Two sides, but not of the same coin: Digitalization, productivity and unemployment

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Abstract

Purpose: This paper aims to examine how input from the digital restructuring of the workplace and productivity affects the risk of job loss and unemployment.

Design/methodology/approach: Relying on the concepts of technological unemployment and the productivity paradox as well as the theory of skills-biased technological change, the analysis incorporated micro-level individual determinants of job loss, macro-level economic determinants of input, and the contribution from 'traditional' (machinery and equipment) vs 'innovative' (ICT) factors of production. The model has been also controlled for 'traditional' indicators of 'outsiderness' in the labour market. The Quality of Work Life Survey, which is a broad-based national interview survey produced by Statistics Finland, for 2018, the latest year available (N = 4,110) has been used in the analysis. Binomial logistic regression has been applied in order to estimate the effects of individual- and macro-level factors on the risk of job loss.

Findings: The results support arguments for the divergence between effects from labour- vs total-factor productivity on the risks of job loss, as well as the divergence between effects for temporary (layoff) vs permanent job loss (dismissal or unemployment). While the contribution from 'traditional' factors of production to labour productivity potentially decreases the risk of permanent job loss, input from 'innovative' factors of production on total-factor productivity potentially causes adverse effects (e.g. growing risks of permanent job loss).

Originality/value: The paper contributes to the theoretical discussion about technological unemployment and productivity by means of including two different concepts into a single econometric model, thus enabling examination of the research problem in an innovative way.

Keywords: Unemployment, Job loss, Productivity, Digital restructuring, Robotics

1 – Introduction

Although research on the relationship between technological change, robotics, productivity growth, and technological unemployment has now accumulated more than ever before, there are still serious scientific differences in results and gaps in the knowledge. In his recent book, the British economist Daniel Susskind (2020) discusses the relationship between technology, automation, and work. The title of his book is provocative: *A World without Work*. Susskind analyses the challenge of technological unemployment. His conclusion is that it is mostly a political issue. Technological development – digitalization and robotization – may or may not cause unemployment; what really matters is how each country responds to technological change.

Alongside the argument about technological unemployment, social scientists have highlighted the argument about the internal division of labour and the polarization of work structures. They have argued that the digitalization of work tends to polarize labour markets (e.g. Acemoglu and Autor, 2011; Eurofound, 2015) and leads to the further restructuring of labour markets (Graetz and Michaels, 2015). One of the consequences of digital restructuring lies in the assumption that a lot of the low-skilled routine jobs are in danger of being replaced by machines (Goos *et al.*, 2014). Likewise, the replacement of middle-skilled workers due to digitalization and robotization has also been observed in the egalitarian Nordic countries, including Finland (Asplund *et al.*, 2011).

In this article, we ask firstly whether digital restructuring increases polarization in workplaces in terms of the risks of unemployment. We ask if technological innovations at work can be considered features of growing unemployment risks that affect mainly low-skilled workers in routine jobs and fixed-term workers, while high-skilled workers in non-routine jobs and those in permanent jobs are in a better position to protect their employment from external risks. Secondly, we ask whether the growth of productivity and input from technological innovations causes changes in the risks of unemployment. We hypothesize that polarization tends to strengthen because of technological innovations at work and divergence between two kinds of productivity (labour vs total-factor) as well as divergence between inputs from 'traditional' (equipment) vs 'innovative' (ICT) factors in production. Finally, we ask whether the impact of industrial division is a crucial factor for the risk of unemployment. We expect that the threat of technological unemployment is a result of the inability of specific industries – e.g. services and agriculture – to keep pace with technological change.

2 – Theoretical background

2.1. – The relationship between technology and productivity

Since the 1970s and 1980s, the economies of many countries have gone through a massive technological transformation. Economists have used the term 'productivity paradox' to describe the situation in which productivity growth has slowed due to rapid technological development in production. For example, Brynjolfsson (1993) has highlighted the negative correlations between the development of information technology and IT capital productivity (information worker productivity) in a variety of manufacturing and service industries. Syverson (2013) found a slowdown in labour productivity from 3.1 % sustained over 1995–2004 to 1.6 % sustained over 2004–2012 due to the implementation of ICT.

Despite massive and growing investments in ICT, there was a slowdown in labour productivity growth in the 1990s to 1–2% in several developed countries (Dewan and Kraemer, 1998). In most European countries, productivity growth slowed down after the mid-1990s (Gordon, 2000). In the USA, productivity has grown faster than in the EU because of greater employment in the ICT sector and faster productivity growth in services using ICT intensively (Van Ark *et al.*, 2003).

Van Ark *et al.* (2008) have argued that the difference between the USA and Europe exists mainly due to the slower growth of the knowledge economy in Europe compared to the United States.

Computerization does not automatically increase productivity by itself, but it is an essential component of a broader system of organizational changes that do increase productivity (cf. Brynjolfsson and Hitt, 1998). Technology is only one component in ICT investment. There are usually also large expenditures on training, process redesign, and other organizational changes accompanying systems investments. Highly productive ways of working decentralize organizational decision-making and problem-solving and thus increase employee commitment. A link between high-involvement work systems (HIWSs) and productive performance is universal, direct, one-way, and unambiguous in respect to other possible outcomes (Edwards and Wright, 2001).

The 'productivity paradox' is a sustainable argument when explaining decreasing productivity. However, many studies have supported the argument that technological development contributes to productivity growth. First, Engelbrecht and Xayavong (2006) have found growth in labour productivity due to technological development in ICT-intensive industries. Li and Wu (2019) have noted that the value added in ICT-intensive sectors grows faster in regions with a faster development of intangible capital. Finally, the effect of ICT technologies seems to be strongly dependent on the sector-specific production processes involved, e.g. energy and electricity (Bernstein and Madlener, 2010).

Increasing labour productivity is caused by ICT, R&D, and new machinery. There is research evidence that positive environmental factors have a great impact in transforming R&D investments into innovation performance. R&D intensity has a positive effect on growth opportunities (e.g. it generates an increase in firm value, and all dimensions of founder human capital increase the R&D intensity of new technology ventures) (Savrul and Incekara, 2015). Machinery has a great effect on labour productivity (Lannelongue *et al.*, 2017). According to Chinese experiences, R&D investments have an impact on the growth of total-factor productivity (TFP). R&D can promote growth in regional TFP by helping to absorb new technologies embodied in foreign trade. The promotion of financial agglomeration and R&D input have a positive impact on the growth of enterprises (Zhang *et al.*, 2019).

