in inequality experienced in many countries since the 1990s. The three scenarios modelled are:

1. high cost, lower uptake
2. low cost, higher uptake
3. low cost with reduced working hours but no pay reduction

The initial potential job loss arising from automation

In each country we consider both the country's sectoral composition (i.e. the employment shares across sectors) and the relative proportion of jobs at a high risk of automation in each of those sectors. The jobs that are at a high risk of automation are those in which a high proportion of tasks normally carried out have a routine, repeatable character that can readily be translated into rules to guide the operation of robots and software. For the EU Member States, we have access to the 2018 Cedefop and Eurofound skills forecast projections of the number of jobs by occupation in manufacturing sectors expected in 2030, and we can use the occupational classification as a proxy for the likely extent of routine tasks. Otherwise we draw on estimates made in the literature, although these estimates are available only for selected countries and in less sectoral detail.[1]

Macroeconomic feasibility of investment in potential automation

However, since the *potential* for automation in much of the literature is determined on *technical* grounds alone, it is necessary to take a view as to how much of this potential will be fulfilled by 2030. This depends on the cost of automation and the scale of investment that can reasonably be assumed.

With respect to the costs of automation, we make assumptions for the cost in 2018 of automating a job from within the wide range of industry estimates, with separate scenarios for high and low assumptions. The costs are assumed to fall over time as technology develops. Multiplying these costs by the number of jobs assumed to be displaced gives a required investment figure.

Initial analysis showed that the scale of investment required to achieve the full technical automation levels suggested for China by 2030 amounted to more than double the level of gross fixed capital formation for the country as a whole. For India, the required investment was even higher. Rather than adopting a case-by-case approach in which different adjustments were made to different sectors in different countries, the approach taken has been to scale the technical automation potentials across the board until the feasibility bounds were no longer breached in an attempt to suggest levels and phasing of investment between now and 2030.

Distribution and demand

The assumptions described above make clear that the uptake of technology to automate work envisaged in the scenarios involves substantial direct job losses, and the estimates show that this is even the case when constraining initial job loss in light of the macroeconomic feasibility. In many respects, the big macroeconomic issue is where the productivity gains are eventually distributed, not least in the context of how the distribution affects demand. In the model, the benefits of increased productivity accrue to capital, ownership that is unequally distributed. For most households, incomes are depressed by the loss of wage incomes. Distribution is skewed further by high-skilled workers, whose labour productivity is boosted in the form of a moderately higher wage. This implies greater

1 To check that the two different methodologies are broadly compatible we have reviewed what the literature we are using for non-EU countries reports for EU countries and compared this with the result that we obtain by applying the occupational method. PwC (2017) reports potential job losses in manufacturing of 46% in the UK and 48% in Germany, which compares with the direct job losses in EU manufacturing of 40% that we assume in the low-cost scenario described below in this report.

polarisation between rich and poor in the distribution of income.

On the other hand, some of the cost savings could be distributed in the form of reduced working hours and a higher hourly pay rate for workers. For this reason, we modelled a version of the low-cost scenario in which labour succeeds in securing a reduction in working hours but not pay.

Another knock-on effect calculated in this scenario is the employment created in the automation and digitisation producers' supply chain. The number of such jobs is expected to be rather limited as these sectors are themselves introducing productivity-enhancing automation.

Summary of the implemented model

The main inputs to the scenario, described in more detail below, are assumptions for:

- the direct loss in employment attributable to automation
- the investment required to replace workers by machines/software and to give additional training for the remaining workers
- changes to each sector's supply chain to reflect a different production process, notably a shift towards purchases of IT equipment and software and away from raw materials and transport
- the reduction in working hours directly attributable to automation and, in one scenario, a compensating increase in average hourly wages

What effects should we expect to see in the scenario outcomes? Ernst et al (2018, p. 9) note the conclusions in the literature that automation affects jobs growth through three channels:

- a displacement effect, i.e. direct substitution of technology for workers
- a 'skills-complementarity' effect, meaning an increased demand for workers with the skills to use and supervise the new technology
- a productivity effect, where the cost reductions brought about by the new technology are passed on in the form of lower prices and higher incomes, which in turn stimulates spending in the economy

In our analysis, we recognise three important channels:

- an investment effect in which the additional demand for machines and software stimulates activity and jobs in the sectors that produce the investment goods and services
- a supply chain effect in which a larger share of the supply chain for products and services is associated with automation and a smaller share for the production and shipping of physical materials
- an income effect in which there is a loss of wage income and a shift from wages to profits in the distribution of income, the net effect of which is likely to be lower real consumer spending

Given the modelling approach, we expect these effects to appear in model outcomes as follows.

- In the scenarios in which there is no compensating adjustment to the hourly wage, we expect a decrease in wage incomes because of the loss in employment (displacement effect) and hence a reduction in consumer expenditure because of the shift in the distribution of income from wages to profits.
- In all scenarios we expect an increase in investment in machines and software as capital is substituted for labour (investment effect).
- We expect changes in the supply chain that boost the sectors supplying the products and services associated with automation/digitisation and reduce demand for producers and shippers of materials (supply chain effect).
- We expect lower unit costs for business because the savings in labour costs more than offset the cost of the new technology, feeding into lower product prices (productivity effect).
- There is likely to be an overall reduction in the demand for labour, depending on the net effects of these changes in the model.

The modelling we have undertaken does not represent explicitly the skills-complementarity effect. The demand for different occupations that we report below takes account of changes in the number of jobs in different sectors, reflecting the extent to which each sector has jobs that are more easily automated, but we do not adjust the shares of each occupation *within any given sector* because the present state of knowledge is inadequate to estimate the potential quantitative scale of such adjustments.

Detailed description of the modelling assumptions

This section describes how modelling assumptions were developed for the three scenarios.

Automation rates determined on the basis of technological potential

The starting point for the possible extent of automation is based on an assessment of the technological potential for different kinds of jobs to be automated and is implemented as follows.

- For EU manufacturing, any jobs from the 2018 Cedefop and Eurofound skills forecast that are not managerial, professional or technical are considered at risk of automation, because these occupations are likely to involve a large proportion of the kinds of tasks that are most readily automated.[2]

2 Managerial, professional and technical occupations are defined as ISCO major groups 1–3.

- Outside of EU manufacturing, potential automation rates are drawn from the literature cited above where this provides quantified estimates, such as PwC (2017) and McKinsey Global Institute (2017).
- For non-EU regions, the potential automation rates are based on the estimates reported in PwC (2017) and McKinsey Global Institute (2017).

The estimates from the literature are summarised in the Annex. These studies have mainly taken the standard approach, namely to determine the tasks most susceptible to automation and then assess how important these tasks are for jobs in different sectors. McKinsey Global Institute (2017) also seeks to take into account some other factors, such as technical feasibility, technology costs and potential competition with labour. The potential automation rates can be quite high and vary considerably among sectors and regions.

Investment in automation

There is considerable uncertainty about the economic feasibility of potential automation indicated in the previous section and industry estimates of the costs of automation vary widely (Engineering 360, undated; Robotworx, undated); we have selected rates that lie within that wide range. In the high-cost scenario, the cost of automating a single job in 2018 is assumed to be €103,060 (in the 2005 price base in which E3ME operates as of February 2019), and in the low-cost scenario we reduce that value by 40%. The economic feasibility of the rate of automation between now and 2030 clearly depends on the cost of automation. While there is now some literature providing estimates to support our assumptions for direct job losses, there is little in the way of quantified estimates for other elements of the automation narrative. This includes the rate at which the cost of automation equipment will fall over time as production expands and further technological advances are made. Also, one would require some estimate of the expected lifetime of the new capital equipment and hence the period over which its cost could be recovered in the prices that firms charge.

Rather than ignore these effects and hence understate the economic impacts of automation, we have made assumptions on the basis of our own judgement and experience in modelling structural change using an input–output model. With respect to the application of robot technology, in all three scenarios we assume:

- a 5% per annum decrease in costs due to technological progress
- a 5% depreciation rate – effectively that a new robot has a lifetime of 20 years
- the cost of investment is recovered over the lifetime of the robot

Using these cost assumptions, the implied investment required for high rates of potential automation is implausibly large in relation to the size of GDP. We have therefore applied lower automation rates than the potential rates using our judgement as to the viability of the scale of investment between now and 2030. The choice of the upper bound for what cumulative investment might be feasible, expressed as a percentage of GDP, is necessarily arbitrary and a rather ad hoc approach has been taken here, allowing lower levels for the developed countries and higher ones for China and India. This is partly reflected in recent actual levels where, in the period 2005–2017, the ratio of investment to GDP in the US and the EU was about 20%, in India it was over 30% and in China over 40%.[3]

The rates of direct job reduction finally adopted in the scenarios, when aggregated across the sectors in the E3ME model,[4] are presented in Table 1.

