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Part 1: Robotics and Employment

Consequences of Robotics and Technological Change for the Structure and Level of Employment

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Executive Summary

Recent advances in the field of digitization and robotics, such as driverless cars, largely autonomous smart factories, service robots or 3D printing, give rise to public fears that technology may substitute for labor on a grand scale. Against this background, the report reviews the existing literature on the employment effects of technological change to derive policy implications and to identify open research questions. We highlight that past technological change has mostly affected the structure of employment, but had only little or even positive effects on the level of employment. In particular, the recent computerization was associated with a declining share of routine-task-intensive middle-skill jobs, while, on net, it has led to an increase of labor demand. The scientific evidence further suggests that technological change in the foreseeable future will continue to mostly affect the structure of labor demand without necessarily changing total employment much. As we argue, the main challenge for the future of work lies in coping with rising inequality, as technological change creates both winners and losers. Policy makers should focus on the qualifications of the workers to ensure that workers' skills match future skill requirements. However, we highlight that there remain many open research questions regarding the need for policy responses, the effectiveness of alternative measures, as well as which skills will be required in the near future.

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Content

1. Introduction

Widespread fears that new technologies displace large shares of the workforce have usually not proven true in the past. Quite to the contrary, as Mokyr et al. (2015) review, technological advances in the 19th and 20th century typically created more jobs than they displaced in the first place. Nevertheless, recent advances in the field of digitization and robotics give rise to renewed fears that technology may now after all substitute for labor on a grand scale. These fears are related to the speed with which new technologies are increasingly able to perform tasks that until recently used to be genuinely human, such as reasoning, sensing and deciding. Brynjolfsson and McAfee (2014) present numerous examples for this “Second Machine Age”, such as the driverless car, the largely autonomous smart factory, service robots or 3D printing. These technologies are driven by advances in computing power, robotics and artificial intelligence and ultimately redefine what type of human capabilities machines are able to do.

Fears that these technological advances may result in a “jobless future” (c.f. Rifkin 1995; Kurz and Rieger 2013) have recently been fueled by Frey and Osborne (2013), who compute that 47 % of US jobs are at risk of becoming automated. In light of such predictions, the likely effect that continued technological progress will have on aggregate employment is at the core of political and public interest. However, while this debate highlights the labor-saving impact of new technologies, the potential of new technologies to complement human labor, as well as the underlying economic processes, often receive only little attention (c.f. Autor 2015). Workers typically adjust to changing capital endowments of firms by changing workplace tasks or by upgrading their skills, so that workers need not lose their employment as new technologies are introduced. Also, due to adaption costs, this introduction often happens slower than expected. A further aspect that is often neglected is that automation technologies allow firms to increase their productivity and to offer a larger variety of products at lower prices. As a result, demand, production and ultimately employment may rise. The aggregate effects of new technologies on employment as well as its heterogeneous impact on workers are therefore far from clear.

This report provides a literature review on the effects of technological advances in the field of automation and digitization on employment. In addition, we discuss the labor market impact of robotics as one important component of recent technological advances. Based on the existing evidence, we derive tentative policy implications for successfully managing the expected technological change, but also highlight research questions that still need to be tackled in the future.

The study is organized as follows. First, we discuss how recent technological changes affect the structure (Section 2) and level (Section 3) of employment. We then turn to potential future effects of technological change (Section 4). Finally, we derive tentative policy implications and highlight open research questions (Section 5).

2. Technological Change, Robotics and the Structure of Employment

Technological change is by no means a recent phenomenon and has affected workers for decades. At least since the industrialization, technological change has been changing the structure of tasks and occupations on the labor market. The economic literature increasingly focuses on potential effects of technological change on inequality. In a first line of research, it was argued that new technologies complement highly qualified workers. As this literature was not able to explain several empirical observations, a second line of research evolved, arguing that technological change substitutes for routine labor. Both lines of research are discussed below.

2.1. Skill-Biased Technological Change

The literature on Skill-Biased Technological Change (SBTC) hypothesizes that technological change is biased towards specific skills or qualifications. The underlying economic theory distinguishes between two skill groups: high-skilled (college graduates) and low-skilled (high school graduates). The model draws no distinction between skills and occupations (tasks) so that high-skilled workers effectively work in separate occupations (perform different tasks) compared to low-skilled workers (Acemoglu and Autor 2011, Chpt. 3.1). Initially, the technology is complementary to low-skilled workers, i.e. higher capital usage leads to an increase in demand for these workers. However, as the technology advances due to technological change, the technology increasingly complements high-skilled workers. This leads to a relative shift in labor demand from low- to high-skilled workers, thus raising the college wage premium, i.e. the wage difference between college graduates and non-college graduates. Besides the relative demand shift, technological change raises productivity, which results in higher wages for both high- and low-skilled workers. Overall, the model predicts an increasing college wage premium, higher wage inequality as well as increasing wages and productivity for both skill groups.

This rather simple model has been frequently applied to explain increasing wage inequality in the US (c.f. Katz and Murphy 1992; Acemoglu and Autor 2011, Chpt. 2.2). Relative demand for high qualified workers increased on average by roughly 3 percent per year in the 1970s and 1980s. It resulted in a decline of relative employment and relative wages for low-skilled workers, which has been documented for the US by several studies (Murphy and Welch 1992; Katz and Murphy 1992; Blackburn et al. 1989).

