11.0 THE ECONOMIC IMPACT OF ROBOTICS AND ARTIFICIAL INTELLIGENCE

By Ben Vermeulen, Andreas Pyka, and Mirheta Omeroviv

ABSTRACT
Mankind is on the brink of the fourth industrial revolution, in which robotics and artificial intelligence are expected to have disruptive effects on types of tasks performed by humans, the level of employment, real wages, and the income distribution. This review provides a short overview of the ongoing discourse on the impact of diffusion and adoption of robotics and artificial intelligence on (i) shifts in tasks performed, skills required, and jobs done, (ii) employment dynamics and the role of education therein, and (iii) real wages, income distribution, and inequality. In addressing these three topics, we pit the 'sector of application' perspective generally followed in literature against a structural change perspective with different types of sectors, both existing and emerging, all (in)directly affect. We also briefly discuss several policy interventions to overcome adverse effects of robotization and implementation of AI and to enhance the dynamic efficiency of structural change.

11.1 Opening

Mankind is on the brink of the much anticipated Fourth Industrial Revolution in which breakthrough technologies in fields such as artificial intelligence, data science, quantum computing, internet-of-things, etc. will enable advanced applications such as social robots, autonomous vehicles, virtual assistants, etc. (cf. Schwab, 2017). At present, the popular media and public debate are captivated by fearmongering headlines such as "Robots will destroy our jobs – and we're not ready for it " (Shewan, 2017), "More Robots, Fewer Jobs" (Rojanasakul & Coy, 2017), "After Robots Take Over Our Jobs, Then What?" (Bernick, 2017), "The Long-Term Jobs Killer Is Not China. It’s Automation." (Miller, 2016), and "Sympathy for the Luddites" (Krugman, 2013). However, it is not just in popular media, also scientific work paints a gloomy picture of the future with structural high levels of unemployment, stagnating median wages, and growing income inequality (e.g. Brynjolfsson & McAfee, 2011; Frey & Osborne, 2017; Ford, 2013; Rifkin, 1995).

However, possibly, these articles are overly somber, as, although, indeed, these (and other) technologies are expected to transform our day-to-day life and business practices, both by increasing productivity, causing unemployment, but also creating demand for new skills possibly in new sectors (e.g. Manyika *et al.*, 2013; Autor, 2015; Stewart, De & Cole, 2015; Gregory, Salomons & Zierahn, 2016; Graetz & Michaels, 2015; Rifkin, 1995). Aptly phrased, Autor (2015) states:

> "*Automation does indeed substitute for labor—as it is typically intended to do. However, automation also complements labor, raises output in ways that lead to higher demand for labor, and interacts with adjustments in labor supply. [..] [J]ournalists and even expert commentators tend to overstate the extent of machine substitution for human labor and ignore the strong complementarities between automation and labor that increase productivity, raise earnings, and augment demand for labor.*"

Historical reflections seem to corroborate this more optimistic perspective. In the past, industrial revolutions triggered structural transformations, which, after recovering from initial technological unemployment, have brought mankind merely frictional unemployment, and prosperity rather than poverty, and it remains to be seen whether it is different this time (cf. Mokyr *et al.*, 2015). From an historical perspective, we may be optimistic that demand for new products develops, new sectors emerge, new skills are required, and jobs are created. Possibly, we are just facing a period of transition with temporary technological unemployment.

However, there is a body of economic literature and consulting reports in which authors argue differently. If anything, it is disconcerting that one school argues that we may see the 'end of work' (e.g. Rifkin, 1995) and head for a 'dystopia' with mass unemployment and poverty, while another argues we head for a 'utopia' with high employment and people doing sensible, gratifying work (cf. Porter & Manjoo, 2016). It is exactly the research goal of this report to provide a short overview of the ongoing discourse on the impact of diffusion and adoption of robotics and artificial intelligence. We hereby discuss three broad questions. Firstly, which types of tasks, skills, jobs, and sectors are affected and how? If anything, advanced technology alleviates humans from tedious, repetitive, or dangerous tasks (cf. Kaplan, 2015; Stewart, De & Cole, 2015; Nilsson, 1985; Rotman, 2013) and allows humans to do more meaningful work requiring creative intelligence, physical flexibility and dexterity, and social intelligence (cf. Frey & Osborne, 2017; Brynjolfsson & McAfee, 2011; Deming, 2015). However, what are the implications for the task content of jobs not being substitute? We know that robots and AI are particularly good at doing routinized tasks and predictive work, so what then is the emerging composition of the jobs in the sector of application? And which sectors are susceptible to robotization and implementation of AI?

Secondly, how is employment affected (over the long term)? We know that the focal technologies bring about a decline in low- and medium-skilled jobs and growth in high-skill, high-productivity jobs (Brynjolfsson & McAfee, 2011), but does that mean we are facing structurally lower levels of unemployment? Or will other complementary sectors 'mop up' the unemployment and is there hence a rebound to old levels of employment? Will new sectors emerge soon enough and will workers be able to be reeducated fast enough to start working in these sectors? And given the important role of education in this race against technological development, how does education determine in which particular scenario of employment we end up?

Thirdly, apart from the effects of these technologies on the level of employment, there is uncertainty on and thereby concern about the effects on real wages/ discretionary income and inequality (e.g. Bivens *et al.*, 2014; Frey & Osborne, 2017; MacCrory *et al.*, 2014; Brynjolfsson & McAfee, 2011).

Our review reveals that dominant analyses do focus too much on the sector of application. Not only do they thus overlook the generation of jobs in the developing & producing (e.g. robotics technology) and supporting sectors (e.g. component producers), but also disregard the facilitating sectors (e.g. education) and sectors receiving spillovers (e.g. leisure). Notable exceptions are Stewart, De & Cole (2015) and Gregory, Salomons & Zierahn (2016). Moreover, the *static* perspective completely ignores the creation of (jobs in) new sectors spawned (cf. Saviotti & Pyka, 2004; Pasinetti, 1981). Consequently, in discussing these three topics, we pay particular attention to how findings differ when following the dominant narrow 'sector of application perspective' or rather our 'multisectoral perspective'. We also briefly discuss several suggested policy interventions.

This report is written in the context of the REELER project concerned with the ethical considerations in designing, applying/ implementing and using robots (and –in its extension- AI). As the UHOH team members are involved in their capacity as evolutionary political economists, we seek to understand the economic processes and devise policy instruments to –in principle- realize sustainable and inclusive growth, 'fair' income distributions, and maintain social cohesion.

Although we will ultimately develop extensions to the TEVECON computer simulation model (Saviotti & Pyka, 2004, 2008) to study the economic development, in this report we have limited ourselves to a (non-exhaustive) review of papers and consulting reports on the labor economic implications of the introduction of robotics and AI. As we will see, economists are divided when it comes to answering whether robotization and computerization will have a more profound or structurally different impact on unemployment than previous (general purpose) technologies (e.g. mechanization, automatization). Moreover, the tasks that robots and AI perform will drive polarization of labor and thereby increasing inequality. On top of that, there is a macro-economic decoupling of wages and productivity. Given these dramatic effects like decoupling of the returns on capital and wages, increasing income inequality, job polarization, and possibly even mass-unemployment, the implementation of robotics and AI seems undesirable from an ethical point of view. However, as said, mankind may also move from tedious, boring, and dangerous work to meaningful, creative and socially intelligent work in dynamic environments. Plus, historically, technology has brought mankind prosperity, longevity, and wellbeing. In fact even the gloomy outlooks of mass-unemployment and rich capital owners and exploited laborers are disputed. The analysis using our multisectoral, structural change-based perspective on economic impacts will reveal that there is reason for optimism and we will provide policy instruments to enhance the dynamic efficiency of the structural transition and labor mobility required.