Table 1: Direct job reduction rates assumed in the scenarios

% of baseline jobs in 2030	High cost, lower uptake	Low cost, higher uptake/ low cost, adjusted working hours
EU28	12.6	17.2
US	11.8	16.6
Japan	5.9	8.2
China	6.4	8.9
India	2.6	3.6
South Korea	6.5	9.1
Rest of the world	3.5	4.7

Source: *Cambridge Econometrics analysis based on PwC (2017) and McKinsey Global Institute (2017)*

Table 1 shows that in the high-cost variant it is assumed that, by 2030, 12.6% of the baseline jobs in the EU28 will be replaced by robots or another form of automation, and that this number rises to 17.2% in the two low-cost variants. This range is broadly consistent with the figure of 14% in the results reported by Nedelkoska and Quintini (2018) and the range 14–18% in the results from Suta et al (2018), cited earlier. They are, however, considerably lower than the range of automation rates suggested in many other studies, for example by McKinsey Global Institute (2017) for Germany (27–47%).

The implication of applying the automation rates (Table 2) is that there would be 30–42 million fewer people in employment, depending on the scenario, than in the baseline by 2030 before wider effects such as the stimulus to jobs in equipment-supplying sectors are considered.

3 Source: Statistics sourced from Eurostat (EU), OECD (US) and World Bank (India and China).

4 For EU Member States, E3ME distinguishes over 60 sectors, defined approximately at the two-digit NACE level. The list of sectors can be found in Appendix B of the E3ME manual (Cambridge Econometrics, undated).

Table 2: Direct employment losses in 2030 as a result of automation (millions)

	High cost, lower uptake	Low cost, higher uptake/low cost, adjusted working hours
EU28	30.8	42.0
US	21.3	29.8
Japan	4.8	6.7
China	49.0	68.6
India	20.2	28.2
South Korea	2.4	3.3
Rest of the world	67.4	89.2

Source: *Cambridge Econometrics analysis*

From all the countries modelled, Japan and Korea will be the least affected in terms of number of people, reflecting the automation rates reported in the literature.[5]

The level of investment required in 2030 to achieve the level of automation is summarised in Table 3.

The highest levels of required cumulative investment in the period 2018–2030 as a percentage of GDP are in India and China. The rate for the EU28 is higher than that in the US, reflecting the higher number of jobs assumed to be automated in the EU28, while the lowest investment levels are in Korea and Japan.

Digitisation of the supply chain and investment changes

The literature offers little in the way of quantified estimates for the impact of digitisation on the supply chain of purchases of inputs and on the investment in equipment and software required, but it seems unreasonable to ignore these impacts. The following assumptions are made in all three scenarios:

- manufacturing purchases of information and communications technology (ICT) services are expected to double by 2030 compared to 2016 levels (IAB, 2016)
- services sector purchases of ICT are expected to increase by 80% by 2030 compared to 2016 levels (IAB, 2016)
- logistics/transport purchases by industry decrease by 1% by 2030 from current values, and logistics/transport purchases by services decrease by 0.6% by 2030 from current values
- raw material and other purchases by industry and service drop by 1% by 2030 compared to current levels
- purchases of education are 2% higher by 2030 compared to 2016 levels to reflect additional training
- an additional €102.8 billion at February 2019 prices spread over 12 years will be spent on updating existing equipment, data storage systems, etc. in the EU28 as a whole
- new investment in systems and equipment amounting to an extra 0.5% annual investment by agriculture and manufacturing (cf. IAB, 2016) and 0.2% by services

Sharing the benefits by reducing working hours

An additional scenario was developed to represent a future in which automation proceeds rapidly, at the same rate and with the same level of investment as in the low-cost scenario, but in which the impact on wage incomes is mitigated by a reduction in average hours worked. At

Table 3: Investment required in the automation scenarios

	High cost, lower uptake			Low cost, higher uptake/ Low cost, adjusted working hours		
	Cumulative, 2018–2030		2030	Cumulative, 2018–2030		2030
	€ trillion, 2005 prices	% of cumulative GDP	% of GDP	€ trillion, 2005 prices	% of cumulative GDP	% of GDP
EU28	3.8	2.1	7.3	3.1	1.7	6.0
US	2.6	1.3	4.3	2.2	1.1	3.6
Japan	0.6	1.0	3.6	0.5	0.8	3.0
China	6.2	5.7	15.5	5.3	4.9	13.1
India	2.4	6.6	18.3	2.0	5.5	15.4
South Korea	0.3	1.2	3.7	0.2	1.0	3.1
Rest of the world	8.3	3.8	12.2	6.6	3.0	9.7

Source: *Cambridge Econometrics analysis*

5 PwC (2017, p. 42) reports the 'lower average automatability of most individual sectors in Japan', even in wholesaling and retailing which are relatively labour intensive in Japan. 'Retail sales workers [spend] a lower proportion of time conducting manual tasks compared with management tasks, such as planning or organising.' The report notes that this could change in the future if retailing in Japan moves to a more self-service model, 'reducing the need for skilled sales staff and increasing the need and scope for automation'. The report also notes that South Korea faced a similarly low risk of automation as Japan (PwC, 2017, p. 33).

the same time, we assume no reduction in the average wage per job, implying an increase in the average hourly wage. The employment losses in Table 1 and Table 2 are the same for both low-cost scenarios (the right-hand column), but they are now interpreted as the reduction in labour input (measured, say, in millions of hours worked) equivalent to the loss of jobs shown in the table if average working hours remained unchanged. The impact of the reduction in labour input seen in both low-cost scenarios on the final number of jobs lost is mitigated when average working hours are reduced.

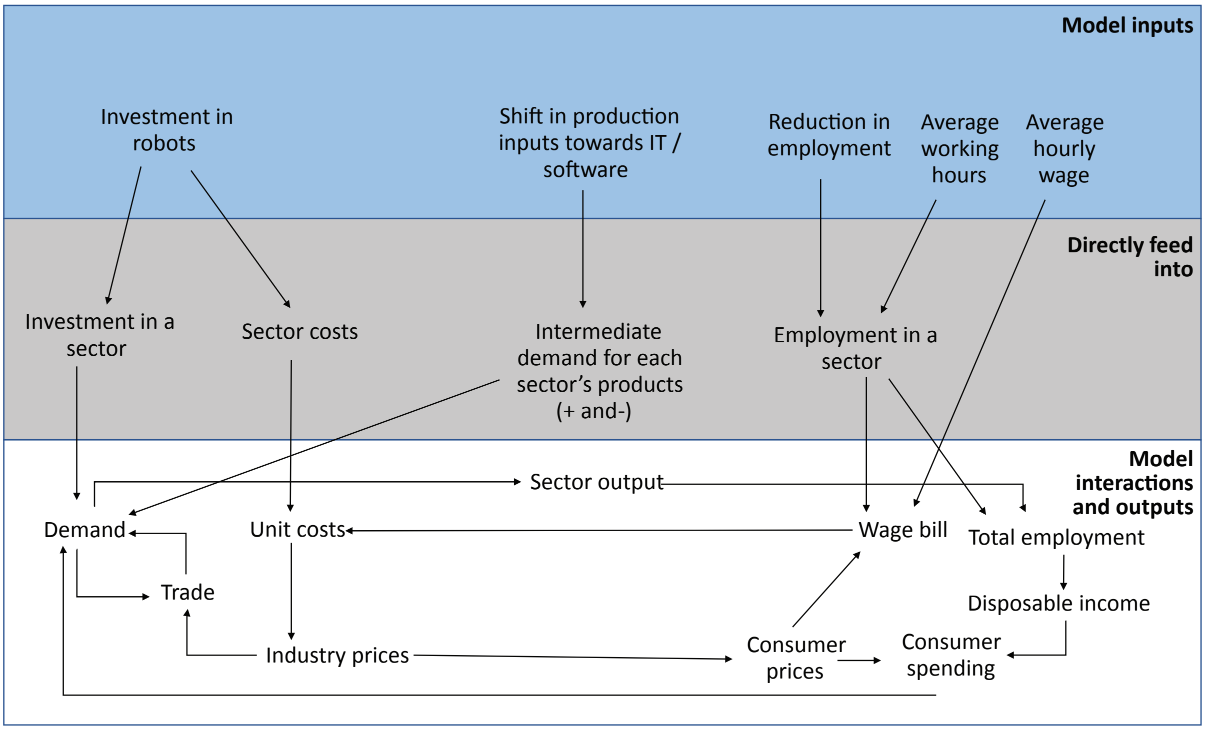
The question then arises as to how this reduction in working hours might come about. In the scenario we have assumed that it is achieved by regulation, introduced in all countries and affecting all sectors, rather than targeted on sectors according to the extent of the reduction in their labour input achieved through automation. With regard to scale, we have assumed a 5% reduction applied across the board. Hence, workers working a 40-hour week would now work a 38-hour week but for the same pay. Part-time workers currently working, say, a 20-hour week would now work a 19-hour week. The effect is both to mitigate somewhat the impact of the reduction in labour input on jobs and, because the direct cost is borne by employers, to increase the wage bill and household employment incomes compared with the low-cost scenario. We make no further assumption about possible consequences, for example an increase in productivity of workers because their working hours are shorter.