Machin and van Reenen (1998) document a comparable shift in relative labor demand and employment towards high-skilled workers in several OECD countries. However, the associated decline in relative wages for low-skilled workers is usually observed only in Anglo-Saxony countries but less in Continental European countries (Freeman and Katz 1994). In Germany, there was actually no increase in wage inequality in the 1980s. These differing results by countries might be explained by the stronger role of labor market institutions for wage setting in Continental Europe. Nevertheless, newer studies report an increase in wage inequality also in Germany with a lag of about one decade compared to the US (Dustmann et al. 2009; Antonczyk et al. 2010).

Several studies indicate that these trends have been caused by technological change. Firstly, the shifts towards high-skilled workers took place primarily within industries and only to a small degree due to shifts in favor of knowledge-intensive industries (c.f. Bound and Johnson 1992; Katz and Murphy 1992; Freeman and Katz 1994; Berman et al. 1994; Machin and Van Reenen 1998). Secondly, the increase in wages of high-skilled workers was associated with an increase in high-skilled employment in most industries (c.f. Katz and Murphy 1992; Lawrence and Slaughter 1993). Thirdly, the shifts towards high-skilled workers were more pronounced in industries or firms which were more strongly affected by technological change (c.f. Berndt et al. 1992; Autor et al. 1998; Machin 1996; Haskel und Heden 1999).

In this literature, technological change is typically interpreted in a very broad sense. That is, technological change in this literature not only refers to techniques and machines, but further covers the organization of production and labor markets, as well as consumer tastes (Acemoglu 2003). Hence, there exists no direct evidence on the role of robots for this period of technological change. However, robots are often treated as one example of technological change, as robots are expected to complement skilled workers (c.f. Johnson 1997), so that they likely are one of the drivers of the increasing inequality and college wage premium. Recent results by Graetz and Michaels (2015) indeed indicate that the application of robots led to an increase in labor demand for high-skilled relative to low-skilled workers, while there is no clear effect on the medium-skilled between 1993 and 2007. However, there exists no hard evidence on robots' effects on employment for earlier periods (Graetz and Michaels 2015).

In summary, the SBTC hypothesis is well able to explain some of the key observations such as the increasing relative demand for college workers during the 1970s and 1980s. However, the framework turns out to be unsatisfactory in explaining other patterns (Acemoglu and Autor 2011, ch. 3.6) such as the decline in earnings among low-skilled workers as well as the decreasing relative demand for middle class workers relative to low- and high-paid workers (job polarization). One reason is that it does no distinguish between skills and tasks (or occupations) although the composition of workers has been changing within occupations in many advanced countries. Moreover, it considers only technologies in a factor-augmenting form and neglects that new technologies such as computers and robots might substitute for or replace workers in certain occupations or tasks.

2.2. Routine-Replacing Technological Change

As the SBTC hypothesis is unable to explain the labor market trends starting in the late 1980s, Autor et al. (2003) developed a more nuanced version called Routine-Reducing Technological Change (RRTC)[2] hypothesis (see Acemoglu and Autor 2011 for a more recent version of the framework). In their approach, Autor et al. (2003) distinguish between the production factors (labor and capital) and the tasks that these factors produce, where in principle each production factor could produce each task. Based on

[2] Note that this hypothesis is sometimes labeled as Routine-Biased Technological Change (RBTC) or Task-Biased Technological Change (TBTC).

this distinction, their approach can model a continuously evolving division of tasks between capital and labor at the level of tasks and occupations. They distinguish between three main sets of tasks – manual, routine and abstract tasks (see below). The RRTC hypothesis then argues that computerization replaces routine labor inputs.

Routine tasks are tasks which follow a well-defined protocol, such that they can be codified and executed automatically based on algorithms using modern ICT. These tasks can be manual-routine or cognitive-routine. Such tasks can often be found in middle-paid jobs including bookkeeping, clerical work or production jobs. According to the RRTC hypothesis, declining costs for computers lead to a decline in relative labor demand for these medium-paid workers.

Manual non-routine tasks are tasks that require situational adaptability, visual and language recognition as well as in-person interactions. Such tasks are widespread in many low-paid service occupations including food preparation and serving jobs, cleaning and janitorial work as well as heath care and security services and can only hardly be replaced by computers.

Abstract (or cognitive non-routine) tasks involve problem-solving capabilities, intuition, creativity and persuasion that cannot be performed by computers yet and often are complementary to computers. Typical jobs in this task domain include professional, technical and managerial occupations. These jobs are particularly dominant at the top-end of the wage distribution.