The structure of this report is as follows. In Section 2, we present our conceptual framework, which basically is a concrete multisectoral perspective on structural change. This will be used to highlight potential developments in skill shifts and employment in the various sectors of an economy. In Section 3, we use an outlook on the developing capabilities of robots and AI to study the impact on tasks performed by humans and the thus emerging polarized composition of the labor force in the sector of application. We then take a look at which sectors are susceptible to robotization and application of AI and the structural shifts in skills profiles. In Section 4, we study the development of employment subject to the introduction of the focal technologies. Also here we explain how findings differ dramatically when one switches from a narrow 'sector of application perspective' to a multisectoral perspective. Notably, we discuss three distinct macro-economic scenarios on employment and how the rate at which displaced workers can be reeducated plays a dominant role. In Section 5, we briefly discuss the decoupling of productivity and wages, and how the polarization in the skill set may in fact be one of the causes. In addition to that, we launch the idea that also structural change may be causing further income inequality. In Section 6, we propose and discuss two categories of policy instruments to overcome adverse effects of robotization and computerization. In Section 7, we provide a brief summary.

11.2 Conceptual framework

We argue that, in the present literature, the impact beyond the sector of application is overlooked. From this *narrow* perspective, robotics and artificial intelligence are expected to either directly replace employees or increase productivity and thereby induce unemployment (and affect real wages) in sectors in which the technology is applied. This is compensated merely by (i) an increase in demand for higher skilled employees in the sector of application to exploit complementarities of using the robot technology, (ii) a(n) (possibly marginal) increase in labor in the sector in which the technology is developed and produced, and (iii) increased demand for products because of lower production costs.

However, as two centuries of technological progress has shown, there is an additional mechanism at work: a sustained, endogenous creation of new sectors which mop up the technologically unemployed (cf. Pasinetti, 1981; Saviotti & Pyka, 2008; Saviotti & Pyka, 2004). In the vein of structural change literature, we propose to take a multisectoral perspective. After all, the impact of the diffusion and adoption of robotics and artificial intelligence on the economy is multi-faceted, affecting not only existing sectors which develop & produce or apply the focal technology. It also affects sectors that supply to the developing & producing sector and sectors that facilitate changes within the various sectors and notably the sector of application ("intra-sectoral transformations"). In addition, there are several positive and negative spillover effects, e.g. the changes in discretionary income of and/or hours worked by employees in developing and (possibly) applying sectors is likely to change the demand for things like leisure and thus may give rise to the development of quaternary sectors.

On top of that, over time, we expect that new sectors are spawned, which may be sectors that further develop or put to new use the focal technologies, or sectors that support/ supply or facilitate. In fact, in the long term, we expect a 'snowballing' of the creation of sectors developing & producing new technologies and spawning of new sectors applying the developed technology, with labor mobility within and across these sectors. In addition to this, there are education and training sectors which facilitate this structural change and mobility within and across sectors. There may also be new sectors emerging which receive spillovers. Moreover, there is a sixth type of sector, which we omit for the moment, namely weakly related sectors which attract employees that got displaced in the sector of application and decide to do something completely different.

To further disentangle the economic impacts of these technologies, we propose the following *sectoral perspective* taking just two dimensions: (i) the type of sector (particularly the five types mentioned above) and (ii) whether the sector was already there or whether it's coming into existence (as a(n) (in)direct effect). Schematically, this is presented in Table 2-1.

Nature **New/existing?**	Developing & producing	Supplying & supporting (e.g. mechanical components; sensors)	Applying (e.g. automotive; banking)	Facilitating/ inhibiting (e.g. education; venture funding)	Spillover (e.g. leisure, tourism)
Existing					
Newly spawned					

Table 2-1. Two-dimensional conceptualization of the multisectoral, structural change perspective.

In further support of our multisectoral perspective, we regard robotics and artificial intelligence as 'general purpose technology'. General purpose technologies have by their nature a pervasive effect on a wide range of sectors and with multifaceted and (possibly) different effects within each. Somewhat problematics is that the impact of general purpose technology is difficult to assess because it (i) may have opportunities revealed only ex post and advance in directions that were unforeseen ex ante, possibly spawning new sectors, (ii) require complementary investments and activities of which the economic impacts can be reaped and observed substantially later, and (iii) gradually diffuse over a range of sectors (see e.g. Helpman & Trajtenberg, 1998; Bresnahan & Trajtenberg, 1995).

Much in line with our perspective, Stewart, De & Cole (2015) identify four mechanisms influencing employment, two direct and two indirect effects. Firstly, technology substitutes for labor (e.g. in manufacturing, agriculture). Secondly, new technology stimulates employment in generating sectors (e.g. software engineering, scientific research). Thirdly, technology generates new labor demand in complementary sectors (e.g. health care, knowledge-intensive business services). Fourthly, technology lowers costs of production and prices which enable consumers to shift spending to more discretionary goods and services (e.g. gym, entertainment).

11.3 Shifts in tasks, skills, jobs, and sectors

11.3.1 The tasks robots and AI can perform

The shift in tasks and jobs performed by human beings depends on the tasks that robots and artificial intelligence can perform, technically and economically. If anything, these technologies have the potential to alleviate humans from tedious, repetitive, or dangerous tasks (cf. Kaplan, 2015; Stewart, De & Cole, 2015; Nilsson, 1985; Rotman, 2013). As such, human beings may devote their time to more meaningful and gratifying work.

However, just as technologies for mechanization and automatization before, robots and artificial intelligence are technologies developed for specific tasks in specific environments. For the first generations of robots (and AI), the domains of application were those where simple instructions could be followed repeatedly, both because the task was simple and the environment stationary (Wolfgang, 2016; see Figure 3-1). With progression of robotics and notably the underlying sophistication and abstraction of instructions, robots and other applications of artificial intelligence can handle more complex tasks in a less structured or even dynamic environment. As such, the tasks that remain for humans are complex tasks in dynamic environments.

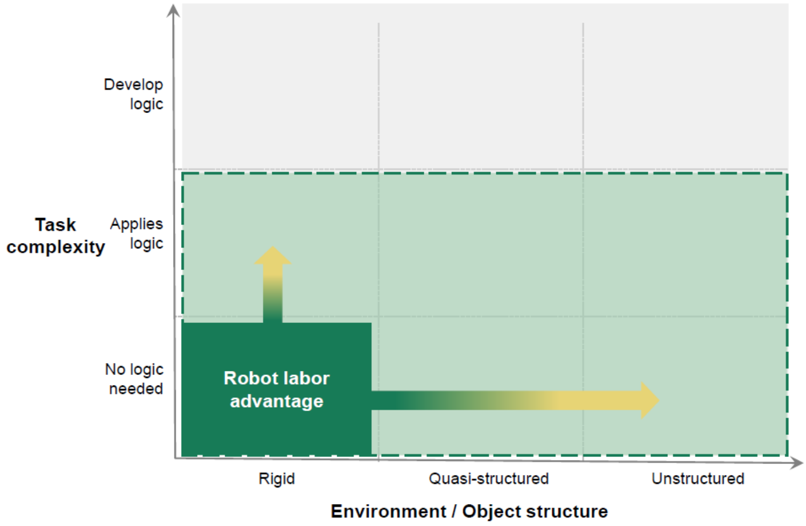

Figure 3-1. Domain of application of robots in terms of environment structure and task complexity. Source: Wolfgang, M. (2016). Boston Consulting Group.