To conclude, as Weitzman (1998) has argued, the ultimate limits to growth may lie not so much in abilities to generate new ideas, but in abilities to process to fruition an ever-increasing abundance of potentially fruitful ideas. This view is also shared by Brynjolfsson and McAfee (2014), who state that growth is not over, it is just being held back by the inability to process all the new ideas fast enough. Although there is much more to be said about the productivity of an economy, considering the recent digital innovations related to ICT technologies that should have enabled higher productivity growth rates, it seems that so far the productivity benefits related to ICT technologies have not been realized in full.

2.2. – What drives technological unemployment?

The poor performance of labour markets in economically advanced European countries appears to be associated with technological unemployment, as many economists have proposed. Nearly a century ago, John Maynard Keynes (1933) argued that technological unemployment is possible when technological progress is so rapid that the skills of the labour force cannot meet the new requirements, and organizations and institutions are not able to keep pace with technological change. As Brynjolfsson and McAfee (2011) have argued, the pace of technological innovation is still increasing as more sophisticated software technologies continue disrupting labour markets by making workers redundant. However, the exponential speed of technological progress highlights the difficulty of making predictions about technological progress.

Increasing job and skill polarization has generated new research on the relationship between job content and increasing computerization (e.g. Autor *et al.*, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013). The studies propose that computers are more substitutable for human labour in both manual and analytic routine tasks. They have also documented a structural shift in the labour market, with workers reallocating their labour supply from middle-income manufacturing to low-income service occupations, i.e. to occupations that are less susceptible to computerization. Frey and Osborne (2013) have noted that around 47 per cent of total US employment is in the high-risk category, i.e. jobs in service occupations and routine tasks, low-skill and low-wage occupations that are highly susceptible to computerization. Pajarinen and Rouvinen (2014) have found that due to the differences in occupational structure, the impact of computerization is around ten percentage points less in Finland than in the US. In particular, the highly skilled and better paid occupations are in the low risk category. On the contrary, a decline in employment is seen in routine intensive occupations.

The original theory of skills-biased technological change (Katz and Murphy, 1992) indicated that the educational system might be of high importance in responding to technological innovations. As argued by Card and DiNardo (2002) and Goldin and Katz (2008), a new labour market segment has the potential to develop dynamically and expand to cover a wider range of services. The skills-based technological change has resulted in an increased wage premium for high-skilled workers, aggregating wage inequality between high- and low-skilled workers in the developed western countries with different institutional settings (e.g. Goos *et al.*, 2009; Michaels *et al.*, 2014). This is what we may call the race between education and technology. On the other hand, the difference in employment shares and relative earnings tended to increase between the low- and high-skilled jobs across developed countries, which led to a phenomenon called job polarization (Goldin and Katz, 2008; Autor *et al.*, 2008).

2.3. – Does productivity drive unemployment?

The extent to which changes in productivity drive unemployment risks has been widely discussed in the scientific literature. W. Arthur Lewis (1954) distinguished already in the 1950s the difference between the ‘capitalist’ and ‘subsistence’ sectors when he analysed the problems of distribution, accumulation, and growth. The expansion of even relatively low-wage, labour-intensive manufacturing raised average labour productivity and earnings. Fields (2004), one of the critics of the Lewis’s model, stated that Lewis’s version of labour market dualism remains a path-breaking analytical starting point for current economies. However, Lewis’s welfare economics focused primarily on growth, paying only limited attention to inequality and poverty, and contemporary analysis should place much more emphasis on the poverty-reduction effects of Lewis-type economic development than Lewis did himself.

Ranis (2004), another critic of Lewis, has argued that the most serious disadvantage of Lewis’ model is the notion that ‘labour surplus’ was interpreted as the zero marginal productivity of agricultural labour in the subsistence sector, while the withdrawal of a large portion of the agricultural population did not potentially lead to a decline in agricultural output. Therefore, any withdrawal of labour from agriculture is likely to be accompanied by a reorganization of production by those who are left behind, i.e. technological change. Lewis thought of the labour surplus in terms of human beings rather than man-hours, and his labour surplus was really defined in terms of an excess supply of labour at the going rate in agriculture, which might be quite low, even if not zero.

Already two hundred years ago, David Ricardo (1821) asked whether technical progress may create employment or increase unemployment in the short term. In the 1960s, the prominent economist Arthur Okun (1962) analysed the effect of unemployment on productivity. He stated that for every 1% increase in the unemployment rate, GDP will be roughly an additional 2% lower than its potential. When estimating the relevance of Okun’s law, Ball *et al.* (2013) found that each of the latest three US recessions was followed by a ‘jobless recovery’ in which unemployment did not fall as much as Okun’s law predicted. Another notion is that the coefficient in the relationship – the effect of a one per cent change in output on the unemployment rate – varies substantially across countries. This variation is partly explained by idiosyncratic features of national labour markets, but it is not related to differences in employment protection legislation. This relationship broke down during the Great Recession of 2008–2009, when there was little correlation across countries between the changes in output and unemployment (Supporting a Balanced Global Recovery, 2010). It seems that Okun's law is consistent with traditional macro models in which shifts in aggregate demand cause short-term fluctuations in unemployment. At this point, Okun's evidence is not consistent with other theories of unemployment, such as those based on sectoral shocks or extensions of unemployment benefits.

In the frame of a long tradition in macroeconomics dating back to Okun (1962), Gordon (1995) argued that while structural shocks may initially create a positive trade-off between productivity and unemployment, they set in motion a dynamic path of adjustment involving capital accumulation or decumulation that in principle can eliminate the trade-off. Gordon (1995) found that the convergence between productivity and unemployment is explained by more rapid capital accumulation, and that the only significant effect of higher unemployment is to cause capital accumulation to decelerate, thus reducing the growth rate of output per hour relative to multi-factor productivity.