The RRTC hypothesis provides three main predictions: Firstly, the declining costs for computers should be associated with a shift of workers' tasks away from routine to manual or cognitive tasks. Autor et al. (2003) show that the share of routine tasks indeed declined in the US in the 1980s and 1990s. Spitz-Oener (2006) provides comparable evidence for Germany for the 1980s and 1990s and distinguishes two dimensions of the change: Routine tasks decline within occupations as workers change tasks within their occupations (intensive margin) and routine tasks decline resulting from a declining employment share of routine-intensive occupations (extensive margin). By using detailed worker-level data, Spitz-Oener (2006) shows that the decline in routine tasks occurred at both margins, while most of the change is explained by the intensive margin. Most studies focus on the extensive margin due to the lack of individual-level task data and find comparable declines in the share of routine-intensive occupations in Anglo-Saxon Countries (Autor et al. 2006; Goos and Manning 2007), European Countries (Goos et al. 2009, 2014; Oesch and Rodríguez Menés 2011; Adermon and Gustavsson 2011) and Japan (Ikenega and Kambayashi 2010). However, these results are challenged by some authors, who criticize the classification of task-items into distinct routine/non-routine domains (Green 2012, Rohrbach-Schmidt and Tiemann 2013, Pfeiffer and Suphan 2015).[3]

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[3] Green (2012) and Pfeiffer and Suphan (2015) find the classification of task-items into the distinct domains routine and non-routine to be problematic. Autor et al. (2013, p. 1306) acknowledge that "*variable choice does matter*", although they argue that their "*results are generally robust to variable choice*". Rohrbach-Schmidt and Tiemann (2013) show that results on RRTC in Germany are sensitive to the subjective classifications.

Secondly, the RRTC hypothesis predicts a decline in the share of routine, middle-paid occupations and thus a polarization of employment, where the middle of the wage distribution is shrinking while the poles (high and low wage occupations) grow. This employment polarization has been documented in many Western economies for the 1990s (Goos and Manning 2007, Autor et al. 2006, Ikenega and Kambayashi 2010, Adermon and Gustavsson 2011, Goos et al. 2009, 2014, Oesch and Rodríguez Menés 2011, Senftleben-König and Wieland 2014, Kampelmann and Rycx 2011). In Europe, for example, the share of middle-paid workers declined by eight percentage points between 1993 and 2006 (Goos et al. 2009). While this phenomenon seems to occur in many Western economies, countries differ in terms of relative employment growth for low paid jobs. In particular, growing shares of low-paid occupations took place foremost in countries where the low-wage sector is relatively unsheltered from market pressure, such as Britain. Country-specific institutions thus seem to matter for the effects of RRTC on employment polarization (Oesch und Rodríguez Menés 2011).

Thirdly, the RRTC hypothesis can explain wage polarization, i.e. faster wage growth at the poles of the wage distribution compared to the middle of the wage distribution. Intuitively, the routine-replacing technologies push workers out of middle-paid jobs, which results in an excess-supply of these workers and hence declining wages for them. However, the technology complements the remaining middle-wage workers which raises their wages so that the net effect on wages remains ambiguous (Autor 2013). Moreover, the effect of RRTC on relative wage growth depends on the comparative advantage of the skill-groups in the different segments of the labor markets and on how the laid-off workers reallocate to these segments (Acemoglu and Autor 2011). According to Autor (2013), wage polarization therefore is a likely, but not a necessary result of RRTC. Empirically, wage polarization has been documented for the US since the 1980s (Autor et al. 2008; Autor and Dorn 2013; Firpo et al. 2011). Atkinson (2008) finds evidence of wage polarization only for some OECD countries. In Germany, the wage distribution became more unequal instead of more polarized throughout the 1980s and 1990s (Dustmann et al 2009; Antonczyk et al. 2010). Comparable results have been documented by Kampelmann and Rycx (2011) and Senftleben-König and Wieland (2014).

Compared to the SBTC hypothesis, the RRTC hypothesis relies on a narrower definition of technological change by explicitly focusing on the computerization through which machines become increasingly able to perform routine tasks. These tasks comprise both manual-routine and cognitive-routine tasks. However, in the data the decline of cognitive-routine tasks is more pronounced than the decline in the manual-routine tasks (Autor et al. 2003), indicating that computerization especially affected clerical jobs and only to a smaller degree production jobs. One explanation for this could be that routine-manual tasks had already been increasingly automated by mechanization, way before computerization. In contrast, cognitive-routine tasks, which focus on information processing, can be automated only using computer technologies (Autor et al. 2003). Thus, computerization likely marks an important change for clerical jobs and less so for production jobs. Therefore, the RRTC mostly applies to clerical jobs, while robots – at least in the 1980s and 1990s – have not been linked to this process. Instead, as noted earlier, the results by Graetz and Michaels (2015) indicate that robots were associated with a relative shift in labor demand from low- to high-skilled workers, rather than declining labor demand for middle-skilled workers, as in the RRTC hypothesis.

To conclude, the RRTC hypothesis is able to explain key labor market trends of the 1980s and 1990 and, hence, has become the dominant view of how recent technological change has changed the labor market.[4] However, it should be noted that RRTC mostly refers to clerical tasks rather than tasks that are closely related to industrial robots. Instead, the use of industrial robots in the 1990s and early 2000s has been biased in favor of high-skilled relative to low-skilled workers.

3. Technological Change, Robotics and the Level of Employment

While the SBTC and RRTC literatures have provided important contributions to understanding trends of inequality and occupational structures, they focus on relative effects. These literatures provide only little evidence on potential effects of technological change in general and of advances in robotics in particular on aggregate employment. The net effect of technological change on the level of employment depends on the relative sizes of several counteracting mechanisms. Subsequently, we first present the main mechanisms put forward by economic theory, before we provide empirical evidence on the relevance of these mechanisms.