While technology generally displaces low-skilled work (Berman, Bound, & Machin, 1998; Graetz & Michaels, 2015), technological substitution of jobs does not necessarily displace *only* low-skilled work (in fact, it may even create it, see Wendling, 2009; Katz & Margo, 2013). We expect, as is the case with automatization (cf. Autor, Levy & Murnane, 2003), that robotization primarily affects routinized tasks and to lesser extent non-routinized tasks, and tasks which merely execute rules rather than require cognitive processing of information (Levy & Murnane, 2005). Particularly jobs with tasks that contain substantial amounts of tacit knowledge hard to codify and hence automatize may be hardly affected (cf. Autor, 2014). That said, in fact, whenever a job has a certain degree of *predictability* in tasks and a large amount of data that can be used for training and machine learning, this job may eventually also be taken over by artificial intelligence (Ford, 2013), even if such a job relies on tacit knowledge (Autor, 2014). So, also knowledge work requiring high skills seems subjective to progressive automation and substitution (cf. Dobbs *et al.*, 2012; Manyika *et al.*, 2013).

Frey & Osborne (2017) discuss how robots and AI gradually become more equipped for non-routine cognitive tasks and non-routine manual tasks, but that technology is still too limited for tasks which require sophisticated perception and manipulation, creative intelligence, and social intelligence. As a consequence, there is a relative increase for and appraisal of social skills, creativity, etc. in jobs (cf. Deming, 2015). Indeed, given the substantial limitations in dexterity and flexibility of robots and AI, there are many manual tasks in dynamic environments (e.g. gardening, preparing meals in restaurants, hairdressing, carpentry) which cannot be conducted by robots and AI any time soon (Brynjolfsson & McAfee, 2011).

Given the limitations of what tasks robots and AI can currently perform, the impact is, so far, limited to routinized, predictable jobs consisting of repetitive simple tasks in stationary environments, see the overview in Table 3-1.

Job content	Routinized/ predictable/	Mixed	Non-routinized/ Unpredictable/

Task type	stationary environment		Dynamic environment
Simple/ repetitive	Substitute completely	Alleviate part of human tasks. Higher joint productivity.	Capital intensive, need many robots each for a simple task or versatile robot/ AI
Complex/ non-repetitive/ requiring dexterity, social or creative intelligence	Limited substitutability	Limited substitutability, limited impact on productivity	No use for robots/ AI, so probably very limited impact.

Table 3-2. Potential impact of robotics/ AI by types of tasks and level of routine in job content

A fine-grained, multi-dimensional decomposition of jobs/ skills into sets of tasks, beyond say merely being 'routinized', is found in MacCrory *et al.* (2014). The multi-dimensional framework can be used to predict (the extent to) which particular jobs are susceptible to substitution by and/or have complementarities with particular technologies.

11.3.2 Impact on sector of application

Robotics and AI are applied in particular existing sectors for one or multiple of the following goals:

(i) to directly replace humans to increase productivity and/or quality and lower unit costs,

(ii) to free humans from tedious, repetitive or dangerous parts of their job,

(iii) to allow humans to focus on sensible, meaningful parts of their job such as social interaction, mental or creative task, and/or

(iv) to be used to enhance output in terms of quality, predictability, etc. (without replacing employees).

So, despite the potential for substitution (first goal), there also is a substantial opportunity for complementarity (other goals) *even within the sector of application*.

However, in addition to affecting the *existing* work force, new employees may be sought to exploit the complementarities of the new technology. Moreover, to be able to implement robots and AI, a particular supporting infrastructure of technology and human skills is required. In this vein, Goldin & Katz (1998) provide a refined look on *intra-sectoral* consequences of the introduction of technology, albeit in 'automatization' terminology. They argue that 'machine installation' and 'machine maintenance' are *complementary* requiring skilled employees, whereas the new technology facilitates 'production' either at higher productivity levels and/or by lower skilled employees at lower wages. Indeed, there is *direct* complementarity in the sense that effective implementation of and thereby reaping the productivity enhancing effect of technology requires skilled workers (cf. Griliches, 1969; Goldin & Katz, 1998).

While this range of multi-faceted effects on the sector of application holds in general, it remains to be seen to what extent complementarities persists to exist in new sectors of application and for new technologies developed in the future. "*As soon as not only the physical but also the controlling 'mental'* *functions involved in the production of goods and services can be performed without the participation of human labor, labor's role as an indispensable 'factor of production' will progressively diminish.*" (Leontief, 1983, p.405). In line with this, we conjecture that the extent of complementarity is a function of the technology itself.

11.3.3 Which sectors are susceptible to robotization?

Apart from looking at the changes in the type of tasks and jobs performed by humans in a sector of application *in general*, some sectors are more susceptible to robotization/ automatization than others and may differ in the changes to the skill/ job profile.

In Manyika *et al.* (2017) a detailed overview is presented of the automation potential of a wide variety of sectors, see Figure 3-2. Wolfgang (2016) presents similar results for the susceptibility of various sectors to robotization based on the level of wages and the 'automatibility' of jobs, see Figure 3-3.

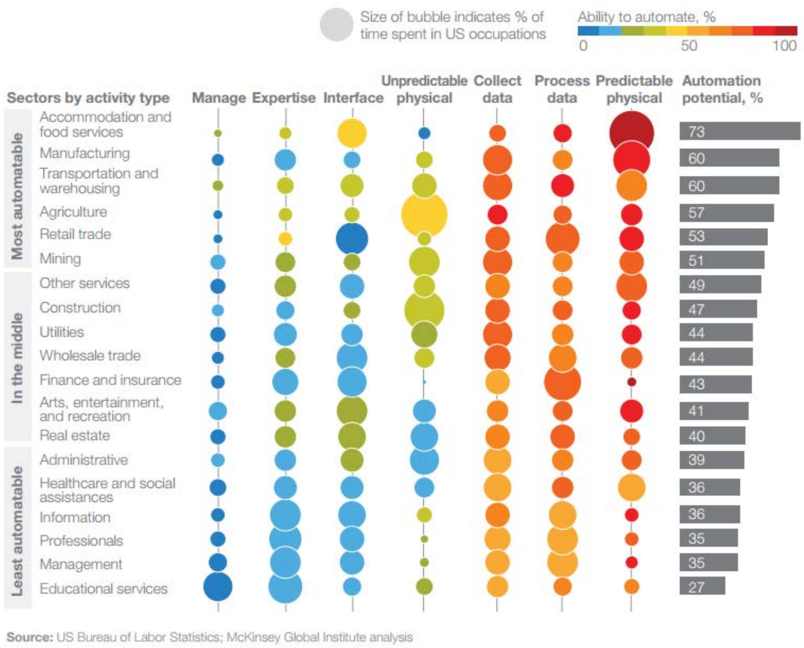

Figure 3-2. Automation potential in various sectors. Source: Manyika et al., 2017, but as contained in McKinsey GI, 2017.