How the modelling represents the impacts

Figure 1 illustrates the model inputs and how these link to other model variables. It shows the economic logic of how the changes in policy are expected to affect the economy. The modelling inputs are shown in the blue panel. The grey panel shows the initial impacts on the economy and in which model variables this will be felt. The white panel summarises the main model links and interactions, that is, the knock-on effects to the wider economy.

In the top right-hand part of Figure 1, the direct employment losses affect employment in each sector and the total employment in a country, which feeds through to disposable incomes in the bottom right-hand part of the figure. The loss in incomes leads to lower consumer expenditure and lower demand for products (bottom left-hand part of the figure). On the other hand, lower employment results in a lower wage bill for companies, allowing them to realise a reduction in unit costs. The investment in automation in the top left-hand part of the figure leads to an increase in demand (bottom left-hand part of the figure) for the products of the sectors that supply the equipment for the additional investment (such as electronics, electrical and mechanical engineering), leading to additional output and employment in these sectors and additional imports (‘trade’ in the figure). But the investment must be paid for and so this is reflected in an increase in unit costs. The net effect of higher

Figure 1: Technology scenario inputs and model links



Source: *Cambridge Econometrics analysis*

capital costs and lower wage costs is a net reduction in unit costs which is passed on, at least in part, to prices. This, in turn, has two main impacts. First, on a domestic level, the lower price levels boost the purchasing power of consumers, mitigating in part the loss in disposable incomes linked to the loss of wage income. Second, lower prices improve firms' competitiveness in export markets ('trade' in the figure). Changes to the supply chain shown in the middle of the upper panel shift the structure of demand towards production inputs associated with new technologies. In the scenario in which it is assumed that the labour input is reduced through lower average working hours but that wage incomes are maintained through a higher hourly wage, the impact on consumer expenditure is mitigated, but so is the reduction in costs for businesses.

2 Results

The results are presented relative to a baseline projection in which there is no acceleration in automation and digitisation. The baseline incorporates the Eurostat population forecast available in 2017 and the short-term macroeconomic forecast produced by DG ECFIN in May 2017 (see Cedefop and Eurofound, 2018).

Global impacts

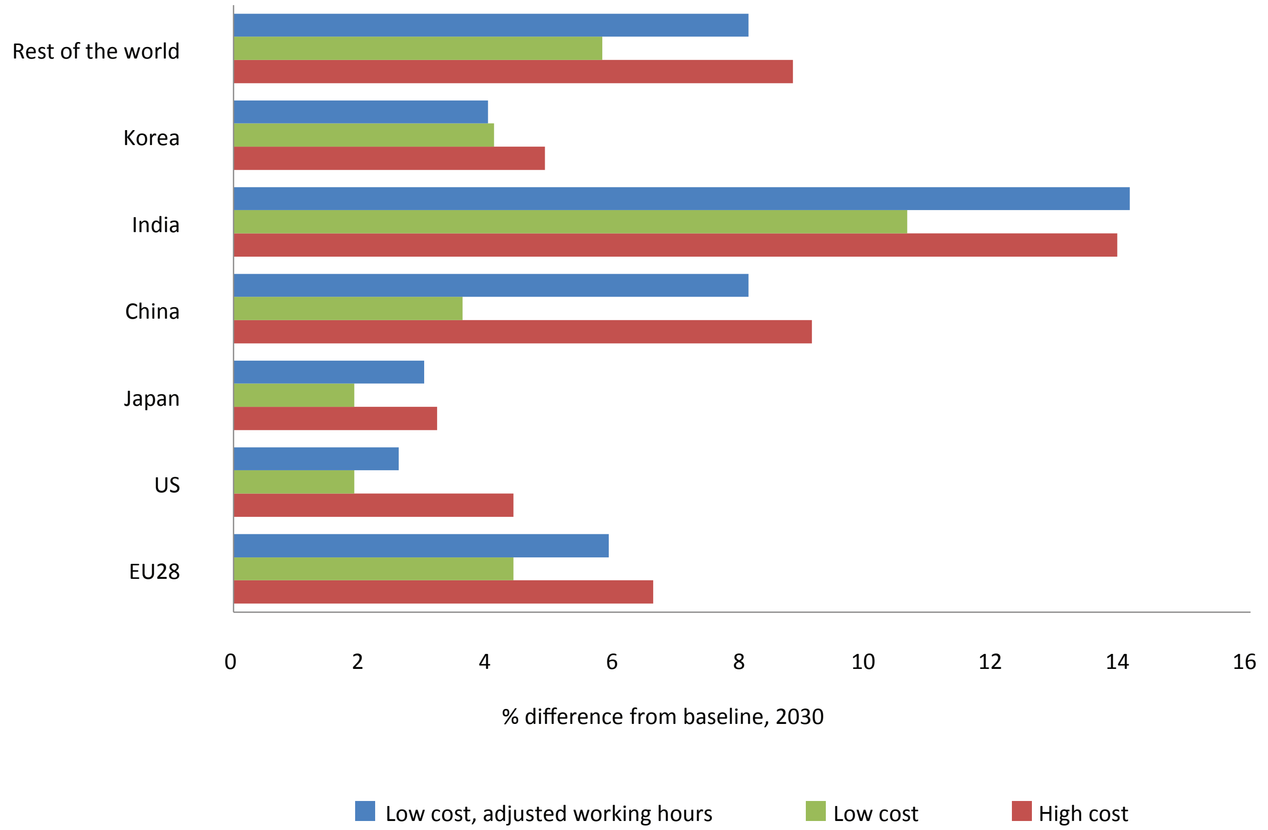
Figures 2 and 3 show the impacts on GDP and employment in 2030 for the three scenarios compared to the baseline.

The differences in impacts on GDP among the countries shown in Figure 2 reflect the scale of the assumptions for the additional investment for automation shown in Figure 3. Hence, the assumption of a higher rate of automation investment in the EU than in the US and Japan is reflected in greater impacts on GDP. The greatest impacts on GDP by 2030 are in India and China, but Figure 3 shows that the scale of investment required is by then reaching shares of GDP in the order of 15–20%, which may be larger than is feasible. In most countries the GDP impact is dominated by the investment impact, which is why GDP effects are generally larger in the high-cost case – in which the scale of investment is assumed to be higher – than in the low-cost case. But when the two low-cost cases are compared, the case in which the benefits of automation are assumed to be shared among workers through a higher hourly wage yields a higher GDP impact because households spend a higher proportion of wage income than capital income.

The differences in percentage employment impacts among the countries shown in Figure 3 reflect the combined effect of the scale of investment and the scale of baseline employment in 2030 in each country. In India, China and the rest of the world, the scale of investment is substantial, as shown in Table 3 (p. 8), but baseline output per job in 2030 is lower in these countries and so baseline employment is large. Consequently, their direct job losses are lower as a percentage of baseline employment in 2030 than in the EU, Japan, Korea and the US, even though the GDP impact, driven by the scale of investment spending, is higher.

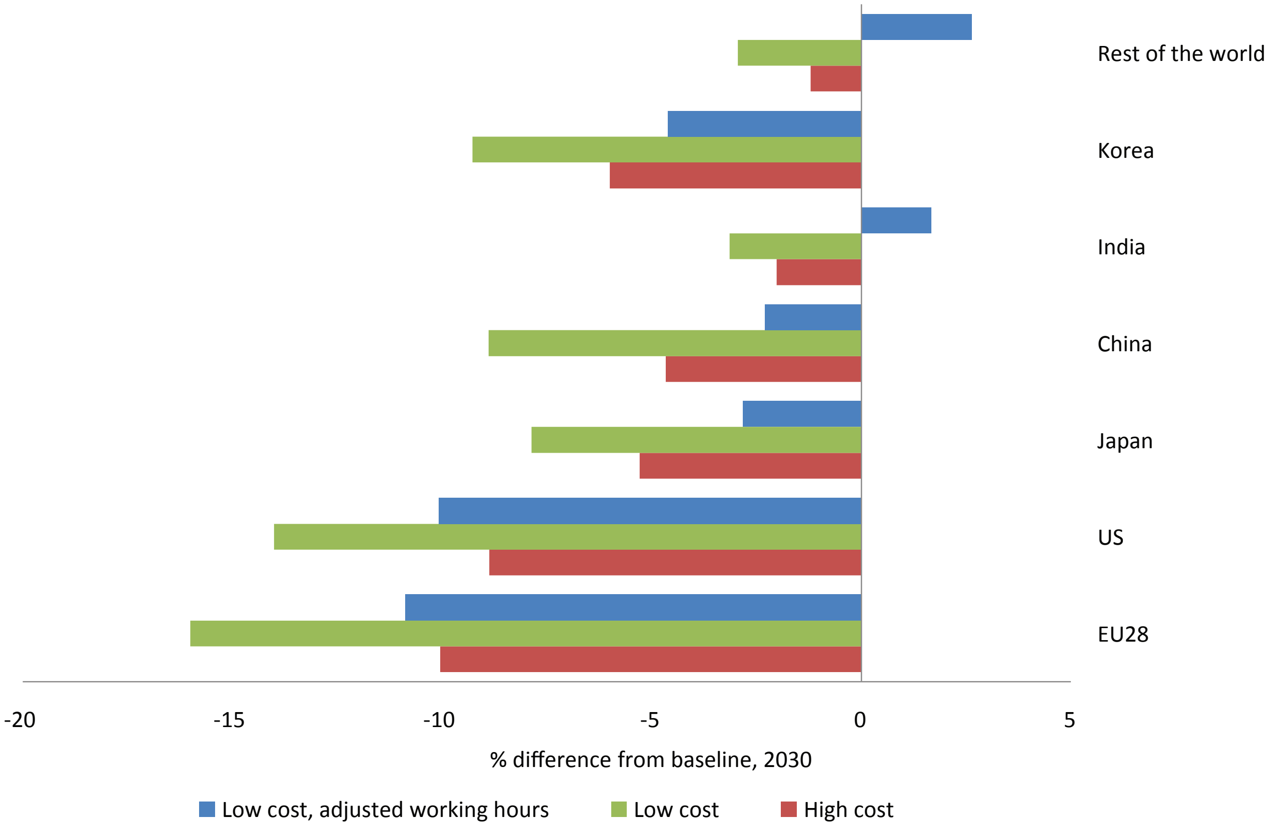
The employment losses are largest in the low-cost scenario with no working hours adjustment: in this case the stimulus to spending coming from investment is less (resulting in less of a stimulus to GDP) while the scale of automation is greater. In all countries there is a marked improvement in the employment outcome in the scenario in which working hours are adjusted, compared with the low-cost case. In India and the rest of the world, this is sufficient to change the outcome for employment from a small net loss in the low-cost case to a small net gain in the case with adjusted working hours.

