Technology and Jobs in the Fourth Industrial Revolution*

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Extended Abstract

Introduction

Although the discussion on labor market consequences of automation technologies and the induced automation anxiety are not new (Mokyr et al., 2015; Autor, 2015), recent advances in the fields of robotics and artificial intelligence have revived the debate once more. According to experts, the upcoming wave of technological advances herald a fourth industrial revolution (henceforth referred to as 4.0 technologies). For producing firms, 4.0 technologies include production facilities up to Smart Factories, Cyber-Physical Systems and Internet of Things. For service providers, they include analytic tools for Big Data, Cloud Computing systems, internet platforms, shop

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systems or online marketplaces. The wave of new technologies have raised the question of whether machines and algorithms will after all make human labor obsolete (Brynjolfsson and McAfee, 2011). The debate has been fuelled by a recent series of 'future of work' studies according to which up to half of the workforce faces a high risk of automation in coming decades (Frey and Osborne, 2017). Although the economic literature suggests that these recent risk assessments may be largely overstating the automation potential (Autor, 2015; Arntz et al., 2016), so far only few studies address the aggregate labor market consequences of modern automation technologies.

According to existing studies, automation technologies replace workers in so called routine tasks. These are tasks that follow well-defined protocols, which can thus be done by algorithms and computer-controlled machines. The rise of processing power thus leads to a substitution of labor by capital in routine tasks, the so called Routine Replacing Technological Change (RRTC) hypothesis. Indeed, the share of routine tasks and routine-task intensive occupations are declining in many western economies in line with the hypothesis, see Acemoglu and Autor (2011) for a review. While most of this literature focuses on changing task- and occupational strucures, Dorn et al. (2015) find that US local labor markets specialized in routine tasks did not experience employment declines whereas Gregory et al. (2016) document even a net positive impact on labor demand of RRTC across European regions. Studies on RRTC typically rely on the initial routine task intensity of occupations, industries or regions to estimate the effects of RRTC. This may be seen as a shortcoming, as this is only an indirect indicator of technological change.

A more recent strand of the literature focuses on the effects of robots on the labor market. Graetz and Michaels (2015) show that industrial robots had no detrimental effect on aggregate employment in developed countries. A somewhat different result has recently been put forward for the US suggesting that regions using more robots experienced a negative effect on employment (Acemoglu and Restrepo, 2017). While these studies rely on direct indicators of technological change, they focus only on a specific technology – namely robots – and thus do not capture the wider range of new automation technologies. For example, robot data mainly captures the employment effects of producing firms, thus neglecting the important role of service providers which rather use computers and algorithms instead of robots.

Moreover, most studies so far rely on occupation-, industry- or region-level data. As has been recently highlighted by Acemoglu (2017), more firm-level evidence is necessary to take into account how firms deal with these new technologies. Among the few exceptions is Cortes and Salvatori (2015) who find no employment losses in firms specialized in routine tasks. However, they rely on routine intensity measures which again only capture technological change indirectly.

Besides, up to the authors knowledge, none of the studies look at the impact of more recent 4.0 technologies on employment, although they are attributed to fundamental changes on the labor market compared to former technologies. For instance, newer technologies have been shown to be adopted faster than older ones (Comin and Hobija, 2010) providing individuals and firms with less time to adjust. Finally, the underlying mechanisms through which technology affects employment are only partly understood. Most studies focus on job destruction channels such as capital-labour substitutions and neglect beneficial channels of technology including positive product demand effects or complementarities between capital and certain task bundles.

The aim is to fill these gaps in the literature by studying the firm-level effects of new automation technologies on employment. More specifically, we provide three major contributions: Firstly, we focus on cutting-edge technologies of the fourth industrial revolution, for which many observers expect more disruptive effects compared to earlier technologies. We thus aim to study whether recent concerns of technological unemployment are justified. Secondly, we neither focus on few specific technologies (such as robots), nor do we rely on indirect indicators of technological change (as the RRTC literature typically does). Instead, we use direct measures of technological adoption from a firm-level survey that we conducted for this purpose. Thirdly, in contrast to most of the literature, we rely on firm-level data. This allows us to explore the mechanisms through which technology affects jobs. For instance, modern automation technologies may either complement or substitute workers, depending on their working area, occupation or tasks within the firm.