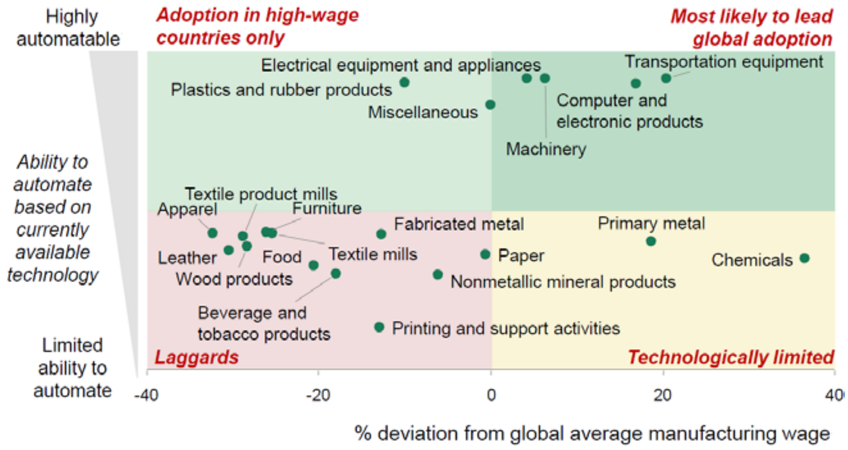

Figure 3-3. Susceptibility of sectors to robotization by manufacturing wage and automatibility of tasks. Source: wolfgang (2016), BCG.

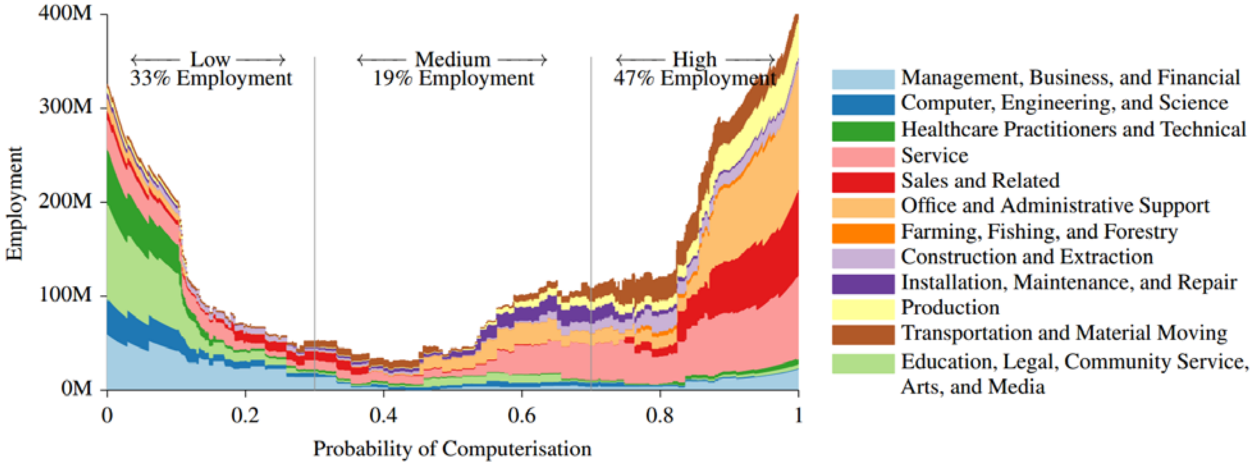

Figure 3-4. Distribution of employment over the probability of computerization

Frey & Osborne (2017) study which occupations are at risk of being computerized/ automatized and they find that almost half of the jobs in the U.S.A. are potentially automatable. Figure 3-4 shows that particularly employees in administration, transportation and logistics as well as labor in production are at risk. Arguably, technological progress may exacerbate the (potential) replacement.

However, we stress that purely looking at which jobs are at risk to be 'destroyed', such as in Manyika et al. (2017) and Frey & Osborne (2017), gives an overly somber perspective on future employment. As argued before, and as underlined by our sectoral perspective, there is ample opportunity for the creation of new jobs as well. First and foremost, in the (existing and newly created) developing & producing, supply & supporting, and 'spillover' sectors, but also in newly created applying sectors. Moreover, as we have seen in the previous section, even in the existing sectors of application in which jobs are displaced, there are new jobs created to support the use of robots and AI. Indeed, the negative effects of substitution may be (and actually are) compensated by increasing demand for (new and existing) products and services and the associated spillovers (Gregory, Salomons & Zierahn, 2016; Gorle & Clive, 2013). As a first indication of the creation of new sectors, new products & services, and new jobs is the creation of new job titles. Acemoglu & Restrepo (2016) report that a substantial amount of employment growth takes place in jobs with new job titles. A detailed reiteration of their results is considered out of scope.

11.3.4 Shifts in skill profile and structural transformation

In our perspective, there are two distinct developments: a polarization in the skill profile of (developed) economies and a structural transformation with permanent shift of jobs to new sectors.

Firstly, there is polarization in the skill profile in (developed) economies. For several decades the focus was on how technology replaces low-skilled work and thus brings about a shift towards high-skilled work. Recently, however, scholars adopted a more refined look on the properties of the *tasks* making up the jobs, particularly in terms of the degree of routine (Autor, Levy & Murnane, 2003) or predictability (cf. Ford, 2013). From the perspective of 'computerization', Autor, Katz & Kearney (2006) further refine the *intra-sectoral* consequences and argue that computers are a complement to the non-routine and cognitive tasks, yet a substitute for the routine and 'rule-based' tasks. The non-routine and cognitive tasks typically are high-skilled jobs with high wages, while the routine tasks generally are found in many traditional medium-skilled and medium-wage jobs. However, from this perspective, jobs that are low-skilled, but are composed of non-routinized tasks in a dynamic and unpredictable environment cannot yet be robotized or computerized. Moreover, jobs which required refined perception and manipulation, creative intelligence/ improvisation, or social intelligence, regardless of whether they are low-skilled or not, are less at risk of replacement. As such, rather than a mere shift to higher skilled work, there is 'hollowing-out' (Katz & Margo, 2013) or *polarization* in the skill profile (Goos & Manning, 2007). A detailed study of the task profile can be made by using the framework in on 'which tasks robots and AI can do' and look at 'which jobs contain such tasks'.

In addition to jobs vanishing because the tasks can be robotized, the task content of jobs changes (see the goals (ii) – (iv) mentioned in 3.2) and the employee needs to –in addition- handle the technology. Moreover, with the rise of new technology, also the sectoral composition of the economy changes with new types of jobs appearing in the emerging sectors. This brings us to the following point.

Secondly, driven by changes in tasks performed by technology, there is a structural transformation in which certain jobs (and employment) vanish from existing sectors and new jobs are created in new, emerging sectors. In the previous subsection, the focus was on the impact of robots & AI on *existing* sectors in which they are applied, and, indeed, one should expect substitution, in part. However, the (existing and new) sectors in which the technology is developed and produced, and (existing and new) sectors supplying and supporting these sectors, and -in addition- even the newly emerging sectors in which the technology is applied, there may very well be net job creation. This is the topic of the next section.

11.4 Employment

Like computerization and –in general- the introduction of ICT before, robotization and the introduction of AI are expected to increase the productivity in the sectors of application, thereby substituting for particular tasks, but possibly also requiring the introduction of new tasks to exploit complementarities. In general, though, the introduction of productivity-enhancing technology is found to lower the net employment in the focal sector of application (cf. Rodrik, 2016). There is technological unemployment if this loss in jobs is not compensated by the creation of jobs elsewhere (cf. Keynes, 1930). Arguably, it is a 'narrow focus' on the (loss of jobs in the) sector of application which gives rise to anxiety about mass unemployment with which we started this review.

In line with the multisectoral perspective of structural change, our contention is that, in general, the displaced employees may find jobs in other sectors such that technological unemployment is merely temporary and may thus be considered a special type of frictional unemployment caused by the immobility of labor. In particular, we argue that new employment opportunities arise both in sectors developing, producing, supplying, supporting robotics and AI technology, as well as in new, freshly emerging sectors. These new employment opportunities 'mop up' unemployment created by application of robotics and AI. Studies that take a more holistic perspective indeed find that there are various mechanisms through which there is a net creation of employment (cf. Stewart, De & Cole, 2015; Gregory, Salomons & Zierahn, 2016). In fact, we may very well face another structural transformation, i.e. that a new industrial revolution (cf. Schwab, 2017) will give rise to the quaternary sector.