Figure 2: Impact on GDP in 2030, by scenario



Source: *Cambridge Econometrics analysis*

Figure 3: Impact on employment in 2030, by scenario



Source: *Cambridge Econometrics analysis*

Figure 4 compares the assumptions for direct job losses with the final outcome when the second-round effects of supply chain purchases and income multipliers are taken into account. The two low-cost scenarios in the lower part of the figure have the same direct reduction in labour requirement in each country and sector (expressed in the figure as 'job losses'), but differ according to how the reduction in labour input is shared among workers throughout each country. As expected, the final job losses are smaller than the direct job losses, but only substantially smaller in the case where working hours are adjusted, demonstrating the importance for household spending and for jobs of how the benefits of higher productivity are shared between workers and employers: when working hours are reduced but the hourly wage is increased in compensation, the distribution of income between profits and wages is shifted in favour of wages, boosting household spending.

EU impacts

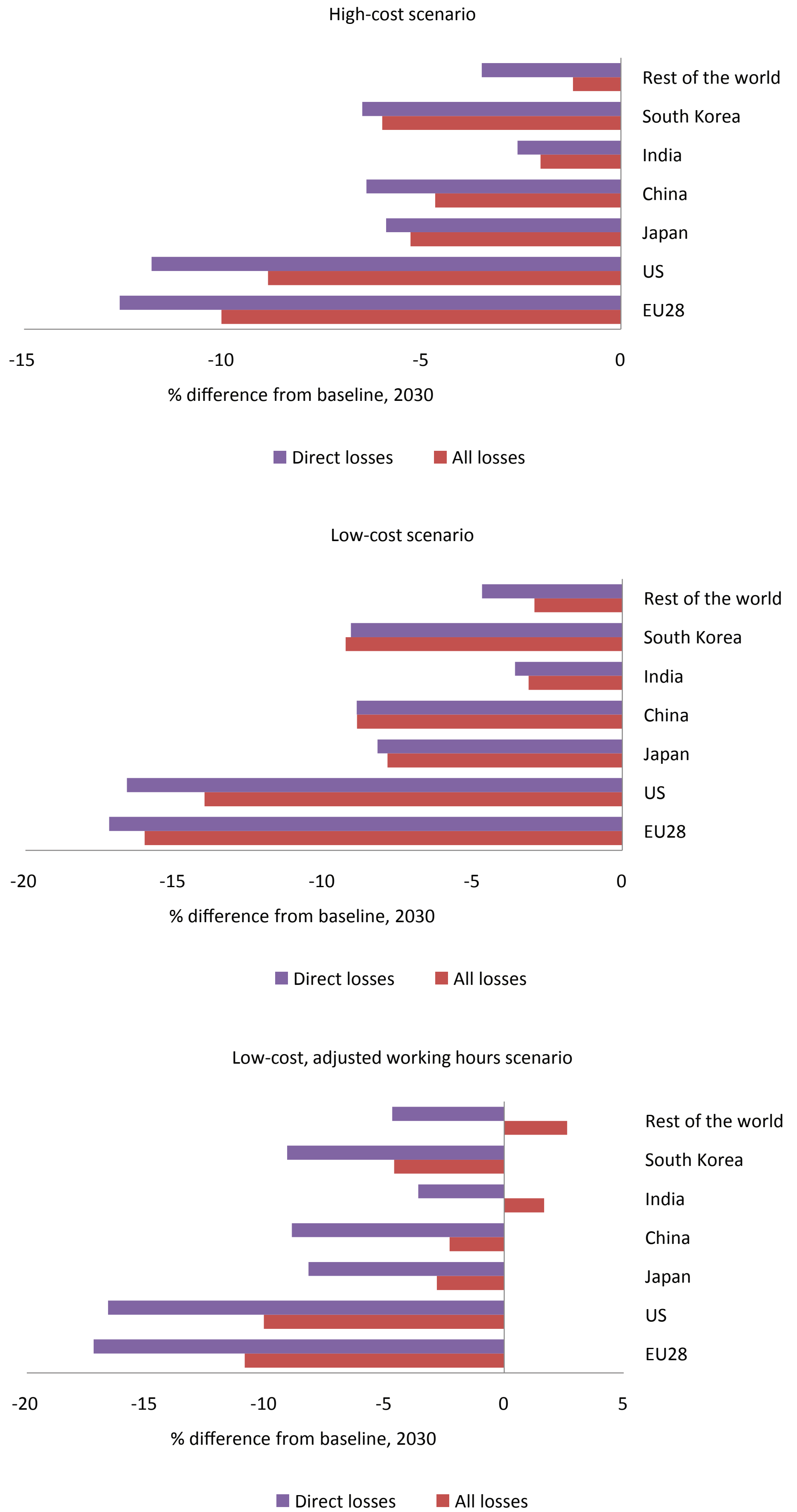
Table 4 shows the impact on macroeconomic indicators in the three scenarios for the EU in 2030 compared with a baseline in which there are no effects from accelerated automation and digitisation.

GDP impacts are larger in the high-cost than the low-cost case because investment is higher and because the lower rate of automation means that job losses (and hence consumer spending impacts) are smaller. Higher investment costs in the high-cost variant are passed on to consumers and so consumer prices fall by less than in the low-cost scenario.

There is a substantial shift from consumer spending to investment because the net loss in employment incomes outweighs the benefits to consumers of lower costs and prices. Underlying this, there is a shift from wages to gross profits in the share of incomes from production, and a larger part of gross profits is devoted to financing the higher investment costs. Figure 5 shows the reduction in the share of wages in the sum of wages and profits in the baseline in 2030 and in the three scenarios. The greater the scale of automation, moving from the high-cost to the low-cost scenario, the smaller the share of wages. However, the reduction in share is mitigated when the low-cost case is adjusted to incorporate lower working hours and a higher wage per hour (the low-cost adjusted working hours scenario). Figure 4 shows that this is because job losses are reduced (from 16.0% to 10.9%, comparing the second and third columns of the table) with the result that the GDP impact is higher. This comes about because the reduction in employment is less while the average hourly wage is increased, and so the reduction in consumer spending is less.

In all cases, net domestic product impacts are much smaller than GDP impacts. Net domestic product excludes the replacement expenditure that firms have to make simply to maintain their existing capital. By 2030 the capital stock is much larger than in the baseline and a substantial part of investment is going towards replacement of automation technology that has reached the end of its useful life.