Gordon (2010) has further argued that the tradition of regarding cyclical productivity fluctuations as a by-product of demand-driven output cycles has been almost forgotten over the past three decades as a result of the widespread adoption of the real business cycle (RBC) model, in which productivity shocks are treated as exogenous, unexplained, unrelated to aggregate demand, and the sole driver of business cycles. However, many studies still include the autonomous 'technological shock' as one cause of short-term business cycle fluctuations. As Blanchard *et al.* (1997) have argued, the discussion of the connection between productivity growth and employment is generally afflicted by deep ambivalence about the role of wide-spread technological unemployment. Gordon (2010) has shown that the cyclical responses of aggregate hours and productivity have changed sharply in the past two decades from those predicted by Okun's law. Productivity no longer exhibits procyclical fluctuations at all, rendering obsolete the modern real business cycle (RBC) literature with its unexplained exogenous procyclical productivity shocks. The ICT revolution has both increased the flexibility of labour markets and provided firms with new tools to boost productivity during economic recoveries as they continue to cut labour costs.

Most recent papers have shown different interpretations of the role of productivity on unemployment. Bräuninger and Pannenberg (2002) found clear evidence that an increase in unemployment indeed reduces the long-term level of productivity. Gallegati *et al.* (2015) have shown that the productivity-unemployment relationship is scale-dependent and changes over different time horizons. Specifically, productivity growth creates unemployment in the short and medium terms, but it creates employment in the long term. Similarly, Chen and Semmler (2018) found that in the short term, productivity growth may increase unemployment while in the long term, productivity growth and unemployment are likely to co-vary negatively.

On the other hand, Benigno *et al.* (2015) have shown that productivity growth and unemployment appear to be negatively related in the long term. Nikulin (2015) has stated that the trajectories of wage, productivity, and unemployment rate development in new EU member states vary across these countries, but the trajectories remain stable and strong. Finally, Nattrass and Seekings (2018) argue that labour productivity growth underpins rising per capita income. However, in the context of high unemployment and rising capital intensity, such a growth path is slower and negative especially for unskilled workers.

3 – Data and method

3.1. – Data

In the analysis, we used the 2018 Quality of Work Life Survey,[1] which is a broad-based national interview survey conducted by Statistics Finland. The survey has previously been conducted in 1977, 1984, 1990, 1997, 2003, 2008, and 2013. By international comparison, the data obtained with the survey form an exceptionally long time series that will soon cover 41 years of working life in Finland. The sample size of the survey has varied from 3,800 to 7,000 persons. The survey widely studies wage and salary earners' physical, mental, and social work environments and gathers data on the contents of work, labour market status, terms and conditions of employment, reconciliation between work and family life, occupational health, and factors at the work organization level. The data are collected with personal face-to-face interviews using a standardized questionnaire. We used the Quality of Work Life Survey data for the latest year available, i.e. 2018 (N = 4110). The data include new variables, which describe issues of the digitalization of work and the use of robotics at work as well as the experience of workers in terms of digitalization and robotics at work.

3.2. – Dependent variable

To construct the dependent variable, we used two variables to establish whether a respondent faces the threat of unemployment, layoff, or dismissal due to the influence of robotics at work. Firstly, in a set of questions, respondents could indicate whether they faced threats or not. We created a dummy variable indicating that someone experiences the threat of unemployment, layoff, or dismissal if that person indicated he or she is under the threat. We included only those who indicated one of the answer options for this question (yes or no) to analyse only those cases where unemployment, layoff, or dismissal is a structural characteristic of perceptions about the job. Secondly, with the aim of producing a variable about robotics (the presence of robots at work), we split the sample into two

[1] Official Statistics of Finland (OSF): Quality of work life [e-publication].
ISSN=2342-2890. Helsinki: Statistics Finland [accessed: 25.11.2019].
Access method: http://www.stat.fi/til/tyoolot/tyoolot_2018-01-04_uut_001_en.html

groups according to those workers who use robots at work and those workers who do not use robots at work.

3.3. – Independent individual-level variables

At the level of individuals, we focused on the association between the degree of outsiderness in the labour market and the threat of job loss (layoff or dismissal) and unemployment. Following the recent dualization literature, we used a risk-based measure to define insiders and outsiders (Schwander and Häusermann, 2013). We employed social class as a proxy for being at risk of unemployment, layoff, or dismissal by using the ISCO-08 classification of occupations to distinguish between occupations with high-general, low-general, and specific skills. Similar to the studies of Fleckenstein *et al.* (2011), Wiß (2015), and Chung (2018), we distinguished 'high-general-skill occupations' including managers, professionals, technicians, and associate professionals, and considered them as insiders. The group of outsiders included 'low-general-skill occupations' and 'specific skill occupations', such as clerical support, service workers, and elementary occupations.

Moreover, we controlled for 'traditional' indicators of outsiderness: working on a temporary instead of a permanent contract and working part-time instead of full-time. Similar to the studies of Gash (2008) and Inanc (2018), we distinguished between temporary and permanent work contracts. Like Hirsch (2005) and Schoukens and Barrio (2017), we distinguished between the regime of full-time (1,600 working hours per year) and part-time (all other working time arrangements) on the basis of hours worked.

We also added a series of control variables to the individual level. We included dummies for gender, marital status, and age group to control for sociodemographic characteristics. Workers were divided into the following age groups: 15–29, 30–44, 45–54, and 55–64 years. Controls for labour market factors include industry. We distinguished 15 groups of industries, using the industry of manufacturing as the leading industry of capital-intensive production (see Manufacturing as part of a vital enterprise structure, 2014) in the quality of the reference group.

Finally, a dummy was included for having routine or non-routine tasks to control for the possibility that jobs with routine tasks are at a higher risk of unemployment, layoff, or dismissal. Similar to the study of Bissessur *et al.* (2020), we distinguished between 'routine' tasks, or repetitive and mundane tasks, which are more likely to be automatable, and 'non-routine' tasks. Another dummy considered whether the work is physically demanding or not. Similar to the study of Robroek *et al.* (2013) and Sundstrup *et al.* (2018), we distinguish between physically demanding and non-demanding jobs when predicting the risk of job loss and unemployment. Summary statistics of the individual-level variables are provided in Table AI of the Appendix.