11.4.1 From narrow focus on sector of application to structural change perspective

Economists have been long studying the effects of technological change on employment. Purely at the level of individual sectors, introduction of advanced production equipment is traditionally associated with an increase in labor productivity and thereby the loss of jobs (cf. Rodrik, 2016). Detailed analyses at the level of (existing) jobs (Frey & Osborne, 2017) and (existing) sectors (Manyika *et al.*, 2017) revealed that many jobs are at risk of being computerized and/or roboticized. These analyses, however, focus exclusively on the sector of application (e.g. manufacturing, agriculture) in which there is predominantly labor substitution and thus underestimate the positive effects of complementarities (both on keeping but also generating jobs). In addition, these analyses do not only overlook the generation of jobs in the developing & producing (e.g. robotics technology) and supporting sectors (e.g. component producers), but also disregard the facilitating sectors (e.g. education) and sectors receiving spillovers (e.g. leisure). Moreover, the *static* perspective completely ignores the creation of (jobs in) new sectors spawned. As such, we conjecture that in most sectors in the multisectoral, structural change perspective (see Table 2-1) in fact may see a (potential) increase in demand for labor and thus may increase employment rate. This is visualized in Table 4-1.

Nature **New/existing?**	Developing & producing	Supplying & supporting	Applying	Facilitating	Spillover
Existing sectors	Increasing employment	Increasing employment	Increasing employment for jobs with	Increasing employment	Increasing employment

	(higher demand)	(higher demand)	complementarities; decreasing employment for jobs due to substitution; Possibly increasing employment due to possibly increasing demand	(higher demand)	
Newly spawned sectors	Increasing employment				

Table 4-3. Conjectured effects of employment in the various sectors in the structural change perspective.

So, in general, the recent labor economic studies on the impact of robotization and automatization lacks a holistic perspective on the economy. There are a few exceptions, though, and indeed these studies come to structurally different conclusions. For instance, in the UK, Stewart, De & Cole (2015) incorporate also complementarities, e.g. increasing demand for labor in supporting sectors such as software engineering, and indirect effects, e.g. enhancement of the output generating more demand for products and lower costs increasing discretionary income. This study then also finds that technological progress, contrary to the narrow studies mentioned above, continues to create new jobs in (i) generating sectors (e.g. software engineering, scientific research), (ii) complementary sectors (e.g. health care, knowledge-intensive business services), and (iii) sectors providing discretionary goods and services (e.g. gym, entertainment) (see Stewart, De & Cole, 2015). Moreover, by including compensation through product demand and local demand spillovers, Gregory, Salomons & Zierahn (2016) come to a similar conclusion: there is a net positive labor demand (here, in 27 European countries). Also Gorle and Clive (2013) claim that the introduction of robotics and artificial intelligence contributes positively to employment because of the many new jobs that will be created in distribution, services and new manufacturing applications.

Studying the difference in employment in a wide variety of occupations in the years 1992 and 2014, see Figure 4-1, Stewart, De & Cole (2015) find that there is predominantly a shift in the sectors offering employment. They find that employment in agricultural and manufacturing sectors is decreasing, yet that this is compensated by employment growth in health care, creative professions, and business service sectors. In line with discussions above, the job loss is highest in jobs with routinized tasks (both cognitive and manual).

Occupations	Employment in		Change since 1992
	1992	2014	
Total employment	24,746,881	30,537,415	23%
Nursing auxilliaries and assistants	29,743	300,201	909%
Teaching and educational support assistants	72,320	491,669	580%
Management consultants and business analysts	40,458	188,081	365%
Information technology managers and above	110,946	327,272	195%
Welfare, housing, youth and community workers	82,921	234,462	183%
Care workers and home carers	296,029	792,003	168%
Actors, dancers, entertainment presenters, producers and directors	47,764	122,229	156%
Financial managers and directors	88,877	205,857	132%
Footwear and leather working trades	40,715	7,528	-82%
Weavers and knitters	24,009	4,961	-79%
Metal making and treating process operatives	39,950	12,098	-70%
Typists and related keyboard occupations	123,048	52,580	-57%
Company secretaries	90,476	43,181	-52%
Energy plant operatives	19,823	9,652	-51%
Farm workers	135,817	68,164	-50%
Metal machining setters and setter-operators	89,713	49,861	-44%

Figure 4-5. Development in employment in various occupations from 1992 to 2014.
Source: Stewart, De & Cole, 2015; Labour Force Survey.

11.4.2 Structural transformation

The findings of Stewart, De & Cole (2015) hint towards an ongoing structural transformation in which employment moves from agricultural and manufacturing sectors to service sectors. Colin Clark was the first to model this transformation from a society with work primarily found in agriculture, to a society with work primarily found in industry, and now to a society in which most people work in services. For a recent, detailed empirical study on structural transformation, the reader is referred to Herrendorf, Rogerson & Valentinyi (2013). A captivating account of this is found in Ford (2015):

> "*The mechanization of agriculture vaporized millions of jobs and drove crowds of unemployed farmhands into cities in search of factory work. Later, automation and globalization pushed workers out of the manufacturing sector and into service jobs. Short-term unemployment was often a problem during these transitions, but it never became systemic or permanent. New jobs were created and dispossessed workers found new opportunities. What's more, those new jobs were often better than earlier counterparts, requiring upgraded skills and offering better wages.*"

Schwab (2017) argues that robotics and AI are part of a set of technologies which will give rise the fourth industrial revolution. As such, mankind may face a structural transformation to a prominent role for a fourth 'broad sector', i.e. the quaternary sector. There are somewhat disparate ideas on what this quaternary sector may comprise, but, obviously, it will host work that robots and IA cannot do, i.e. work revolving around socially intelligent interaction & interpretation, creative intelligence, physical flexibility & dexterity in a dynamic environment, etc. (see Frey & Osborne, 2017). In our perspective, it may very well include the entertainment industry (literature, movies/show/series, literature, theater, etc.), journalism, sports, leisure & tourism industry, design & fine arts industry, and handicraft & culinary sector, sectors focusing on self-realization, etc.

As stressed before, we should not look only at existing sectors of application, but take a multisectoral perspective so as to prevent underestimating the economic impact. It is in fact quite easy to underestimate the employment creation, because robotics and AI are 'general purpose technologies'. Assessing the (technological) impact of general purpose technology is notoriously difficult as (i) technologies only gradually diffuse (and we seem to be only at the onset of this), (ii) directions for further development become clear only ex post, and (iii) complementary investments are required to reap benefits (and often only reveal themselves upon implementation) (cf. Helpman & Trajtenberg, 1998; Bresnahan & Trajtenberg, 1995).

11.4.3 Covert structurally lower employment levels?

Studying the macro-economic employment figures contained in the dataset of the Bank of England, plotted in Figure 4-2, we see there is a slightly positive trend in unemployment, but the noisy data mostly reveals that unemployment is driven by global crises of a non-technological nature (e.g. financial market, real estate, dot-com speculation bubbles, etc.). As such, there is no strong indicator of structurally higher levels of technological unemployment. However, quite in contrast to the fearmongering messages in popular media and in the 'narrow focus' in Ford (2015) and Frey & Osborne (2017), macro-economic literature concludes that the introduction of productivity-enhancing technology may in fact *increase* employment. Empirical evidence in Basu, Fernald & Kimball (2006) and Trehan (2003) indicates that a short-run dip in employment is followed by a bounce back to 'regular' levels of (frictional) unemployment.