Figure 4: Direct and total job losses in 2030, by scenario



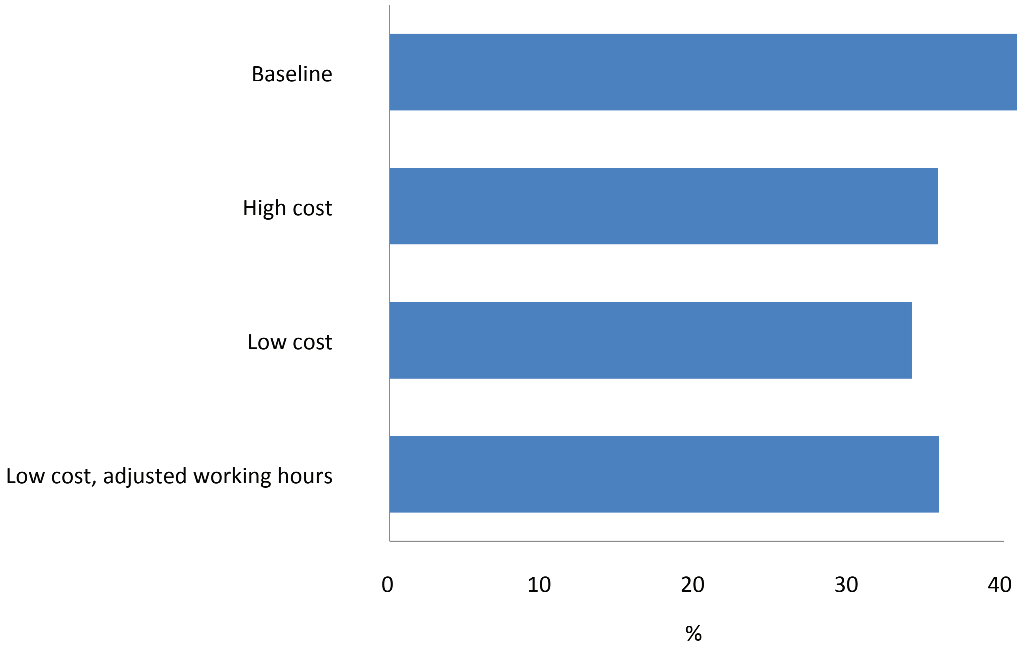
Source: *Cambridge Econometrics analysis*

Table 4: EU28 macroeconomic effects in 2030, % difference from baseline

% difference from baseline			
	High cost	Low cost	Low cost, adjusted working hours
GDP	6.6	4.4	5.9
Net domestic product	2.9	1.4	3.7
Consumer spending	-5.3	-6.7	-4.6
Investment	39.9	34.7	33.5
External exports	5.9	5.6	6.3
External imports	5.0	4.5	4.6
Employment	-10.0	-16.0	-10.9
(of which direct)*	-12.6	-17.2	-17.2
Consumer prices	-1.9	-4.8	-2.1

Source: *Cambridge Econometrics analysis*
Note: **'Direct' job losses are those introduced by assumption.*

Figure 5: Share of the wage bill in wages and profits in 2030, EU28



Source: *Cambridge Econometrics analysis*

In all cases the fall in consumer spending is less than the fall in employment, partly because of lower consumer prices but also because household incomes are drawn from several sources, not just wage income. But there are clear distributional implications (a shift from wage earners to the owners of capital, and income from capital is very unequally distributed among households) in that we have not modelled the effect of different propensities to consume for households at different income levels, and so the reduction in consumer spending could be larger than shown here: richer households spend less of any given boost to income than poorer households.

The results illustrate the importance of:

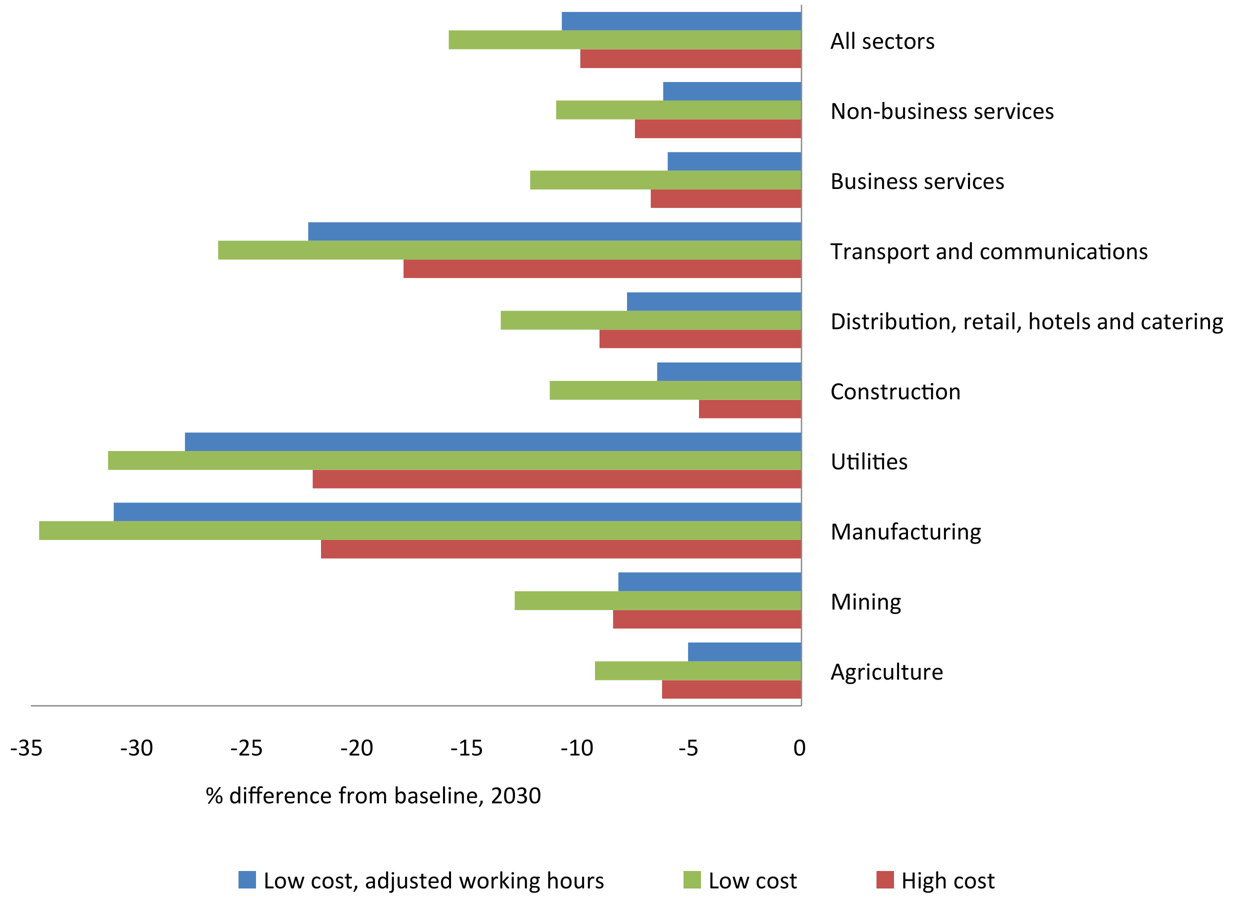
- a competitive market environment to promote full pass-through of productivity benefits to consumers
- an innovative and globally competitive production capability in the supply of automation and digitisation equipment and software, to capture a high proportion of value added in the supply chain that would otherwise be lost to Europe

Sectoral impacts

Figure 6 shows that, in all three scenarios, the sectors experiencing the largest proportional impacts are manufacturing, utilities and transport and communications.

Employment in manufacturing and utilities is expected to be 20% lower than the baseline in the high cost/low uptake case, rising to 30–35% in the low cost/high uptake case. All sectors see an improvement relative to the low-cost case if the benefits of automation are shared among workers by raising the hourly wage while reducing hours worked. This comes about because the difference between the two low-cost scenarios involves a redistribution of

Figure 6: Impacts on EU sectoral employment, 2030



Source: *Cambridge Econometrics analysis*

income from capital to labour and so household spending is higher. The effects are felt across the whole economy, but most directly in distribution, retail, hotels and catering, which is the sector most directly affected by household spending.

Figure 7 shows that EU productivity, measured as value added per job, is some 20–25% higher as a result of the additional investment in automation. The impact on productivity is largest in the sectors in which automation is most pervasive: manufacturing, utilities and transport and communications. As expected, productivity growth is stronger when lower automation costs support faster take-up. The impact of automation on value added per job is smaller in the case where the reduction in working hours means that there are more jobs, but the impact on value added per hour worked would be similar in the two low-cost scenarios. However, since we assume that the hourly wage is increased in the reduced working hours, the unit cost faced by employers will be higher than in the low-cost scenario.