Approach

Our paper relies on a labor demand model that is able to explain technology adoption at the firm-level and which explains the underlying mechanisms of technology's impact on jobs. The model differentiates between job-types that differ in their task structure, and technology-types that differ in their degree of automation. The model directly links technologies to job-type specific firm labor demand, which enables us to estimate the relationship between the different technologies and job-types. Hence, we can estimate, which technologies substitute for or complement which job-types. This is in contrast to the RRTC literature, which relies on the assumption that computer-controlled machines substitute for routine tasks. Our model moreover explains the main job creation and job destruction channels arising from technology. These include capital-labour

Table 1: Work equipment by automation degree

Production equipment (p)	Electronic office and communication equipment (d)
1. manually controlled (k_1^{prod}) e.g. drilling machine, motor vehicles or X-ray machine → humans are largely involved in work process	**1. not IT-supported** ($k_1^{O\&C}$) e.g. telephones, fax and copy machines → humans are largely involved in work process
2. indirectly controlled (k_2^{prod}) e.g. CnC machines, industrial robots or process engineering systems → humans are only indirectly involved in work process	**2. IT-supported** ($k_2^{O\&C}$) e.g. computers, terminals, electronic checkout systems or CAD-systems → humans are only indirectly involved in work process
3. self-controlled (k_3^{prod}) e.g. production facilities up to Smart Factories, Cyber-Physical Systems and Internet of Things → work processes are largely performed automatically	**3. IT-integrated** ($k_3^{O\&C}$) e.g. analytic tools for Big Data, Cloud Computing systems, internet platforms such as Amazon, shop systems or Online-Markets → work processes are largely performed automatically

substitutions and complementarities across technology and job-types, as well as product demand effects. Product demand effects arise as machines allow firms to operate more cost efficient, leading to lower product prices and, hence, higher sales and firm labor demand. The model provides testable predictions for total firm labor demand as well as the underlying transmission channels. The effects, among others, depend on the substitution elasticity between job tasks as well as the elasticity of substitution between goods across firms and industries.

To empirically implement the model, we conduct a representative "IAB-ZEW Labour Market 4.0" firm survey among 2.032 producing firms and service providers in Germany. Within the survey, we ask firms about their technology investments between 2011 and 2016. Among others, we gather detailed information on firm's current, past and future work equipment (machines, computers, robots, etc) including production equipment (mostly used by producers) as well as electronic office and communication equipment (mostly used by service providers). As a major novelty, we thereby distinguish between their degree of automation (digitization) in order to identify technologies of the fourth industrial revolution (compare Table 1). We then link the survey data to employment biographies from social security records (BeH) of all workers employed in the surveyed firms. We thus establish a unique linked employer-employee panel data set among German firms in a recent period of rapid technology adaption. Among others, the data set allows us to (1) draw a first and detailed representative picture on the extent and change in modern automation technologies and to (2) relate these changes to changes in the level and structure of employment at the firm-level.

We empirically assess the impact of modern technology on total firm employment by estimating (1) worker-group specific labor demand as a function of firm's technology investments in order to derive implications on whether modern technologies substitute (or complement) certain worker groups within a firm. We define worker-groups by occupations, tasks and other risk categories. In order to explore indirect channels of technologies' impact on jobs, we then estimate (2) product demand as a function of firm's technology investments, which tells us to what extend firms' product demand profits from technology through lower product prices. In all estimates, the unique linked employer-employee panel data set allows holding constant a rich set of firm characteristics and controlling for endogenous changes in capital, wages and revenues within an instrumental variables (IV) approach.