A critical remark is, though, that the atomistic view on singular jobs as employment measure is somewhat misleading; also a decrease in the median number of hours worked per week may be considered a relative decrease in employment. As the number of hours worked per week indeed is decreasing, see Figure 4-3, this might also account for part of the technological unemployment. We consider the involved relationship between employment and the hours worked out of scope of the present report.

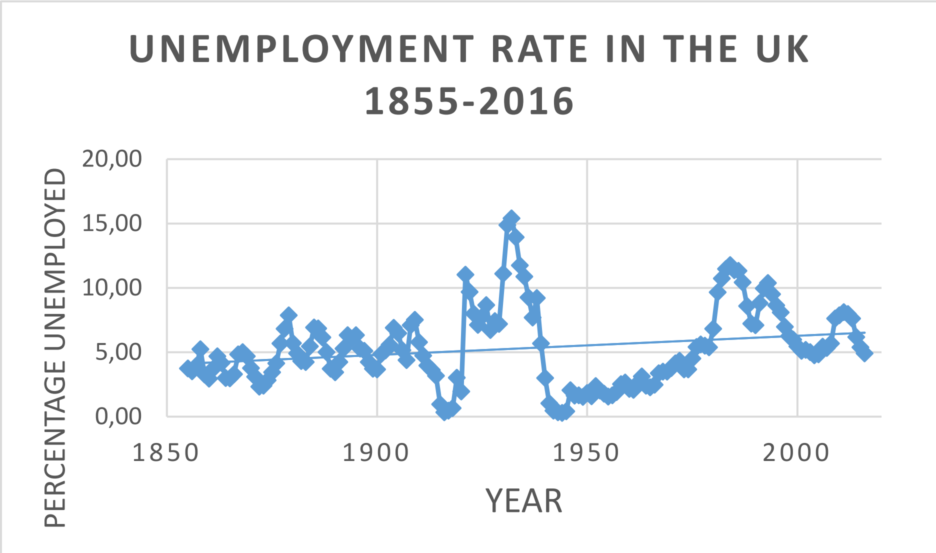

Figure 4-6. Unemployment rate in the UK over the year 1855 – 2016. Source: Bank of England, 'Millennium of Data' dataset. own visualization.

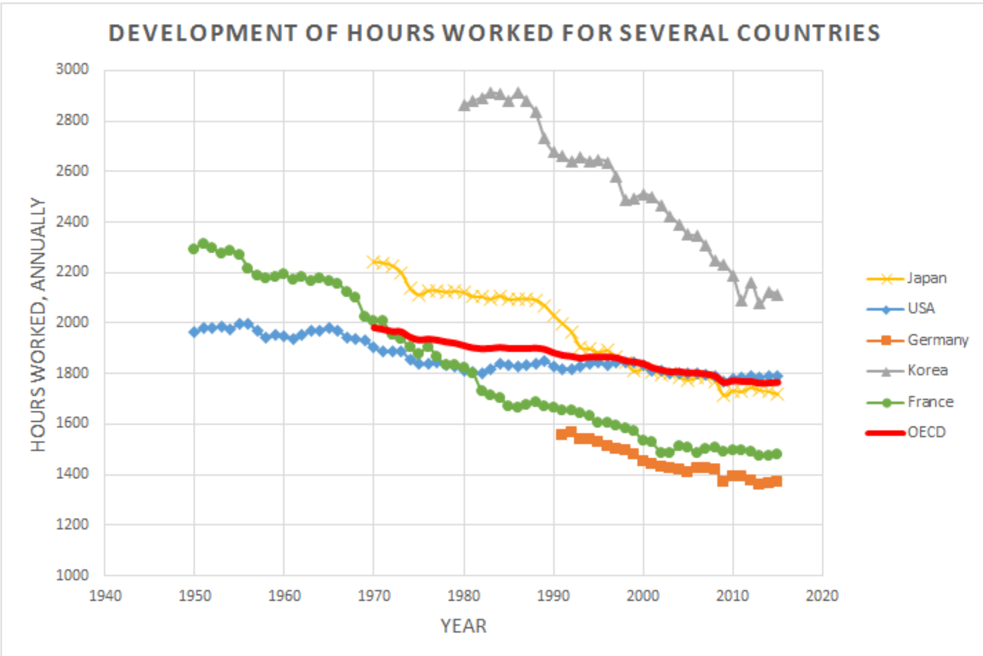

Figure 4-7. Development of hours worked, annually, for several countries (Source: OECD data, own visualization)

11.4.4 Speculative, macro-economic scenarios and the role of education

From the descriptions above, we discern three scenarios on the effects of labor-substituting robotics and AI on the total employment, see Figure 4-4.

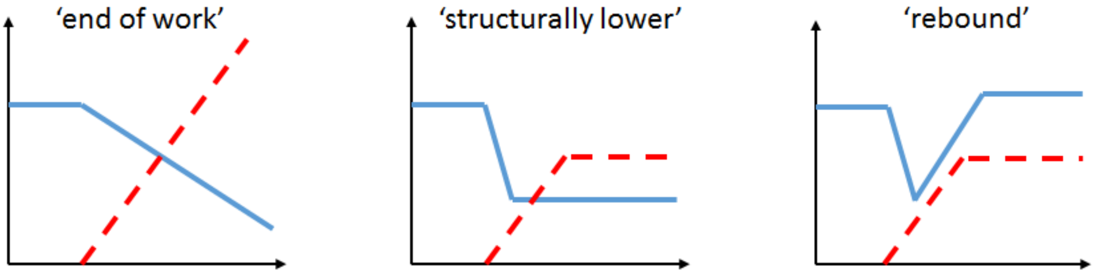

Figure 4-8. Three scenarios on effects on employment (Y-axis) of labor-substituting robotics and AI over time (X-axis). employment/ labor share: Blue, continuous line; capital share: red, dashed line. Own visualization.

Firstly, there is the 'end of work' scenario. In this case, robotics and AI will become so advanced that any jobs, *including those created in new sectors*, are soon taken over by technology again. We will end up in this scenario if the rate at which humans can be reeducated and retrained for employment is lower than the rate of technological advancement. Moreover, it requires that the job destroying potential of technology through substitution outpaces the job creating potential of technology through complementarities (cf. MacCrory *et al.*, 2014).

Secondly, in the 'structurally lower' scenario, some jobs are destroyed by robots definitely, but (a proportional part of the) displaced employees can be reeducated to find job in other and possibly newly created sectors. One argument in favor of this scenario is that technological advances in new sectors stifle if education cannot foresee the necessary skilled workers. As such, education in fact moderates the pace of technological progress. Note that the 'structurally lower' levels of employment may also be because the number of hours worked per week may further decline.

Thirdly, in the 'rebound' scenario, after a shock due to the introduction of labor-substituting technology, the level of unemployment returns to a 'regular' rate of frictional unemployment. Just like in the 'structurally lower' scenario, education moderates the pace of technological progress, but employees can catch up faster than technology can progress.

Note that also a 'structural transformation' with the rise of a range of quaternary sectors (which may contain sectors revolving around creativity and knowledge-intensive work, sectors focusing on self-realization, personal development, entertainment & leisure, etc.) would allow for a rebound by offering opportunities at a rate higher than the rate at which people become unemployed can reap.