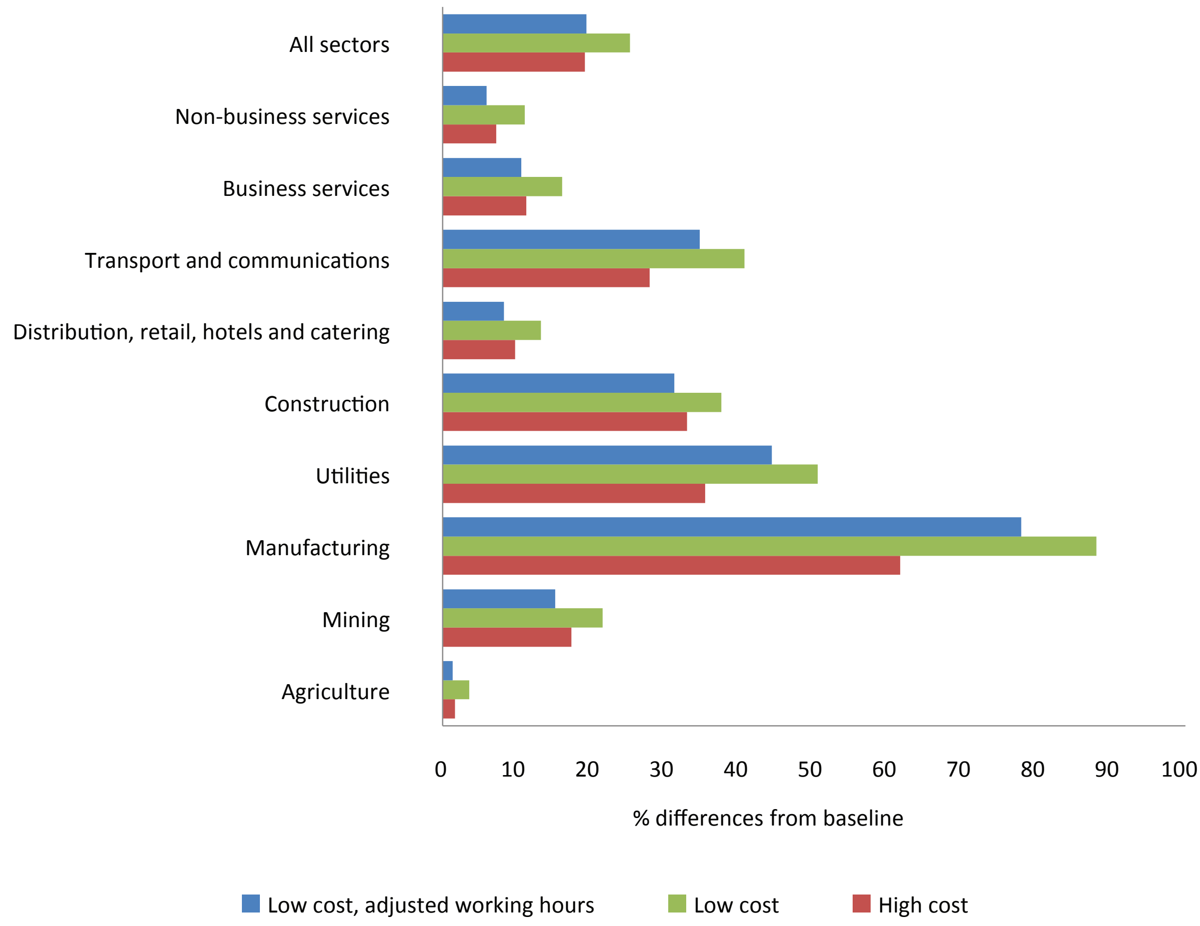
Figure 8 compares the assumptions for direct job losses entered into the modelling and the model outcome for all job losses in the three scenarios. Again, the two low-cost scenarios in the lower part of the figure have the same direct reduction in labour requirement in each country and sector (expressed in the figure as 'job losses'), but differ according to how the reduction in labour input is shared among workers throughout each country. In most sectors the final job losses are a little less than those directly imposed, as the higher investment creates demand for the output of the producers of automation equipment and software and their supply chain. The exception is distribution, retail, hotels and catering. This sector does not benefit significantly from the additional investment spending, and suffers the additional impact of a reduction in consumer spending in the scenario as income is shifted from wage earners to the owners of capital. However, when working hours are reduced but the hourly wage is increased in compensation, in the low-cost adjusted working hours scenario, this redistribution of income is mitigated and so there are fewer final job losses in distribution, retail, hotels and catering than direct losses.

Occupational impacts

Occupational employment patterns within industries are assumed to be unchanged between scenarios. This is a simplifying assumption in the absence of any robust information about how these patterns might be affected. This is especially significant in these technology scenarios where (in principle) one might expect the patterns to be affected by automation. Table 5 shows the projected employment levels and changes by two-digit occupational category between the baseline and all of the technology scenarios.

In contrast to the baseline – in which there are growth areas among many white-collar, non-manual occupations in the professional and associate professional categories as well as among a few blue-collar, manual occupations, including some less skilled occupations such as cleaners and labourers – all three technology scenarios paint a much more negative picture. Significant job losses are still projected for clerks and many skilled manual trades, but these are now sharper and accompanied by significant declines for many other skilled, semi-skilled and unskilled occupations. These are especially pronounced in the low-cost technology scenario. Any significant growth in employment is projected in only a few occupations such as ICT professionals, legal, social and cultural professionals, science and engineering associate professionals, legal, social, cultural and related associate professionals and customer services clerks.

Figure 7: Impacts on EU sectoral productivity, 2030



Source: *Cambridge Econometrics analysis*

Figure 8: Direct and all job losses in EU sectors in 2030, by scenario

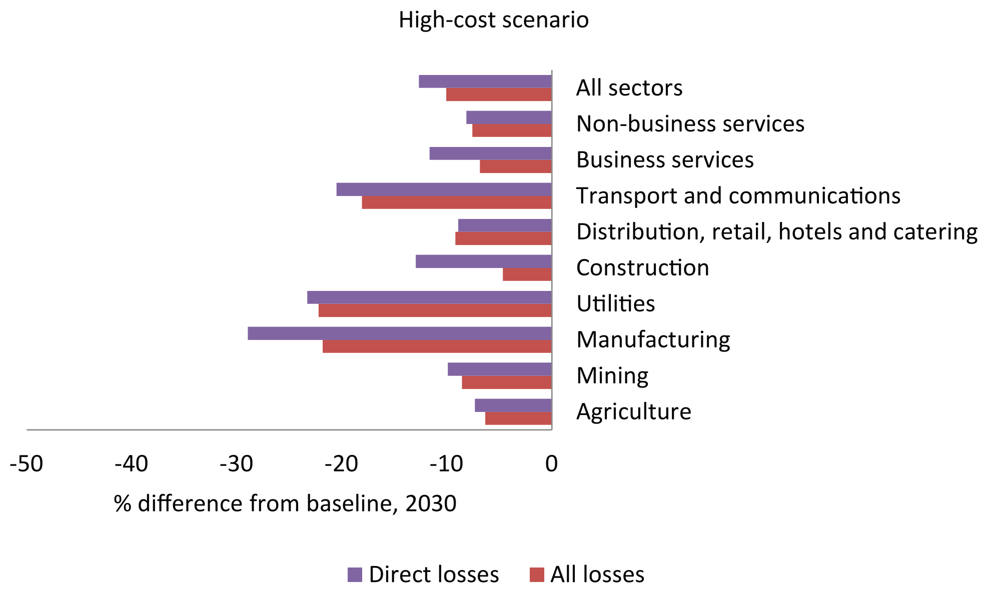
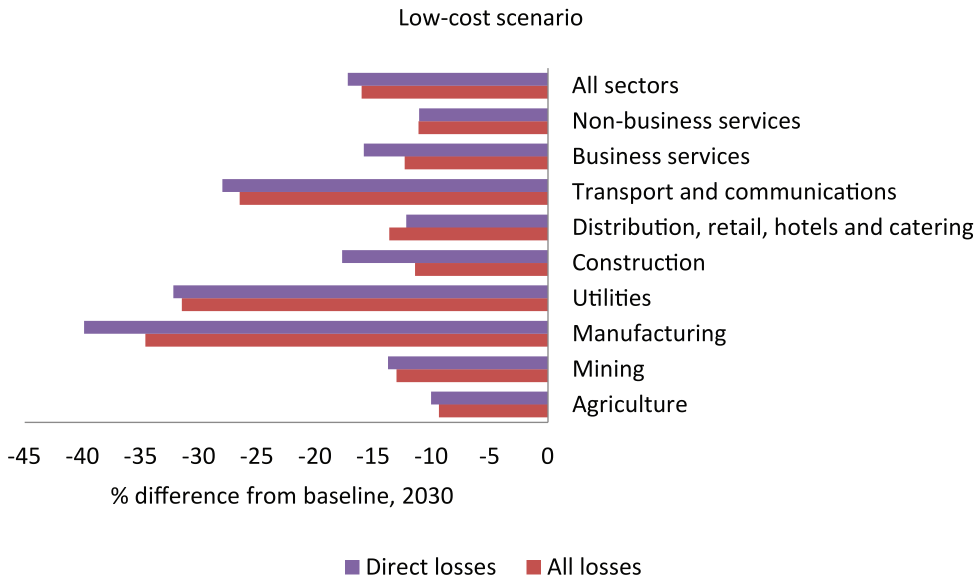
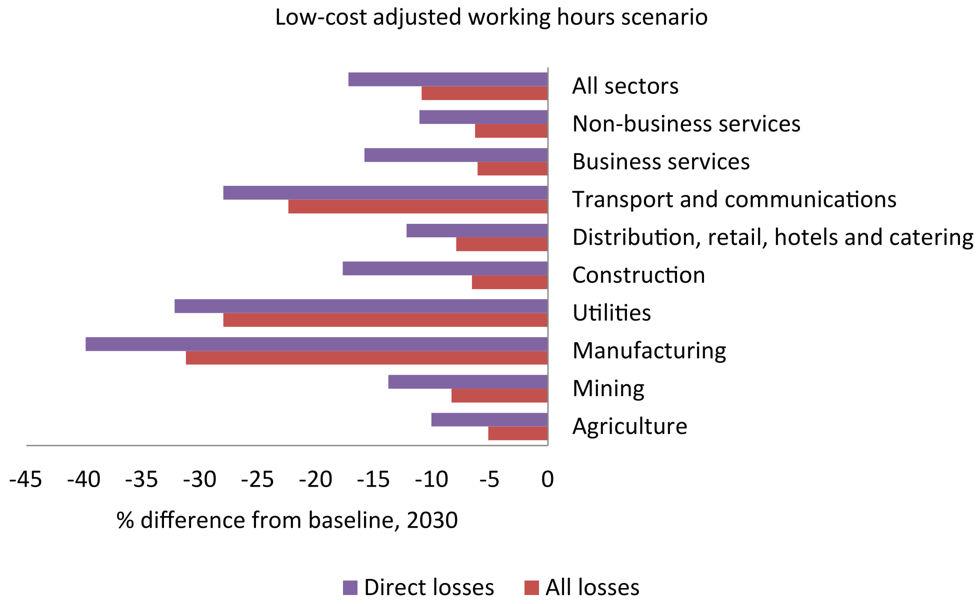