3.4. – Macro-level variables

At the macro level, to analyse variation in the extent to which changes in productivity[2] drive the risks of unemployment (Nattrass and Seekings, 2018; Chen and Semmler, 2018), we used the indicators of total-factor and labour productivity for 2017, or the latest year available, considered separately for 21 industries according to the Statistical Classification of Economic Activities in the European Community (NACE, Rev. 2, 2008). A composite indicator for productivity dynamics was created with the use of change in the value added to total-factor and labour productivity considered by industry in percentage in comparison to the previous year (2016).

To measure how capital intensity affects labour productivity, we included three different variables. Similar to the studies of Engelbrecht and Xayavong (2006), Li and Wu (2019), Bernstein and Madlener (2010), we estimated the influence of technologies on labour productivity by means of the contribution of ICT capital intensity. In line with the study of Savrul and Incekara (2015), we

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[2] Statistics: Productivity surveys [e-publication].
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Access method: http://www.stat.fi/til/ttut/tau_en.html

estimated the contribution of R&D intensity to changes in labour productivity. Based on the study of Lannelongue *et al.* (2017), we estimated the contribution of equipment and machinery capital intensity to labour productivity.

To measure how capital input affects total-factor productivity, we included three different variables. Similar to the studies of Porcher (2012) and Niebel (2018), we estimated the influence of ICT capital input on total-factor productivity. Like the study of Zhang *et al.* (2019), we estimated the contribution of R&D capital input to TFP. Summary statistics on the macro-level variables are provided in Table AII of the Appendix.

3.5. – Methods

We applied binomial logistic regression to fit a regression curve, $y = f(x)$, when y is a categorical variable. The categorical variable y, is binary, meaning that it can assume the value 1 (risks exist) or 0 (risks are absent). We used the *logit* command in STATA 12.0 to fit a binomial logistic regression model and estimate the effects of individual- and macro-level factors on the risk of unemployment, layoff, and dismissal. In the first step, we analysed the effects of the individual-level variables in the model considered separately for individuals using robotics at work and for individuals not using robotics at work. Next, we added macro-level effects to analyse whether changes in contribution to productivity can explain variation in the risks of unemployment, layoff, and dismissal.

4 – Results

4.1. – Descriptive results

When studying the measure of association between individual-level variables and the risk of unemployment, layoff, and dismissal (presented in the Table I), we found that a better association exists between the industry variable and risk of unemployment (Cramer's V = 0.1163, p=0.000), risk of layoff (Cramer's V = 0.1591, p=0.000) and risk of dismissal (Cramer's V = 0.1097, p=0.000).

Figure 1 shows the proportions of the study population who experience the risk of unemployment, layoff, or dismissal by industry. As regard the risk of unemployment, the percentages range widely from 11.6% in public administration and social security up to 25.4% in household service activities and other service activities. The average across the industries is 18.5%. On the other hand, as regards the risk of layoff, the percentages range widely from 3.8% in public administration and social security up to 22.5% in agriculture, forestry and fishing, mining and quarrying. The average across industries is 14.1%. Finally, as regards the risk of dismissal, the percentages range widely from 9.4% in public administration and social security up to 23.4% in information and communication. The average across industries is 15.6%.

<Figure 1 about here>

Due to the factor of robotics at work, the positive association between industry and the risk of unemployment changes slightly (Cramer's V = 0.1163 for organizations without robotics at work and Cramer's V = 0.2494 for organizations with robotics at work). As regards the risk of layoff, the association with industry also changes slightly (Cramer's V = 0.1610 for organizations without robotics at work and Cramer's V = 0.2666 for organizations with robotics at work). Finally, as regards the risk of dismissal, the association with industry also changes slightly (Cramer's V = 0.1078 for organizations without robotics at work and Cramer's V = 0.2525 for organizations with robotics at work).

4.2. – Regression models

4.2.1. – Micro-level determinants

Table I shows the results of the binomial logistic regression analysis. Reported are robust coefficients of determination for regression estimated in the form of odds ratios with standard errors for each covariate. The reduction in the Log pseudolikelihood in the full model (-1433.6514 and -

225.97791 for Models 1a and 1b, respectively) compared to the null model (-1601.2445 and -263.53519 for Models 1a and 1b, respectively) indicates a statistically significant improvement in the model's fit.

<Table I about here>

The results confirm our expectation that workers working on a temporary basis (temporary work contract) are at a substantially higher risk of unemployment than those with a regular work contract. The risk of unemployment seems to be higher in organizations using robotics at work in comparison to organizations not using robotics at work.

There was no statistically significant association between occupation, gender, and marital status and the risk of unemployment as regards both types of organization (practising and not practising robotics at work). In addition, part-time work positively related to a lower risk of unemployment, which contradicts claims that part-time employment produces a higher risk of unemployment. Despite part-time work being positively related to a lower risk of unemployment in organizations not practising robotics at work (Model 1a), the presence of robots at work potentially decreases this positive effect (Model 1b). Higher risks of unemployment are more common among workers who are older than 30 years and especially among 45–54-year-old workers. However, this finding concerns organizations not practising robotics at work. In those organizations where robots are present, the effect of age on the risk of unemployment is not seen (not statistically significant). We found that the risk of unemployment is lower in particular sectors in comparison to the manufacturing sector (e.g. in public administration and social security, and human health and social work activities). However, this finding concerns organizations not practising robotics at work. There were some differences between sectors and the risk of unemployment when organizations practise robotics at work. This circumstance remarkably increases the risk of unemployment in administrative and support service activities.

Table I shows that the effect of job loss initiated by organization (layoff or dismissal) is consistent with the degree of robotics usage at work. We have found evidence that those on fixed-term contracts, overall, are more likely to experience the risk of dismissal than those with a permanent contract. However, we did not find evidence that those on fixed-term contracts, overall, are more likely to experience the risk of layoff than those with a permanent contract, although workers aged 55–64 were somewhat more likely to experience the risk of layoff or dismissal due to robotics in the workplace (Table I).

4.2.2. – Macro-level determinants

As the estimates for the associations between robotics at work, occupation, and full-time vs part-time employment with the risk of unemployment were not statistically significant in the models (Table I), we continued the analysis focusing on the work contract variable and industry variable. In the next step, we introduced models for the industry variable and the work contract variable as the most important factors for the risk of unemployment. To identify the macro-level factors that explain the risk of unemployment, layoff, and dismissal, the gap between industries, and two different work contract schemes, we included the macro-level variables in the models. Each type of organization (with or without robotics at work) was examined separately as in the case of the individual-level variables (Table I). All of the other individual-level variables were kept as in Model 1a and Model 1b in Table I.