3.1. Theoretical Background

There are several adjustment mechanisms of technological change. To understand these channels, consider the related literature on the effects of innovation on employment. This literature distinguishes between employment effects of product and process innovations (for a review see Pianta 2009 and Vivarelli 2007). Product innovations are thereby related to new products, whereas process innovations refer to new ways of producing a certain product. It is often argued that product innovations are more likely to be associated with positive employment effects than process innovations, as the former potentially generate new demand and could thus lead to rising production and employment. Process innovations, on the other hand, can lead to declining employment as they often reduce the required labor inputs per unit of output. Technological change can be viewed as product innovations for those firms that develop and produce these technologies. In these firms, employment might increase when other firms buy more of these technologies.

Mechanism 1 – Direct labor-creating effect:
Technological change can raise employment in the firms that develop or produce new technologies.

Firms typically use these new technologies as process innovations, aiming at raising the efficiency of production. The rising efficiency due to these process innovations can reduce labor input per unit of output, which would lead to a labor-saving effect.

[4] Some authors oppose this view; see e.g. Mishel et al. (2013) for a critique.

Mechanism 2 - Direct labor-saving effect:
Technological change initially reduces employment in firms that introduce new technologies to reduce their production costs.

However, this does not necessarily imply declining aggregate labor demand. Process innovations raise productivity and competitiveness, which generates new demand and thus can raise production and employment. Whether the latter effect is strong enough to partly, fully or even over-compensate the labor-saving effects of new technologies thus crucially depends on the elasticity of product demand (Appelbaum and Schettkat 1993, 1994; Blien and Sanner 2014).

Mechanism 3 – Productivity-induced labor-enhancing effect:
Labor-saving technologies can reduce costs and prices, inducing higher demand, output and employment.

In addition, the expansion of production is associated with an increase in income (wages, profits, capital-income), which will be (partly) spent on the products and services also in sectors that are not directly affected by the new technologies. These demand spillovers can therefore generate positive employment effects also in other sectors of the economy (c.f. Gregory et al. 2016).

Mechanism 4 – Income-induced labor-enhancing effect:
Technological change can generate new income that induces higher demand, production and employment, also in sectors that are not directly affected by the new technologies.

Moreover, in a competitive labor market, a decline in aggregate labor demand due to technological change would depress wages. This would raise the attractiveness of labor as an input factor, which would partly counteract a declining aggregate labor demand. Furthermore, low wages as a result of an excess supply of labor would reduce incentives to develop labor-saving technologies in the first place.[5]

Mechanism 5 – Wage-induced labor-enhancing effect:
In a competitive labor market, wage adjustments partially counteract employment effects of technological change.

3.2. Empirical Evidence

Whether technological change positively or negatively affects aggregate employment is ultimately an empirical question. In the following section, we discuss studies that focus on aggregate employment effects and/or the underlying transmission channels. We distinguish between studies on the firm-, sectoral and regional level.

3.2.1. Firm-Level Evidence

At the firm level, empirical studies often find positive correlations not only between product innovations and employment, but also between process innovations and

[5] For example, Acemoglu (2010) shows that labor scarcity encourages labor-saving innovations.

employment. The latter evidence speaks in favor of both Mechanisms 1 and 3. Further evidence suggests that innovative firms typically grow faster and generate more employment, independent of other firm characteristics (see Chennells and Van Reenen (1999), Pianta (2009) or Vivarelli (2007) for surveys). Smolny (1998, 2002) provides corresponding evidence for Germany. In contrast, Jäger et al. (2015) look at the impact of robots in seven European countries and find no significant correlation between robot use and employment growth at the firm level.[6] Overall, the studies suggest a positive effect of technological progress on firm-level employment, although the use of robotics might be less labor-enhancing.

A main drawback of many firm-level studies is that the correlations cannot be interpreted in a causal way, as the causality might be reversed (see Box). Instead of robots causing employment growth in firms, a positive correlation between the use of robots and employment growth could simply reflect that fast-growing firms with higher investments rates are more likely to invest in robotic technologies. For example, fast growing firms could be subject to fierce competition, forcing them to be innovative or to use new technologies (Antonelli 2001). Moreover, results at the firm level cannot be transferred to aggregate employment effects, as potentially positive employment effects for innovating firms can be more than compensated by induced employment losses in competing firms.

Box: A Note on Causality in Regression Models

The empirical studies presented here usually rely on regressions. Regressions are statistical models to measure the linear relationship between one or more explanatory variables *x* and a dependent variable *y*,

$$y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i,$$

where the β's represent the relationships between the individual explanatory variables *x* and the dependent variable *y*. The statistical model further contains an error term ε which captures remaining factors that are not included as they are either unobservable or purely random. The relationship β_1 between the explanatory variable x_1 and the dependent variable *y* is often interpreted as the *effect* of x_1 on *y.* Nevertheless, the interpretation of β_1 as a causal effect is only valid if there is no systematic correlation between the explanatory variable x_1 and the error term ε. This assumption is, however, often violated in practical work, since typically not all relevant factors can be observed, so that the error term ε likely contains factors which are both linked to the explanatory variable x_1 and the dependent variable *y*.