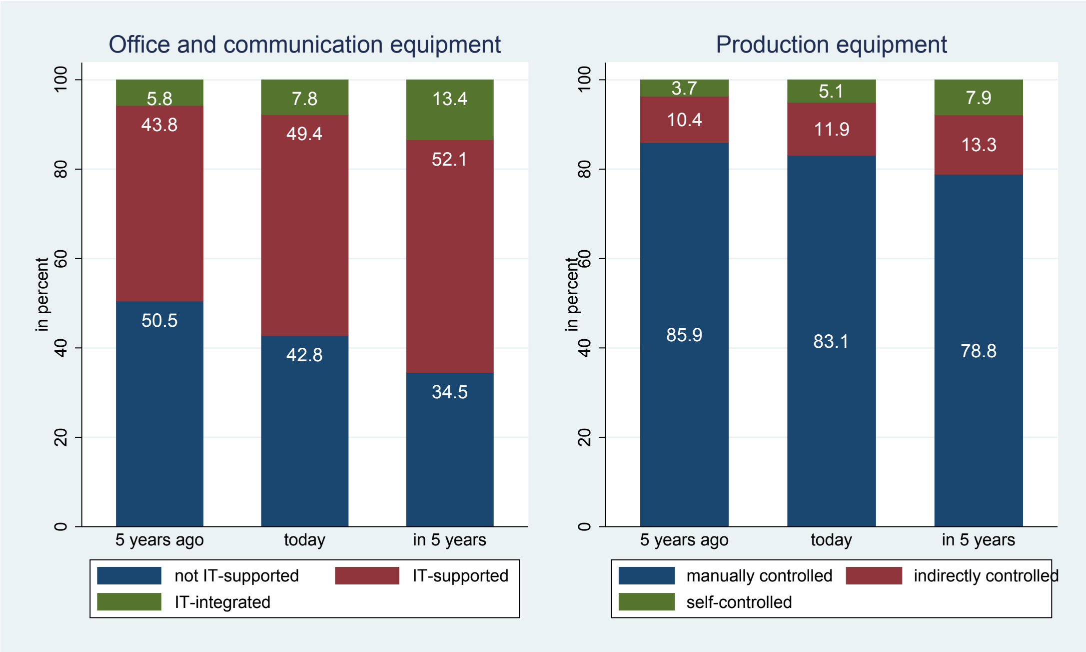
Based on the theoretical framework, we decompose aggregate firm-level employment into a part reflecting capital-labour substitutions and product demand effects. The aggregate employment effect is theoretically ambiguous and depends on the relative size of the job creation and job destruction channels. Since our labor demand and product demand estimates provide us with necessary parameters for the substitution elasticity between job tasks as well as the elasticity of substitution between goods bundles across industries, we are able to empirically quantify the relative size of the channels, i.e. relative importance of different transmission channels.

First Results

First descriptive results suggest that firms adapt new technologies only very slowly. About half of German firms use new technologies, whereas the other half does not, despite differences across firm size, industry and other firm characteristics. However, the share of self-controlled and IT-integrated work equipment that can be assigned to 4.0 technologies among all machines, computers, etc. amounts to 7.8% and 5.1%, on average (compare Figure 1). The majority of work equipment can thus be associated to indirectly controlled / IT supported or manually controlled / non IT supported work equipment, although office and communication equipment seems more automated. According to firms, the reasons for slow technological diffusion lie in the following challenges related to technology investments: (1) large expenditures for data security and cyber security, (2) larger skill demands (3) changes in education and training content (4) high investment costs and (5) stronger dependencies on external services. Despite a moderate use of 4.0 technologies, Figure 1 suggests that their relevance is increasing.

Regarding the impact of such technologies, our preliminary estimates suggest that technology investments are not associated with negative aggregate employment effects as job creation and job destruction effects seem to balance out. In particular, our labor demand estimates suggest

Figure 1: Current, past and future level of firms' work equipment by automation degree (in percent of all work tools)



that certain occupational and task groups benefit from technology, depending on the degree of automation, whereas others workers are replaced. We also find that certain task combinations are responsible for lower and higher group-specific labour demand effects from technology investments. Finally, our tentative results suggest that technology significantly affects firms' employment structure trough product demand.

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