In general, the gap in the risk of unemployment between permanent and temporary work contract workers is larger in organizations without robotics at work than it is in organizations with robotics at work (Table AIII in the Appendix). This finding concerns all the models. Therefore, a temporary work contract potentially causes a higher risk of unemployment, especially in organizations without robotics at work. Basically, we found that a higher contribution of equipment and machinery capital intensity to labour productivity is associated with a lower risk of unemployment in organizations using robotics at work (Model 3c). Figure 2 shows that in the sectors of manufacturing, agriculture, and construction, the risk of unemployment is lower in organizations that practise robotics at work. However, the general tendency shows an increase in the risk of unemployment due to the contribution of equipment and machinery capital intensity to labour productivity in the majority of industries relating to services, and in cases where organizations practise robotics at work.

<Figure 2 about here>

On the other hand, we found that the contribution of ICT capital input to total-factor productivity potentially causes a higher risk of unemployment in organizations without robotics at work (Model 2d), while a more pronounced effect is found for organizations with robotics at work (Model 3d). Figure 3 shows that the described tendency is relative to all the industries (except the manufacturing and art activities sectors) when showing a higher risk of unemployment in organizations practising robotics at work.

<Figure 3 about here>

Table AIV in the Appendix reports the results of this analysis, showing the same estimates for the relevant covariates as shown in Table AIII in the Appendix, but these are considered for the risk of layoff. The factor of the industry of work contract does not have a statistically significant effect on the overall risk of layoff. We found that the contribution of ICT capital intensity to labour productivity is associated with a lower risk of layoff in organizations using robotics at work (Model 5a), while the contribution of R&D intensity to labour productivity (Model 4b) and the contribution of R&D capital input to total-factor productivity (Model 4e) are also associated with a lower risk of layoff in organizations not using robotics at work. Figure 4 shows that due to the contribution of ICT capital intensity to labour productivity, the risk of layoffs is, basically, lower in the agriculture and construction sectors in organizations practising robotics at work. However in such service sectors as transportation, accommodation, administrative activities, and art activities, the risk of layoff is higher in organizations using robotics at work.

<Figure 4 about here>

On the other hand, we found that an increase in the contribution of machinery and equipment capital input to total-factor productivity causes a higher risk of layoffs in organizations without robotics at work (Model 4f), while a more pronounced effect is found for organizations with robotics at work (Model 5f). Figure 5 shows the increase in the risk of layoffs for the sector of agriculture and for organizations practising robotics at work.

<Figure 5 about here>

Finally, we analysed the risk of dismissal (Table AV in the Appendix). We found that the factor of industry is meaningful for changes in the risk of dismissal as regards Model 6c (adjusted for the contribution of equipment and machinery capital intensity to labour productivity) and Model 6d (adjusted for the contribution of ICT capital input to total-factor productivity). In particular, the risk of dismissal is potentially lower in industries not relating to manufacturing and in organizations without robotics at work.

We also found that the gap in the risk of dismissal is higher between workers with permanent and temporary contracts in organizations without robotics at work, i.e. workers with temporary contracts have a higher risk of dismissal in comparison to workers with permanent contracts (Models 6a–6f). Finally, we found that the contribution of equipment and machinery capital intensity to labour productivity is associated with a lower risk of dismissal in organizations without robotics at work (Model 6c). This tendency is relative to all industries (except the manufacturing and agriculture sectors) when showing an increase in the risk of dismissal, especially in organizations practising robotics at work (Figure 6).

<Figure 6 about here>

On the other hand, an increase in the contribution of ICT capital input to total-factor productivity potentially causes a higher risk of dismissal in organizations without robotics at work (Model 6d). In all the industries (except manufacturing), the risk of dismissal is higher in organizations practising robotics at work (Figure 7).

<Figure 7 about here>

5 – Discussion and conclusion

In this research, we analysed the role of digital restructuring and productivity in relation to the risks of unemployment in workplaces. We found that the polarization of work contracts increases the risk of unemployment for those in 'outsider' positions. This means that old divisions take on a new shape and are deepened by the use of robots at work. This result is in the line with research on 'traditional' indicators of outsiderness, showing that temporary employment is most likely to lead to further unemployment (Gash, 2008) or to affect the subjective well-being and unemployment of spouses within households (Inanc, 2018).

We also found support for the divergence between the effects of two kinds of productivity on the risk of job loss and divergence between short-term job loss (layoff), absolute job loss (dismissal), and unemployment. The result confirms the lower risk of unemployment and dismissal due to a higher contribution of fixed capital (equipment and machinery) on labour productivity, which is in line with basic economic arguments that labour capital endowment is one of the main factors of labour productivity growth: the more fixed capital (machinery and equipment) accounts for one worker, the greater the final output is in terms of produced goods and commodities.

In the scientific literature, Bräuninger and Pannenberg (2002) have shown that the impact of unemployment on productivity growth depends heavily on the influence of human capital in the production function: an increase in unemployment indeed reduces the long-term level of productivity.

Therefore, if human capital matters, the level of labour productivity has a long-term effect on unemployment and vice versa. Relative to the study of Lannelongue *et al.* (2017), we found that in the sectors of manufacturing, agriculture, and construction, the risk of unemployment is lower if the organization practises robotics at work. However, the general tendency shows an increase in the risk of unemployment in the majority of industries relating to services and in cases where organizations practise robotics at work.

As regards the studies of Engelbrecht and Xayavong (2006) and Bernstein and Madlener (2010), who verified that the growth of labour productivity depends on technological development in more ICT-intensive industries and regions with a faster development of intangible capital, we found that a lower risk of layoff is associated with a higher input from ICT on labour productivity. According to the basic economic argument, production automation allows for increasing labour productivity. However, the final output from production automation depends on the degree of labour complexity. Until the growth of system complexity in the production requires the workers to be more qualified, the output from labour productivity for 'simple' and 'complex' labour will be different. On the contrary, the further complication of labour leads to a drop in the required skill level of workers and the creation of 'without human capital' production. Labour productivity in this case drops down to zero.