For example, studies that analyze the effect of robots (x_1) on employment (*y*) cannot control for all relevant other firm characteristics. It is very likely that the remaining error term ε contains unobservable factors (such as the quality of management, etc.) that both affect employment (*y*) and the number of robots (x_1). The empirically observed relationship β_1 then contains both, the effect of the quality of management on employment, as well as the effect of robots on

[6] Their study covers Austria, Denmark, France, Germany, the Netherlands, Spain and Switzerland.

employment. Therefore, β_1 cannot be interpreted as the causal effect of robots on employment.

Many scientific studies therefore rely on particular methods to identify the causal effect of the explanatory variables on the dependent variable. These studies typically exploit exogenous variation in the explanatory variables to identify the effect. Instrumental Variable approaches, for example, rely on an exogenous variable (z) that has an effect on the explanatory variable (x_1), but no credible effect on the dependent variable (y). This implies that there is no systematic relationship between the exogenous variable (z) and the error term (ε). These studies exploit only the variation of x_1 that is explained by the exogenous variable z to identify the causal effect of x_1 on y, because this part of the variation of x_1 is not systematically correlated with the error term ε. The key challenge of such studies is that exogenous variation is very difficult to find.

3.2.2. Sectoral-Level Evidence

Other studies focus on the effects of technological change on net employment at the sector level. They partly take into account the potential reallocation from less to more productive firms, as long as these take place within sectors, and thus better approximate potential macroeconomic employment effects of technological change. An important study in this respect is the one by Graetz and Michaels (2015). They show that the use of robots raised both productivity and value added at the sectoral level and had neutral effects on total hours worked, although the effects on working time differ across skill groups (see Section 2.2). The key advantage of their approach is that it allows them to interpret their findings as causal effects of robots on employment. Another study by Goos et al. (2014) also finds that the substitution of routine workers by new technologies (Mechanism 1) was partly compensated by rising product demand in the routine-intense sectors (Mechanism 3), although they focus on the effects of technological change on the employment structure, not on aggregate employment.

Besides the above studies, there exists a large and closely related literature on employment effects of innovations and new technologies at the sectoral level which documents quite heterogeneous results – see for example the surveys by Feldmann (2013), Pianta (2009) or Vivarelli (2007). A drawback of many - especially older – studies is that they often do not build on causal identification strategies or that their causal identification strategies rest on strong assumptions, so that it remains unclear whether the relationship between new technologies or innovations and employment can be interpreted in a causal way.

3.2.3. Regional-Level Evidence

Another set of studies analyzes the effects of technological change at the regional level. These studies also take into account adjustment processes between sectors, as long as these take place within regions. By viewing regions as small economies, the effects can be interpreted as macroeconomic effects. Autor and Dorn (2013) for example find that regions which had an initially strong focus on routine tasks experienced larger subsequent investments in computer capital. This led to stronger employment and wage polarizations in these regions. Simultaneously these regions were characterized by increased immigration of both low- and high-skilled workers, indicating positive net effects of computerization on aggregate employment. Senftleben-König and Wieland (2014) provide comparable results for German regions.

In a further study, Gregory et al. (2016) investigate the effects of RRTC on net employment in the European Union (EU27) between 1999 and 2010 and distinguish between different mechanisms. The authors firstly show that computerization has led to a substitution of labor by capital in the tradable sector (mostly production), thus reducing labor demand (Mechanism 2). They secondly show that routine-intensive regions became more productive and competitive as a result of lower production costs, which led to lower goods prices and higher product demand (Mechanism 3). The latter effect actually more than compensated the former effect. Thirdly, computerization raised income which was partially spent on local non-tradable goods (mostly services), inducing positive local spillover effects on employment in the non-tradable sector (Mechanism 4). Overall, they find that labor demand increased by 11.6 million jobs due to computerization between 1999 and 2010 in the EU 27, thus suggesting that the job-creating effect of RRTC overcompensated the job-destructing effect.

While regional level studies get close to nation-wide effects of technological change on employment, one can only take into account all relevant adjustment processes (reallocation of employment between firms, sectors and regions) at the national level. However, at the national level, the identification of causal effects of technological change on employment is difficult, as many other factors operate simultaneously. Studies from the 1980s and 1990s for Great Britain showed that innovations do not raise unemployment, which implies that the compensating mechanisms are strong enough (Layard und Nickell 1985; Layard et al. 1994, 2003). For nine OECD countries, Pini (1995) confirmed that the labor-creating effects are as large as the labor-saving effects of technological change.[7]

While the existing evidence suggests that past technological change had positive or neutral net employment effects, the effects seem to depend on the market environment and institutional setting. For example, in an environment of stagnating demand and international competition, process innovations tend to be associated with declining employment (Mechanism 2) (Feldmann 2013; Pianta 2009; Vivarelli 2007). In Italy, the price declines induced by innovations (Mechanism 3) were not strong enough to compensate employment losses (Vivarelli 1995). Tancioni and Simonetti (2002) argue that this was due to the low competition in Italy. Simonetti et al. (2000) show that the compensation of the labor-saving effects through wage-adjustments (Mechanism 5) are only relevant in countries with flexible labor markets and that product innovations induce positive employment effects (Mechanism 1) only in technologically leading countries. However, they find the income effect of technological change (Mechanism 4) to be relevant in all countries.