Several questions following from these scenarios which are not yet conclusively answered in literature are:

1. Does displacement outpace the rate at which new jobs are created both in existing as well as new sectors? Hence, will we see a growing, declining, and/or a structurally lower employment level or rather a temporary dip? Or, is the rate at which new opportunities arrive higher than the rate at which people become available to reap these opportunities (e.g. through reeducation).
2. Given the acceleration of technological change, can education keep up the pace of 'upskilling' displaced workers and thus accommodate the structural change? (cf. Goldin & Katz, 2007).

11.5 Real wages, income development, and inequality

Empirical evidence indicates that there is stagnation in the median wages and an increase in income inequality (cf. Frey and Osborne, 2017). There is a strong relationship between (i) (the gap between supply and) demand for people with particular skills (i.e. ability to perform particular tasks), (ii) the value that these employees add in terms of market value of the output, and (iii) the wages employers are willing to pay. Given that robotics and AI will reduce the demand for labor performing particular routinized tasks, we expect a decrease in their wages, yet an increase in the demand for labor performing complementary tasks. Moreover, there is an increasing demand for labor in existing developing, producing, supplying and supporting (and even spillover receiving) sectors, and hence expected increases in wages. Moreover, this particularly holds for newly emerging sectors related to robotics and AI, even new sectors applying these technologies.

Here, we discuss two major developments in the distribution of income. Firstly, so called 'decoupling', which is caused in part by increasing competition for both high-skilled as well as low-skilled jobs. Secondly, an increasing income inequality, caused by (i) polarization in sectors of application, but also (ii) by an increasing demand for and the creation of new high-skilled jobs with strong complementarities to the technologies both in existing and newly created sectors.

11.5.1 Decoupling of labor productivity and wages/ income

The introduction of technology in the workplace drives an increase in labor productivity. The productivity increase may be particularly in the jobs with strong complementarities with the technology introduced, effectively increasing the demand and wages for such jobs (cf. Autor, Katz & Kearney, 2006). Moreover, both the jobs creating and developing the technology in question, but also the jobs in which the new technology is applied are (increasingly) in high demand and well-paid (cf. Bessen, 2016). However, this is not what is observed in practice. Although the labor productivity increases, the wages are falling behind and the gap is growing, see Figure 5-1 (cf. Bivens et al., 2014; Fleck, Glaser & Sprague, 2011). Arguably, with the substitution of capital for labor, the capital share increases, such that, capital owners' income increases relative to labor income (Brynjolffson & McAfee, 2011; Frey & Osborne, 2015). Indeed, ever since the 1980s, there is a global decline in the labor share of income, which is largely attributed to computerization and substitution of labor with capital (cf. Karabarbounis & Neiman, 2013). With the labor share declining and the capital share increasing, it is expected that the compensation for labor decreases (Fleck, Glaser & Sprague, 2011). As such, the adoption of labor-substituting capital causes a 'decoupling' of the increase in productivity and employees' wages (Brynjolfsson & McAfee, 2011; Bivens *et al.*, 2014). Consequently, capital owners exploit technology to appropriate more of the generated economic value at lower costs.

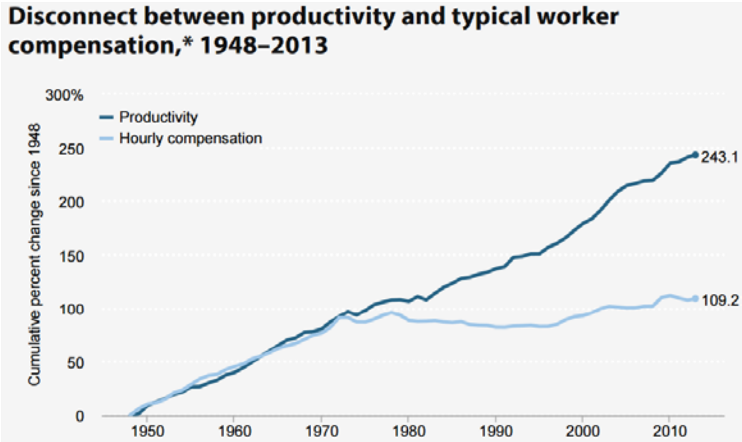

Figure 5-9. Disconnect between productivity and typical worker compensation. Source: Bivens et al., 2014.

11.5.2 Polarization and labor market competition causes decoupling?

Here, we provide a detailed, yet speculative account of how and why the introduction of labor-substitution capital causes the decoupling. We point to three distinct mechanisms at work in the *sector of application* which increase the competition for jobs that are not substituted and thus diminish an increase in wages proportional to the increase in productivity.

Firstly, computerization and robotization will replace low- and medium-skilled workers with jobs composed of routinized, predictable tasks. A drop in wages is to be expected for the jobs at risk of being replaced. Whenever a job in a sector of application can be perfectly replaced with a robot or AI, the demand for employees will fall to a level at which the competitive wages for these employees equal the expenses for the robot or AI replacing them. Indeed, empirically, job polarization reflects in a secular decline of middle-income jobs (Autor & Dorn, 2013; Goos, Manning & Salomons, 2009).

Secondly, in part, the displaced medium-skilled workers relatively easily 'down-skill' to compete for lower skilled jobs (that is, those less susceptible to computerization or robotization). The crowding over these jobs drives down the bargain power of (potential) employees and thereby the wages the (potential) employer is willing to pay. It must be said, though, that many of the jobs at the low-skill end do require a vocational training and substantial amount of working experience (think for instance of carpentry in the construction sector, hairdressing in the personal care sector, etc).

Thirdly, the introduction of technology may well complement higher skilled jobs with clear complementarities, thus increase the productivity and the wages employers are willing to pay for employees with particular skills. However, part of the medium-skilled worker will try to 'up-skill' through education, and hence increase competition for high skilled work as well, thus diminishing the rise in wages.

So, although the polarization in the skills reflects in U-shaped wages (Autor & Dorn, 2013), the increasing competition for the higher skilled jobs and, particularly, the lower skilled work will diminish any increase in the compensation for the higher productivity. As a consequence, the competition on the labor market caused by polarization may cause decoupling.

11.5.3 Structural change as additional source of growing income inequality?

Substitution may very well not only cause decoupling, but also the emergence of a U-shape in wages (see Autor & Dorn, 2013) and thereby the observed income inequality. However, structural change is another potential source of growing income inequality. With the emergence of new technologies and associated market opportunities, jobs with high complementarities to the new technology will be in demand, which will–in expectation- cause a steep increase in the wages of these jobs. This is true for jobs in the sectors of application as discussed before.

Given that, with increased robotization and computerization, employment in (readily existing as well as new) sectors in which the robotics and AI technology are developed & produced, supported or supplied is actually expected to increase. With labor in these sector being in high demand, we expect an increase in the wages accordingly. With the median wages in the sectors of application stagnating and those in the sectors of development, production, supply, etc. increasing, there is progressive income inequality.

As such, technological change is expected to drive income inequality both within the sector of application as well as across sectors during structural change.

11.6 Mitigation and policy interventions

The stagnation in wages, decreasing labor share, increasing income inequality, and considerable uncertainty about the future of employment jeopardize social cohesion (see, for instance, Leontief, 1983). Several policy interventions have been proposed both in popular media by captains of industry and by scholars in political economic literature. Here, we discuss three types of policy interventions and ways to mitigate negative effects of the adoption of robotics and artificial intelligence:

- "prevent introduction": forbid, regulate, or tax implementation of robotics;
- "counter the adverse effects" of substitution: interventions to reduce the income disparity, to counter the adverse effects of substitution, and curb the adoption;
- "enhance dynamic efficiency of the structural transition": iron out techno-frictional unemployment, stimulate the creation of new ventures, and ensure inclusion of the (low-skilled) unemployed by facilitating/ stimulating upgrading skills.