However, in the case of total-factor productivity, the input from production automation can be even more crucial for job loss and unemployment. Hypothetically, the more ICT replaces labour, the lower labour productivity turns out to be; labour productivity ceases to be a factor leading to effective production. In this, we see the idea of a fundamental elimination of labour. Similarly, as Gordon argued in 1995, a higher unemployment rate depends on higher capital accumulation as regards increasing total-factor productivity relative to reducing the growth rate of output per hour. We find support for the results of Dewan and Kraemer (1998) and Syverson (2013), who found a slowdown in labour productivity growth due to IT-related factors. As Porcher (2012) found, the regulation of ICT-capital input has a positive effect on the growth of total-factor productivity when industries are closer to the technological frontier. Niebel (2018) called into question the argument that developing countries are 'leapfrogging' through ICT and intangible capital accumulation, but he did not find positive spillovers from ICT use on total-factor productivity.

ICT as a part of fixed capital in total-factor productivity is more of a matter of fact than ICT is in labour productivity. Both in the case of machinery and equipment and ICT, expenses for maintaining production function include expenses for materials and resources, the amortization of fixed assets, and the wages of workers. When production turns out to be in crisis, expenses for labour are the first to be cut. This circumstance explains the massive withdrawal of workers from workplaces especially in times of recession.

We expected that the threat of technological unemployment would be the result of the inability of specific industries to keep pace with technological change (e.g. the service industry and agricultural sector). As Nattrass and Seekings (2018) have argued, the discourse about capital-intensive production vs labour-intensive production, or about the 'high road' vs the 'low road' to growth, presents policy-makers with a false choice, leading to an unsustainable and undesirable 'race to the bottom'. We find that due to the factor of digital restructuring at work, the risk of job loss and unemployment is higher in service sectors and lower in the manufacturing sector. Therefore, supportive arguments in the discussion about capital-intensive vs labour-intensive production are obvious: in the discourse about capital-intensive production vs labour-intensive production, or about the 'high road' vs the 'low road', capital-intensive production has advantages in lowering the risk of job loss and unemployment due to the influence of digital restructuring at work.

The topic of technological unemployment is not new in the scientific literature. However, despite the availability of various approaches to estimating what reasons drive technological unemployment, rather little research combines various aspects of this multidimensional topic into a single wide concept. In this respect, the present research fills the gap in understanding different aspects of technological unemployment as driven by job polarization (Katz and Murphy, 1992), technological advancements and their influences on productivity (Brynjolfsson, 1993), and productivity and its consequences for unemployment (Okun, 1962).

We were able to analyse the multidimensionality of the topic of technological unemployment by means of a combination of micro-level determinants and macro-level determinants in the analysis, which is peculiar to multilevel modelling analysis. In this circumstance, we see this as a strength in our research. However, our research was limited to the analysis of a single European country (Finland). In this respect, we were not able to study what impact the national context of other European countries has on the issue of technological unemployment and inclusive development. Cross-national comparative analysis of European countries would enrich our understanding of the global processes of technological unemployment because, at the present time, research in this area has been limited to the analysis of 1–3 countries. Thus, this topic needs to be developed in further studies.

An emphasis on inclusiveness as an equality of opportunities for humans and robots to co-exist in an organization and to realize job tasks jointly has a bipolar meaning for different industries as regards their belonging to either capital- or labour-intensive production. The latter often 'loses the fight' and prefers the replacement of human capital with robots. However, if inclusive growth has a long-term perspective, the rapid replacement of human intangible assets with another asset will impact the long-term strategy of social welfare development, which is based on active inclusion of human capital in labour relations. Furthermore, it will also shift the focus from productive employment and the exclusion of job polarization in society to the politics of the minimization of labour costs and the achievement of quick economic profits.

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Figures in the text

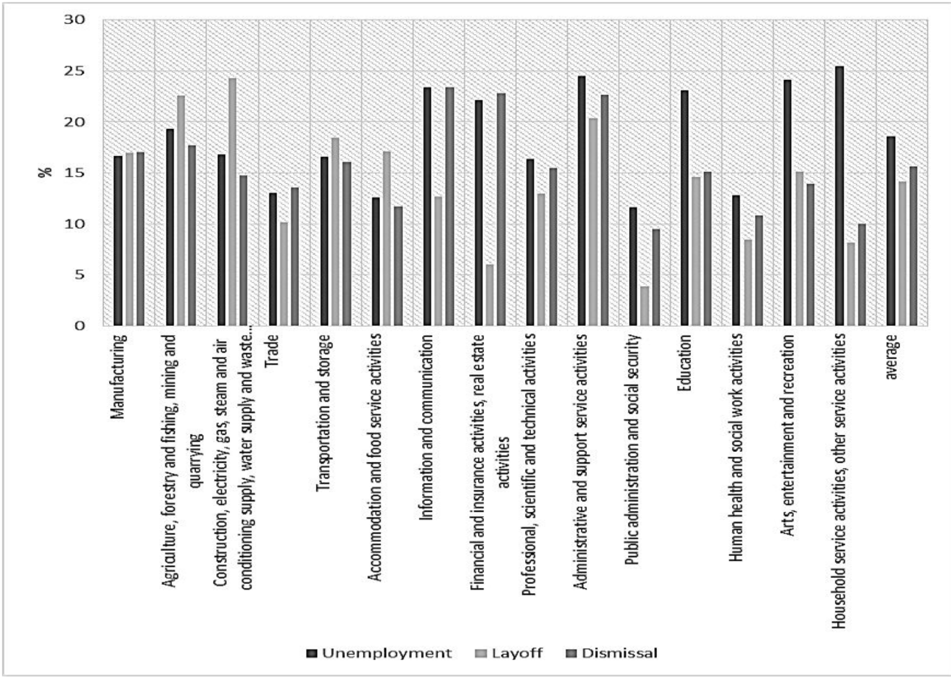

Figure 1. Proportion of the study population, who experience risks of unemployment, layoff or dismissal, per industry (N for unemployment=699, N for layoff=547, N for dismissal=611)