[7] These countries are Belgium, France, Italy, the Netherlands, the United Kingdom, West Germany, Canada, Japan and the United States.

Other studies highlight the relevance of the time horizon. For instance, Feldman (2013) concludes in a study on 21 industry countries[8] for the period 1985 to 2009 that innovations and technological progress do not have long-term effects on unemployment, so that the job-creating effect seems to be strong enough to compensate the labor-saving effect of technological change. However, he finds that they raise unemployment in the medium run. A potential reason for the medium-run effect on unemployment could be due to sluggish adjustments of workers to changing labor market requirements. Technological change leads to changing requirements. If technological progress accelerates and workers are unable to adjust to the changing skill requirements at the same speed, the matching of workers skills and firms' demands worsens. This results in longer search unemployment and therefore leads to higher unemployment in the medium term (Aghion and Howitt 1994). However, this depends crucially on the type of technological progress. Mortensen and Pissarides (1998) show that this effect only holds true if new technologies are implemented in new jobs whereas the old jobs are destroyed. If, instead, the new technologies are introduced by updating the existing jobs' equipment so that the workers have the chance to adjust their skills to the new requirements within their jobs, the effect is actually reversed and new technologies lead to lower unemployment.

In summary, the evidence seems to be in favor of a positive or neutral net employment effect of new technologies, although the evidence is not fully conclusive. Labor-creating effects often seem to outweigh the initially labor-saving impact of technological advances, but the impact seems to depend on the market environment, the institutional setting as well as the ability of workers to adjust their skill sets to the changing demands that are related to the introduction of new technologies.

4. Potential Future Effects of Technological Change and Robotics

Fears of new technologies replacing large numbers of jobs came up periodically in the past two centuries, but human labor did not become obsolete, so far (Autor 2015). Past technological change has had only little effects on the overall level of employment, but it affected the structure of employment, as highlighted in Sections 2 and 3. Still, recent advances in artificial intelligence and machine learning are often perceived as a potentially more disruptive dimension of technological change as these technologies allow for automating tasks that until recently seemed to be fully limited to the human domain (such as driving a car). Moreover, the domain that continues to be limited to humans appears to shrink sizably as machines are increasingly able to perform cognitive tasks such as learning. In the course of improved computing power, some authors argue that we will soon enter the "second half of the chessboard" (Brynjolfsson and McAffee 2011, 2014) or experience a "Cambrian Explosion" (Pratt 2015), where the speed of

[8] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States.

technological progress accelerates at unprecedented rates.[9] This speed, as some authors fear, could exceed the capabilities of many workers to adjust to this change, putting their jobs at risk (see e.g. Brynjolfsson and McAffee 2011, 2014; Frey and Osborne 2013).

Reliable predictions on future technological capabilities and the effect these might have on employment are challenging. In the public debate, a study by Frey and Osborne (2013) has caught widespread attention. The authors argue that as much as 47 % of US employment is “at risk” of computerization within the next 10 to 20 years. Other authors have made similar forecasts for Finland (Pajarinen and Rouvinen 2014), Germany (Brzeski and Burk 2015) or the European Union (Bowles 2014) and find similarly large numbers. A comparable study was conducted by McKinsey for the US (Chui et al. 2015). This has led to widespread fears that unemployment might significantly rise in the foreseeable future in many Western economies.

However, these figures are criticized by a recent study by Bonin et al. (2015). They argue that these studies likely exaggerate the automation potentials of these technologies as these studies focus on the automatibility of occupations. The actual task-content of jobs often differs from the occupational descriptions. The focus on occupations might therefore lead to an overestimation of job automatibility because even workers in occupations that are considered to be at high-risk of automation often still perform a substantial share of tasks that are hard to automate, such as interactive tasks. Bonin et al. (2015) therefore rely on individual-level task data and follow a task-based approach to reassess the study by Frey and Osborne (2013) and to calculate similar figures for Germany. By taking account of the full heterogeneity of tasks performed both across as well as within occupations, they find that only 9 % of US workers and only 12 % of German workers have a relatively strong focus on tasks that could be automated. These findings have been confirmed by several studies. For instance, Dengler and Matthes (2015) find that only 15 % of workers in Germany work in occupations with a relatively strong focus on potentially automatable tasks. Moreover, in a recent survey among Germany employees, only 13 % consider it somewhat or very likely that their job could be replaced by a machine within the next 10 years (Arnold et al. 2016). Finally, Arntz et al. (forthcoming) follow the approach by Bonin et al. (2015) to calculate the job automatibility for 21 OECD countries and find similar results for these countries.

Despite lower figures, the estimated share of “jobs at risk” in the spirit of Frey and Osborne (2013) should still not be equated with actual or expected employment losses from technological advances for three reasons, as highlighted by Bonin et al. (2015) and Arntz et al. (forthcoming). Firstly, the technological capabilities that are reported by Frey and Osborne (2013) are based on subjective assessments of technology experts, who tend to overstate technological possibilities (Autor 2014, 2015; Pfeiffer and Suphan 2015). Furthermore, new technologies face several economic, ethical and legal hurdles.