Figure 8: (continued)





Source: *Cambridge Econometrics analysis*

Table 5: Projected employment change between baseline and technology scenarios, 2018–2030 EU28

	Baseline scenario				High cost			Low cost			Low cost, adjusted working hours		
	2018	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)
01. Armed forces	1,196	1,034	-161	-1.2	929	-266	-2.1	884	-311	-2.5	930	-264	-2.1
11. Chief executives, senior officials and legislators	1,810	1,998	188	0.8	1,799	-11	0.0	1,670	-138	-0.7	1,778	-30	-0.1
12. Administrative and commercial managers	3,816	4,367	551	1.1	3,873	61	0.1	3,586	-224	-0.5	3,822	12	0.0
13. Production and specialised services managers	4,765	5,330	564	0.9	4,752	-10	0.0	4,373	-385	-0.7	4,635	-123	-0.2
14. Hospitality, retail and other services managers	4,254	4,664	410	0.8	4,158	-92	-0.2	3,884	-364	-0.7	4,156	-92	-0.2
21. Science and engineering professionals	6,567	7,572	1,005	1.2	6,763	201	0.3	6,219	-338	-0.4	6,586	29	0.0
22. Health professionals	5,895	6,218	323	0.4	5,770	-119	-0.2	5,521	-366	-0.5	5,836	-51	-0.1
23. Teaching professionals	10,027	9,788	-239	-0.2	9,385	-639	-0.5	9,172	-849	-0.7	9,666	-356	-0.3
24. Business and administration professionals	8,519	9,882	1,363	1.2	8,851	340	0.3	8,243	-263	-0.3	8,807	301	0.3
25. Information and communications technology professionals	3,581	3,976	395	0.9	3,928	347	0.8	3,629	51	0.1	3,888	311	0.7
26. Legal, social and cultural professionals	6,051	7,107	1,056	1.3	6,576	530	0.7	6,242	198	0.3	6,626	583	0.8
31. Science and engineering associate professionals	7,936	8,290	355	0.4	7,202	-727	-0.8	6,471	-1,451	-1.7	6,849	-1,073	-1.2
32. Health associate professionals	6,219	6,755	536	0.7	6,120	-94	-0.1	5,800	-411	-0.6	6,152	-59	-0.1
33. Business and administration associate professionals	16,743	18,415	1,671	0.8	16,551	-179	-0.1	15,440	-1,279	-0.7	16,486	-233	-0.1
34. Legal, social, cultural and related associate professionals	5,263	7,495	2,231	3	6,781	1,522	2.1	6,375	1,119	1.6	6,787	1,530	2.2

		Baseline scenario			High cost			Low cost			Low cost, adjusted working hours		
	2018	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)
35. Information and communications technicians	1,897	1,995	98	0.4	1,936	40	0.2	1,814	-81	-0.4	1,931	36	0.2
41. General and keyboard clerks	6,848	6,142	-707	-0.9	5,611	-1,234	-1.6	5,250	-1,590	-2.2	5,581	-1,259	-1.7
42. Customer services clerks	6,192	7,740	1,548	1.9	6,994	808	1.0	6,524	341	0.4	6,978	796	1.0
43. Numerical and material recording clerks	7,712	6,860	-852	-1	5,973	-1,731	-2.1	5,464	-2,234	-2.8	5,841	-1,857	-2.3
44. Other clerical support workers	2,828	2,346	-482	-1.5	2,055	-769	-2.6	1,894	-929	-3.3	2,017	-805	-2.8
51. Personal service workers	11,657	11,905	248	0.2	10,768	-879	-0.7	10,195	-1,447	-1.1	10,882	-760	-0.6
52. Sales workers	16,019	16,599	579	0.3	15,064	-943	-0.5	14,250	-1,749	-1.0	15,184	-814	-0.4
53. Personal care workers	7,884	8,249	365	0.4	7,686	-191	-0.2	7,376	-498	-0.5	7,796	-78	-0.1
54. Protective services workers	3,796	3,752	-44	-0.1	3,393	-400	-0.9	3,164	-626	-1.5	3,364	-426	-1.0
61. Market-oriented skilled agricultural workers	7,642	7,094	-548	-0.6	6,562	-1,074	-1.3	6,267	-1,367	-1.6	6,645	-989	-1.1
62. Market-oriented skilled forestry, fishery and hunting workers	378	383	5	0.1	347	-30	-0.7	328	-49	-1.2	347	-30	-0.7
63. Subsistence farmers, fishermen, hunters and gatherers	495	422	-73	-1.3	386	-108	-2.0	370	-124	-2.4	388	-106	-2.0
71. Building and related trades workers, excluding electricians	8,768	9,435	666	0.6	8,823	48	0.0	8,156	-611	-0.6	8,655	-113	-0.1
72. Metal, machinery and related trades workers	8,187	7,277	-910	-1	6,327	-1,851	-2.1	5,646	-2,524	-3.0	5,983	-2,187	-2.6
73. Handicraft and printing workers	1,208	1,147	-61	-0.4	964	-242	-1.8	846	-359	-2.9	894	-311	-2.5
74. Electrical and electronic trades workers	3,395	3,194	-201	-0.5	2,918	-475	-1.2	2,679	-712	-1.9	2,841	-549	-1.5
75. Food processing, woodworking, garment and other craft and related trades	4,081	3,588	-493	-1.1	3,004	-1,070	-2.5	2,659	-1,411	-3.5	2,823	-1,247	-3.0

(continued)

Table 5: (continued)

	Baseline scenario				High cost			Low cost			Low cost, adjusted working hours		
	2018	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)	2030	Net change (000s)	Growth (% per annum)
81. Stationary plant and machine operators	5,001	4,971	-29	0	4,011	-981	-1.8	3,443	-1,543	-3.0	3,639	-1,348	-2.6
82. Assemblers	1,724	2,123	399	1.7	1,785	64	0.3	1,555	-165	-0.8	1,642	-77	-0.4
83. Drivers and mobile plant operators	9,443	9,428	-15	0	8,072	-1,359	-1.3	7,380	-2,044	-2.0	7,806	-1,618	-1.6
91. Cleaners and helpers	10,000	10,859	858	0.7	10,042	49	0.0	9,473	-515	-0.4	10,144	155	0.1
92. Agricultural, forestry and fishery labourers	1,920	2,162	242	1	2,020	102	0.4	1,944	26	0.1	2,046	128	0.5
93. Labourers in mining, construction, manufacturing and transport	6,673	7,933	1,260	1.5	6,877	211	0.3	6,275	-385	-0.5	6,684	24	0.0
94. Food preparation assistants	1,882	1,880	-2	0	1,606	-273	-1.3	1,482	-396	-2.0	1,608	-270	-1.3
95. Street and related sales and service workers	204	185	-19	-0.8	171	-33	-1.5	164	-40	-1.8	173	-31	-1.4
96. Refuse workers and other elementary workers	2,579	2,671	92	0.3	2,361	-215	-0.7	2,194	-380	-1.3	2,325	-249	-0.8
All occupations	**231,056**	**243,232**	**12,176**	**0.4**	**219,197**	**-11,672**	**-0.4**	**204,298**	**-26,421**	**-1.0**	**217,221**	**-13,499**	**-0.5**

Source: *Analysis by the Warwick Institute for Employment Research*

3 Concluding remarks

The first point to emphasise is the very high uncertainty of these projections. The point of departure is a large-scale automation driven by digitisation. There are by now many empirical estimates that suggest such a radical loss of jobs due to the substitution of labour by these technologies. These initial job losses are of a scale that transforms economies, societies even, and obviously it is hardly possible to predict the economic, social and political repercussions of such a transformation. A notable uncertainty in this potential technologically driven transformation is that, unlike previous ones, it will occur simultaneously in most of the world and not be led, as before, by Europe and the US. The contribution of this report is to extend the analysis beyond just the technologically feasible substitution of workers by machines by incorporating some economics into the analysis. This includes the macroeconomic feasibility of the investment cost of automation and the multiplier effects of loss of demand – not only because of initial job loss but also as a result of the shift away from other labour incomes – and job creation in the supply chain emanating from the increased demand for ICT equipment. There is one important empirical result that should be deemed reasonably credible, namely that while the indirect employment effects are positive, they only marginally compensate the job losses as were the initial assumptions fed into the model; in the high-cost alternative they reduce the initial job loss of 13% to a net employment decline of 10% and in the low cost alternative the reduction is from the initial 17% to a net employment decline of 16%. However, in this low cost alternative if one allows for a compensated working time reduction, this leads to the much smaller a net employment decline of 11%.