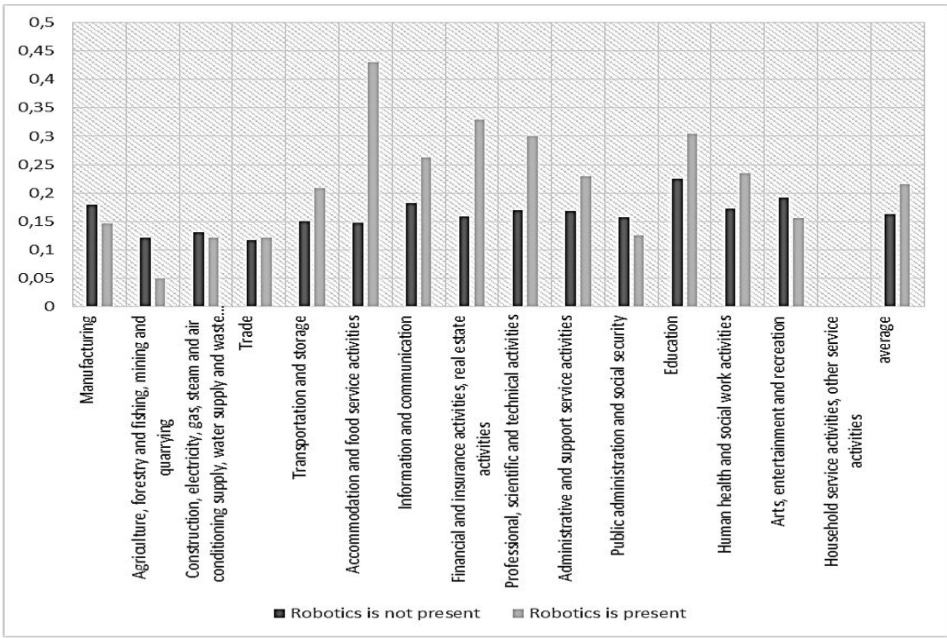

Figure 2. Predicted fitted mean values after binomial logistic regression for the threat of unemployment and contribution of equipment and machinery- capital intensity on labour productivity

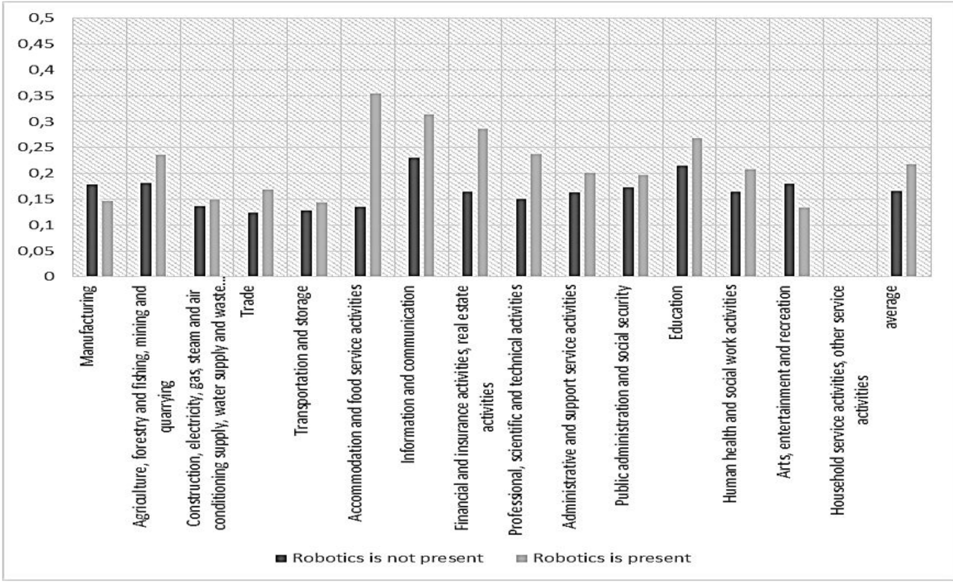

Figure 3. Predicted fitted mean values after binomial logistic regression for the threat of unemployment and contribution of ICT-capital input on total-factor productivity

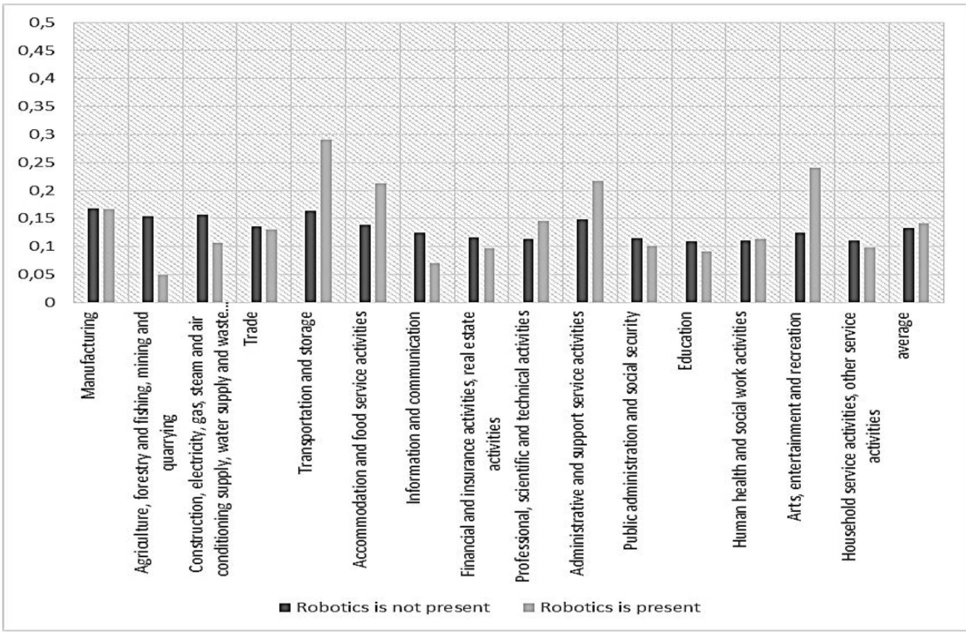

Figure 4. Predicted fitted mean values after binomial logistic regression for the threat of layoff and contribution of ICT-capital intensity on labour productivity