[9] However, note that this optimistic view of technological capabilities is opposed by other authors who, quite contrarily, argue that we are in a phase of „secular stagnation“, among others due to slow productivity growth (see for example Gordon 2015 or Eichengreen 2015).

For example, new technologies will only be implemented if there is a cost advantage compared to human labor. For many tasks, however, humans are likely to hold the comparative advantage for some time. In addition, there may be a strong preference for human labor as in the case of health care or similar tasks that slows down technological diffusion. Moreover, legal issues arise and need to be settled, such as in the case of the driverless car, before new technologies can be implemented on a large scale. Although these hurdles might be overcome at some point, they slow down the widespread and prompt implementation of new technologies.

Secondly, even if technologies enter the economy, they often change jobs rather than replacing them. In fact, most of the adjustment that occurred with the introduction of the computer happened within occupations rather than between (see Section 2.2). For example, the computerization was associated with a significant decline in routine tasks for workers, but this occurred within occupations by more than 99 %. That is, workers changed their task schedules within their occupations. Less than 1 % of the overall decline in routine tasks can be explained by shrinking employment shares of routine-intensive occupations (Spitz-Oener 2006). This highlights that workers are able to adjust to a constantly evolving division of tasks between machines and humans by increasingly taking over new tasks that are complementary to the new technologies (Autor 2013; Acemoglu and Restrepo 2015).

Thirdly, even if new technologies initially lead to declining employment in some segments of the labor market, they also create new jobs, as was discussed in Section 3. The reason is that technological advances also lead to new and cheaper products and hence trigger macroeconomic adjustment processes that counteract potential job losses.

For all these reasons, negative aggregate employment effects of the upcoming technological progress seem unlikely. This view is confirmed by several recent studies. For example, Nordhaus (2015) develops a theoretical model to derive the necessary conditions for a “singularity”, i.e. the situation where human labor becomes obsolete. He then checks whether these conditions are fulfilled using indicators for the US. His results suggest that the obsolescence of human labor is unlikely to become relevant during this century. Another study by Wolter et al. (2015) develops and calibrates a macroeconomic model to study potential responses of the German economy to an accelerated digitization, labeled “Industrie 4.0”. The results show only little effects on the level of employment, although the authors predict large shifts between occupations and industries. The main concern posed by this study is related to potentially unequal employment opportunities among workers with different occupational and educational backgrounds rather than the level of employment.

In fact, Bonin et al. (2015) and Arntz et al. (forthcoming) find that the automation potentials are very unevenly distributed among workers. It is particularly low-skilled and low-paid workers who face the largest automation potentials. This implies that these workers might face a high pressure to adjust to technological change, as they might have to upgrade their skills through training, undergo occupational retraining to switch to growing occupations or as their remuneration and employment stability might worsen. However, often these workers receive fewer further training and qualification than higher skilled workers (Albert et al. 2010, Bassanini und Ok 2004). The findings suggest that the main challenge for the future of work could lie in the structure of jobs – and in particular in potentially rising inequality – rather than in the number of jobs.

5. Implications and Open Questions

5.1. Policy Implications

Although it remains to be seen how the future of work will develop in the course of the next decades, current scientific evidence suggests that net job losses on a large scale are unlikely. Even though the upcoming technological changes will differ from previous advances in that machines and robots likely increasingly enter the sphere of cognitive abilities that used to be the exclusive domain of human labor, the mechanisms that counteract labor-saving effects of new technologies should still be in force. However, the upcoming technological advances might be more disruptive than past technological change if the speed of technological innovations and its diffusion increase, although legal and ethical hurdles will slow down this process to a certain extent.

Hence, rather than creating job losses on a large scale, the upcoming advances in the field of automation, digitization and robotic technologies will likely affect the structure of employment towards jobs and occupations where worker hold a comparative advantage over machines. Moreover, these changing demands for tasks, skills and qualifications might take place within a shorter time span compared to previous technological advances, as argued by some authors (c.f. Brynjolfsson and McAffee 2011, 2014; Pratt 2015). However, some authors oppose this optimistic view of technological capabilities and instead argue that we are in a phase of secular stagnation due to slow productivity growth (Gordon 2015, Eichengreen 2015). If the technology optimists are right and the speed of technological change increases, the flexibility of workers to adjust to these changes will be crucial to realize the potential gains from technological change and to spread these gains to individual workers.

One important means of achieving the necessary adjustments in terms of skills and qualifications is an educational and further training system that concentrates on skills and competencies that remain difficult for machines to acquire, at least in the foreseeable future. These skills might include problem-solving capabilities, creativity and communicating abilities, but there exists no hard evidence on this, so far. As in the past, educational and further training systems likely will have to adapt to these changing skill demands by redefining their curricula and offering sufficient programs for re-training and also upgrading of qualifications. In addition, workers likely will need to be flexible in updating their skills and change occupation if necessary, as in previous phases of technological change. Policies could support firms in establishing a human resource management that is dedicated to continued training and life-long learning, but also encourage individuals in their efforts to adjust to a changing demand for skills by offering incentives to updating their skills. In Sweden, for example, workers can use an unlimited educational leave to participate in training and qualification measures that entitles them to return to their pre-leave job (Schulte-Braucks 2013).