References

All Eurofound references are available at www.eurofound.europa.eu

Ambrosetti, (2017), *Technology and labour: Steering the change,* web page, accessed 28 February 2019.

Arntz, M., Gregory, T. and Zierahn, U. (2016), *The risk of automation for jobs in OECD countries: A comparative analysis*, Working Paper No. 189, OECD Publishing, Paris.

Cambridge Econometrics (undated), *E3ME: Technical manual, version 6.0*, available at https://www.camecon.com/how/e3me-model/, accessed 7 February 2019.

Cedefop and Eurofound (2018), *Skills forecast: Trends and challenges to 2030*, Publications Office of the European Union, Luxembourg.

Citi (2016), *Technology at work v2.0: The future is not what it used to be*, New York.

Davies, R. (2015), *Industry 4.0: Digitalisation for productivity and growth*, European Parliamentary Research Service Briefing, European Parliament, Brussels.

Engineering 360 (undated), *What is the real cost of an industrial robot arm?*, web page, accessed 19 February 2019.

Ernst, E., Rossana, M. and Samaan, D. (2018), *The economics of artificial intelligence: Implications for the future of work*, International Labour Office, Geneva.

Eurofound (2018), *Game changing technologies: Exploring the impact on production process and work*, Publications Office of the European Union, Luxembourg.

Eurofound (2019), *Energy scenario: Employment implications of the Paris Climate Agreement*, Publications Office of the European Union, Luxembourg.

Eurofound (forthcoming), *Trade scenario: Employment implications in Europe of a large increase in global tariffs*, Publications Office of the European Union, Luxembourg.

Frey, C. B. and Osborne, M. A., (2013), *The future of employment: How susceptible are jobs to computerisation?*, Oxford Martin School, Oxford, UK.

IAB (Institute for Employment Research) (2016), *Economy 4.0 and its labour market and economic impacts: Scenario calculations in line with the BIBB-IAB qualification and occupational field projections'*, IAB-Forschungsbericht, Nuremberg.

McKinsey Digital (2015), *Industry 4.0: How to navigate digitization of the manufacturing sector*, McKinsey and Company, New York.

McKinsey Global Institute (2017), *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey & Company, New York.

McKinsey Global Institute (2018), *Notes from the frontier: Modeling the impact of AI on the world economy*, McKinsey & Company, New York.

Nedelkoska, L. and Quintini, G. (2018), *Automation, skills use and training*, OECD Social, Employment and Migration Working Papers No. 202, OECD Publishing, Paris.

PwC (PricewaterhouseCoopers) (2017), 'Will robots steal our jobs? The potential impact of automation on the UK and other major economies', *UK Economic Outlook*, March, pp. 30–47.

Robotworx (undated), *Frequently asked questions: How much do industrial robots cost?*, web page, accessed 19 February 2019.

Suta, C., Barbieri, L. and May-Gillings, M. (2018), 'Future employment and automation', in Hogarth, T., *Economy, employment and skills: European, regional and global perspectives in an age of uncertainty*, Vol. 61, Fondazione Giacomo Brodolini, Rome, pp. 17–43.

World Economic Forum (undated), *The future is automated, but what does that really mean for jobs*?, web page, accessed 28 February 2019.

Annex: Occupations that could potentially be automated

This Annex reports on estimates, mainly drawn from the literature. Note that they are not the estimates plugged into the model assumptions as they may be capped due to the macroeconomic unfeasibility of the scale of the investment cost associated with high automation rates.

For the EU Member States, the numbers expected to be working in each occupation and sector in 2030 are drawn from the detailed baseline results taken from the latest Cedefop projections (Cedefop and Eurofound, 2018). We then calculate, for each sector in manufacturing, the share of manufacturing workers not employed in managerial, professional or technical occupations in 2030 as a proxy for jobs most vulnerable to automation. These rates are shown in Table A1 for the largest EU countries.

For non-manufacturing sectors in the EU and non-EU regions the assessment is drawn from the literature. The main sources used are:

- PwC (2017) (results summarised in Table A2)
- Ambrosetti (2017) with information about automation rates for Italy (results summarised in Table A3)
- McKinsey Global Institute (2017) (results summarised in Table A4)

Table A1: Share of manufacturing workers not in managerial, professional or technical occupations expected in 2030

%	France	Germany	Italy	Poland	Spain	UK
Food, drink and tobacco	58.6	84.1	72.3	67.7	73.5	69.8
Textiles and leather	49.7	66.8	75.3	77.7	60.1	65.0
Wood and wood products	55.3	74.3	72.6	67.5	65.0	67.3
Paper and paper products	55.3	74.3	72.6	67.5	65.0	67.3
Printing and reproduction	55.3	74.3	72.6	67.5	65.0	67.3
Coke and refined petroleum	16.8	64.5	48.4	51.6	23.1	49.5
Other chemicals	26.0	48.9	38.2	51.8	44.8	36.3
Pharmaceuticals	20.1	40.8	36.1	43.8	30.9	28.7
Rubber and plastic products	52.8	74.0	71.1	75.0	67.3	62.3
Non-metallic mineral products	52.8	74.0	71.1	75.0	67.3	62.3
Basic metals	49.4	78.9	74.6	71.9	74.3	52.3
Fabricated metal products	49.4	78.9	74.6	71.9	74.3	52.3
Computer, optical and electronic equipment	19.2	45.4	37.2	70.0	38.2	25.8
Electrical equipment	37.4	52.5	48.5	53.6	56.7	47.6
Other machinery and equipment	45.8	59.5	52.4	64.6	57.4	59.4
Motor vehicles	30.1	50.7	57.3	84.2	70.9	59.2
Other transport equipment	25.2	59.0	55.5	53.5	36.3	38.0
Furniture; other manufacturing	56.9	60.8	57.2	68.7	67.5	54.2

Source: *Cambridge Econometrics analysis based on Cedefop and Eurofound (2018)*

Table A2: Summary of automation rates reported in PwC (2017)

%	Germany	Japan	UK	US
Wholesale and retail trade	42	25	44	47
Administrative and support services	30.4	20.4	37.4	35.4
Transportation and storage	64.4	33.4	56.4	76.4
Professional, scientific and technical	21.6	24.6	25.6	32.6
Human health and social work	24	11	17	25
Accommodation and food services	30.5	18.5	25.5	44.5
Construction	40.7	25.7	23.7	34.7
Public administration and defence	29.1	16.1	32.1	33.1
Information and communication	29.3	19.3	27.3	45.3
Financial and insurance	40.2	13.2	32.2	61.2
Education	8.5	3.5	8.5	11.5
Arts and entertainment	15.3	21.3	22.3	17.3
Other services	18.6	18.6	18.6	18.6
Real estate	28.2	28.2	28.2	28.2
Water, sewage and waste management	62.6	62.6	62.6	62.6
Agriculture, forestry and fishing	18.7	18.7	18.7	18.7
Electricity and gas supply	31.8	31.8	31.8	31.8
Mining and quarrying	23.1	23.1	23.1	23.1
Domestic personnel and self-subsistence	8.1	8.1	8.1	8.1

Source: *PwC (2017)*

Table A3: Summary of automation rates for Italy

%	Italy
Education and health services	6
Information and communication services	9
Other collective and personal services	10
Real estate and business services	12
Hotels and restaurants	15
Construction	15
Public administration and defence	16
Finance and insurance	17
Transport and warehousing	17
Manufacturing	19
Trade	20
Fisheries	25

Source: *Ambrosetti (2017)*

Table A4: Summary of automation rates (2017)

%	China	India
Agriculture	49	49
Manufacturing	64	67
Retail trade	54	56
Construction	41	42

Source: *McKinsey Global Institute (2017)*

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This report looks into the impact of the accelerated application of automation and digitisation technologies on the wage and tasks structure of employment in Europe.

Despite the high level of uncertainty of these projections, the contribution of this report is to extend the analysis beyond just the technologically feasible substitution of workers by machines by incorporating some economics to the analysis. This includes the macroeconomic feasibility of the investment cost of automation, the multiplier effects of loss of demand – not only because of initial job loss, but also as a result of the shift away from other labour incomes – and job creation in the supply chain emanating from the increased demand for information and communications technology (ICT) equipment.

The analysis is carried out using the E3ME macroeconometric model, which provides information on sectoral impacts, together with the Warwick Labour Market Extension model for occupational analysis. Further analysis of the employment developments in Europe is undertaken using Eurofound's European Jobs Monitor.

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, employment 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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