Jack Ma of Alibaba warned for the negative consequence of AI and basically called upon mankind to have AI (and robots) do only what humans cannot. This type of regulation is basically a policy of the first sort. The first one is generally quite inconceivable in an open, capitalist economy and not discussed here. Several of the instruments presented below concern the other two type, but will have multi-faceted effects.

11.6.1 Counter adverse effects

As discussed in length, the introduction of robots and AI is expected to cause income inequality and unemployment, particularly in the sector of application. However, there are various instruments to counter these adverse effects.

Some advocate the implementation of a system to redistribute income. Elon Musk (PayPal, Tesla, SpaceX, etc.), argues that if robotization indeed replaces millions of jobs, a system of wealth distribution such as the 'universal basic income' may be required. "*A basic income is an income paid by a political community to all its members on an individual basis, without means test or work requirement*" (Van Parijs, 2004). There are numerous open issues related to the sourcing and the effects (e.g. on growth, inflation rates).

Alternatively, given that part of the inequality is due to ownership, one could tax material capital. Bill Gates (Microsoft) advocated introducing a 'robot tax' to assist those that got unemployed due to automation and robotization. Note that the 'bit tax' with similar ideas (see Soete & Kamp, 1996) never made it. An additional effect is that such a 'robot tax' would lower the return on investment, and thereby reduce the substitution and unemployment.

11.6.2 Enhance dynamic efficiency

Despite several industrial revolutions, the level of unemployment has been surprisingly low over time. In a process of structural transitions, emerging sectors 'mopped up' unemployment in old sectors (Pasinetti, 1981). Central in our sectoral perspective on economic implications of the introduction of robotics and AI is already that new sectors are expected to spawn. This concerns both new sectors furthering the focal technology, but also new sectors in which the technology is applied, and new sectors supporting the technological change.

Rather than reducing the substitution in the sectors being roboticized and automatized or alleviating those being replaced, the structural transition of the economy could be facilitated by educating the employees being substituted in the existing sectors to find a job in the new sectors emerging. This has strong ties with the Danish concept of 'flexicurity'. As discussed before, those made unemployed are medium- and low-skilled workers mostly doing routinized work at relatively low wages. The employees thus replaced generally lack the skills required for jobs in the newly created sectors. The European Commission (2007) argues that an integrated mix of policy measures is required to close such a skill gap. Central in this is that the poorly-skilled unemployed receive adequate training to facilitate sustainable, upward mobility. In addition to that, contractual arrangements are to be put in place to entice and encourage employers to hire low-skilled employees.

In addition to that, countries may seek stimulate the education system to develop a labor force with skills which computers, robots, and AI will complement rather than substitute. OECD data reveals a substantial percentage of adults in OECD countries still have no or insufficient experience in using computers, while only a small percentage has the 'highest level' of ICT skills (see Figure 6-1).

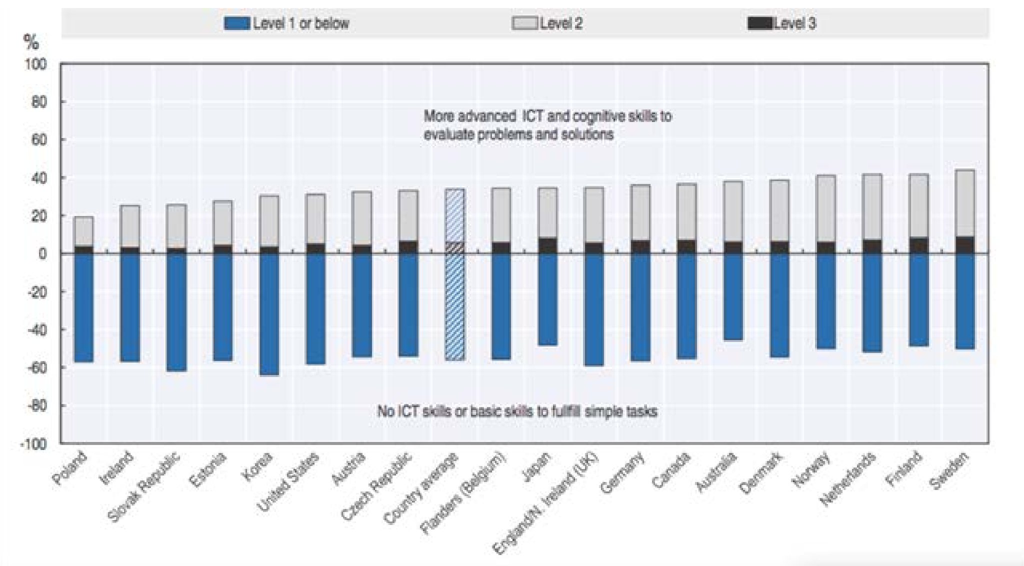

Figure 6-10. Level of proficiency in problem solving at country level. Source: OECD, 2014

We contend that, to further enhance the dynamic efficiency of the structural transition, entrepreneurial activities should be encouraged as this will enhance the creation and exploitation of opportunities in existing sectors and (formation of) new sectors. Fortunately, a study commissioned by the European Commission revealed a similar insight by policy makers and, in addition, shows that there are substantial opportunities for entrepreneurs (Forge *et al.*, 2010).

11.6.3 Conclusions and outlook

This report lays down findings from a broad review of academic and consulting literature on the economic impact of robotics and AI. As for any literature review, it is not possible to give a short conclusion while doing justice to all the details of the intellectual discourse. Here, we present a highly condensed summary of our review along the lines of the three questions posed in the introduction.

Firstly, robots and AI may well substitute and complement employment within the same sector of application (Goldin & Katz, 1998; Autor *et al.*, 2003; 2006). Technological substitution of jobs does not necessarily displace low-skilled work, but rather routinized work (Autor, Levy & Murnane, 2003). As routinized work is often executed by medium-skilled workers, this substitution effectively polarizes the labor force (with the sector of application) (Autor, Katz & Kearney, 2006; Goos, Manning & Salomons, 2009). Not surprisingly, particularly sectors dominated by jobs with routinized work in a predictable environment (and high wages) are susceptible to robotization and AI and will face polarization.

Secondly, taking a narrow 'sector of application perspective', the effect of substitution on employment may well outweigh the effect of job and task creation to exploit complementarities. However, taking a 'multisectoral perspective', there are many more conceivable sources of (new) employment. Education is to 'upskill' (within the sector of application) and training for new jobs (new sectors) employees at the rate at which they are laid off due to substitution (cf. Goldin & Katz, 2007).

Thirdly, the productivity-enhancing substitution causes decoupling of productivity and wages. We argue that this may in fact be (partly) caused by competition at both end of the skill-level continuum of the labor market due to polarization. On top of that, the labor market polarization reflects in the income distribution (Autor & Dorn, 2013). In addition, we provide an additional multisectoral explanation for growing income inequality.

In our analysis we constantly pitted the findings of academics following a narrow 'sector of application' perspective against the multisectoral, structural change perspective we tout. Although the findings following the later perspective are speculative (mostly because they hinge on potential employment and wage growth in sectors not yet existing), the outcome is much less pessimistic about the future of employment.

For the REELER project, this actually is good news, because the positive, albeit somewhat speculative conclusion is that we are heading towards a future with high levels of employment, with jobs in new sectors, with people doing meaningful rather than tedious or repetitive work. This takes away moral objections to advocate the diffusion and adoption of robots and AI. That said, there are certain instruments required to enhance the dynamic efficiency of the structural change, notably those pertaining to education and retraining workers that are laid off for new jobs (in new or existing sectors) and stimulating the creation of new sectors of various sorts.

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