Compared to skilled and high-skilled workers, low-skilled workers will probably face even higher adjustment needs since they tend to perform a higher share of tasks that are prone to automation. Hence, extensively investing in further training and occupational re-training may be a means of ensuring the employability of these workers. Studies indeed show that training raises the employability of low-skilled workers (Sanders und de Grip 2004) and of older workers (Picchio und van Ours 2013). Despite these positive effects, low-skilled workers in the past received much less training than their skilled and high-skilled counterparts (Albert et al. 2010, Bassanini and Ok 2004). Hence, given current technological trends, policies should address potential barriers to the participation of low-skilled workers in training and qualification measures.

One reason for lower participation rates among low-skilled workers could be a higher preference for consumption and leisure, and unfavorable non-cognitive skills such as, for example, a lower openness to new experiences (Fourage et al. 2013). Moreover, the participation in training may be less attractive for low-skilled workers due to the lower wage-returns for this group. Low-skilled workers participate more often in intra-firm training measures since their career perspectives are typically better on the intra-firm labor markets compared to the external labor market (Sanders und De Grip 2004). However, intra-firm training measures typically yield lower wage returns compared to external training measures (Kuckulenz und Zwick 2003). Hence, participation rates among low-skilled workers are low although firms are often willing to invest in training their workers irrespective of workers' qualification levels (Leuven and Oosterbeek 1999, Maximiano 2011). In addition, there is evidence that firms still tend to underinvest in the training of their low-skilled workforce (Schulte-Braucks 2013).

Hence, policies could focus on raising the participation rates of low-skilled workers in training measures that improve their chances to retain their job and employability in the long run. However, if technological change increasingly raises the pressure on low-skilled workers, such policies might not suffice to overcome the barriers to training for this segment of the workforce. Public training programs could complement private efforts to create incentives to participate in training. Such active labor market programs could help workers in dealing with new technologies to ultimately develop skills that are complementary rather than substitutable to machines. Moreover, such measures could have a preventive nature, where workers participate in such programs while still working to ideally avoid job losses or occupational downward switches. Sweden has already implemented a preventive public training program that offers programs to workers that are still on the job but want to update their skills and qualifications (Schulte-Braucks 2013).

While training may ensure the employability in many cases, occupational re-training may be necessary for workers in shrinking occupations or for those unemployed and lacking the skills that are needed on the labor market. Evaluations of active labor market policies typically show that vocational training has beneficial medium and long-term effects on participants, although in the short run lock-in effects can arise (Bernhard et al. 2009; Card et al. 2010; Kluve 2013). For example, Bernhard and Kruppe (2012) show that vocational training in Germany raised the employment rate of participants by up to 13 percentage points in the medium term.

Hence, policies need to be tailored to different needs for training and occupational re-training and to the differential access of workers to such measures in order to improve the chances of all groups of workers to benefit from upcoming technological advances.

5.2. Open Research Questions

Due to the lack of studies, it remains unclear which measures are most effective in assisting workers in coping with new technologies. Further research is necessary to reliably evaluate the effects of different training and qualification measures on workers in the context of technological change. Moreover, we need to better understand the different needs for training and occupational re-training across groups of qualification as well as across different sectors. In order to provide first evidence in this direction, the ZEW and the Institute for Employment Research (IAB) are currently collecting establishment-level information on training measures, investments into new technologies and workers' task structures in Germany. This data offers the chance to examine how technological change, the adjustment of workers' task structures and training measures are related and may thus provide insights whether and how training may indeed assist workers' adjustment process to changing skill requirements.

Moreover, today there is almost no evidence on which skills will be required in the future. The existing evidence suggests that new technologies likely will raise the demand for skills which are required for developing and producing the new technologies, as well as skills that are complementary to the new technologies – such as for example creativity, interpersonal skills or problem-solving skills. But these are only very rough descriptions that hardly suffice to develop adequate training measures. More research is necessary to evaluate, which skills are required by the new technologies. In their establishment-level survey, the ZEW and IAB therefore also collect information on the required skills to draw a more detailed picture of potential future skill requirements across different types of firms.

Although negative aggregate employment effects appear unlikely as discussed above, the potential future effects of technological change remain unclear. In particular, studies need to take into account all relevant adjustment processes to draw credible scenarios. The study by Wolters et al. (2015) already provides insights into potential effects of the future digitization on the German industry. However, their macroeconomic model relies on numerous assumptions to develop a scenario of accelerated digitization. Future research should focus on alternative approaches to check the reliability of these scenarios. The ZEW, for example, currently develops a structural model to derive potential scenarios for the effects of technological change in the next one to two decades based on firms' assessments of their likely future investments into new technologies.

Finally, many studies on RRTC are based on the assumption that certain tasks are routine and can thus be replaced by machines, whereas other tasks are manual or cognitive and are therefore less likely to be automated. Afterwards, these classifications are often applied to estimate the effects of past computerization on changing task structures, occupational structures or wages. However, as noted in Section 2.2, the classification of certain tasks as routine or non-routine is arbitrary and is challenged by some researchers. Direct evidence on how new technologies actually affect task structures, occupational structures and wages, however, is rare. Future research therefore should focus on examining this link in more detail. The ZEW currently investigates recent technological change at the worker and establishment level to develop a link between investments into new technologies and the consequences for workers' task structures, occupational structures and wages.

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