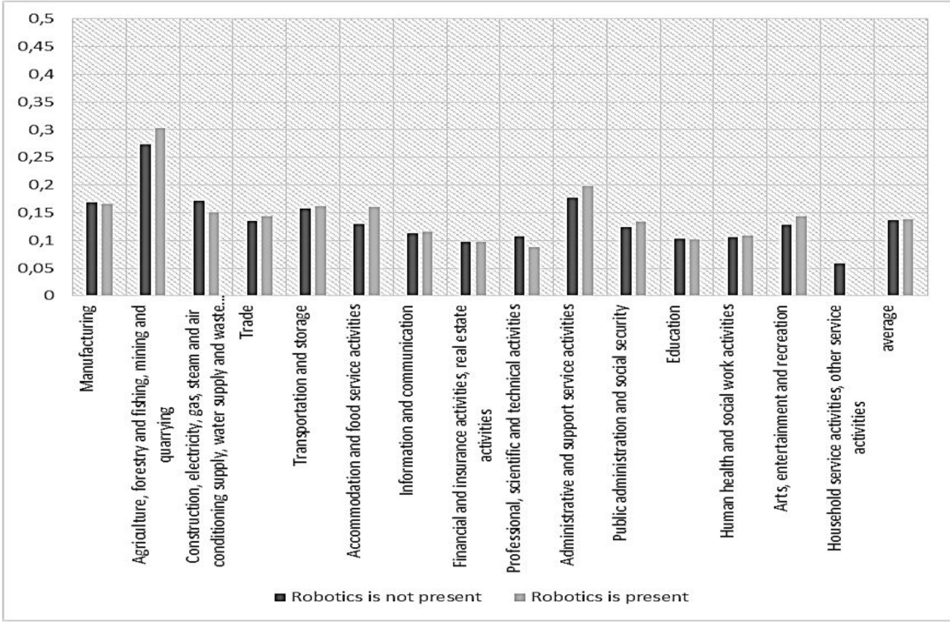

Figure 5. Predicted fitted mean values after binomial logistic regression for the threat of layoff and contribution of machinery and equipment- capital input on total-factor productivity

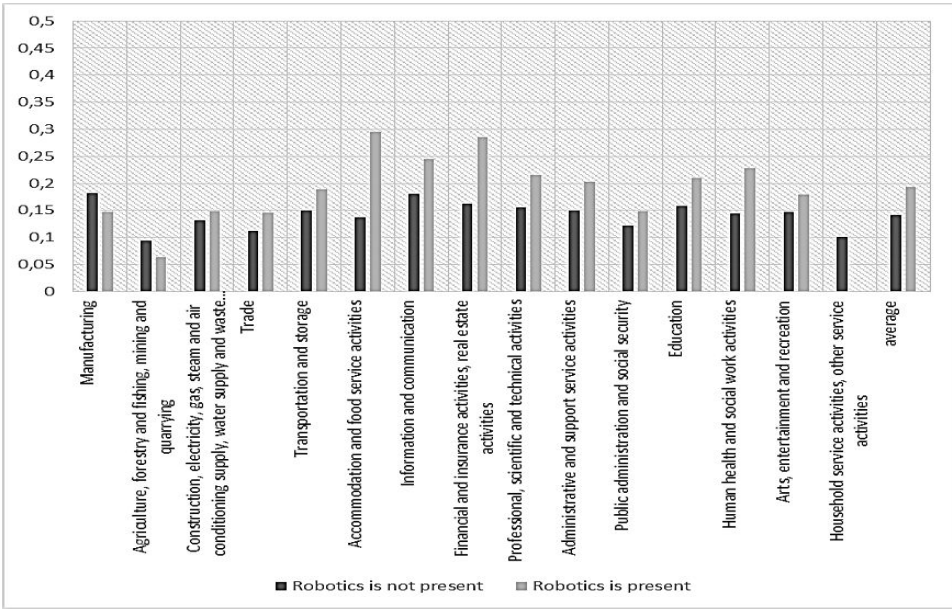

Figure 6. Predicted fitted mean values after binomial logistic regression for the threat of dismissal and contribution of equipment and machinery- capital intensity on labour productivity

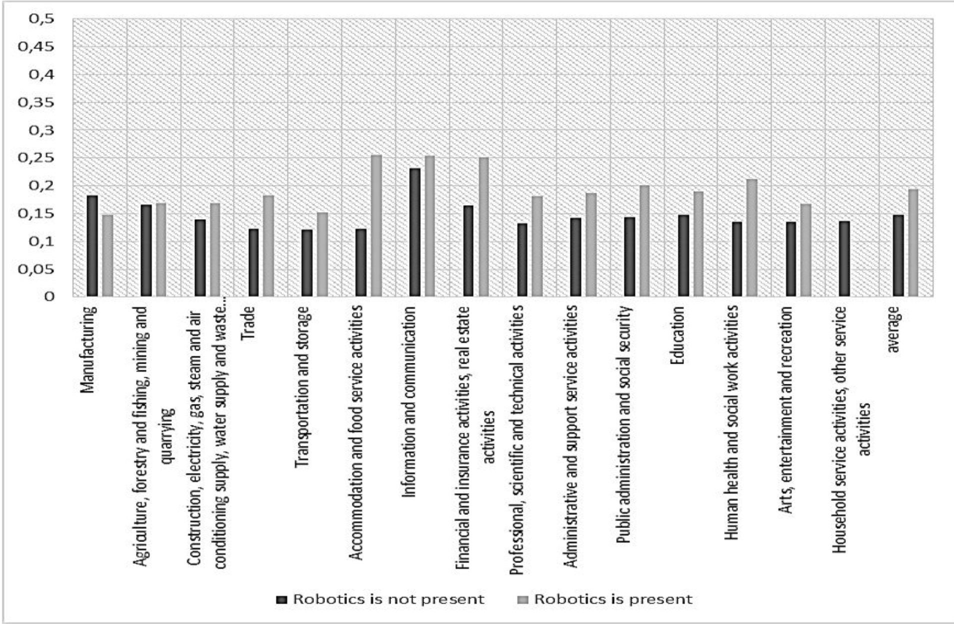

Figure 7. Predicted fitted mean values after binomial logistic regression for the threat of dismissal and ICT- capital input on total-factor productivity

Tables in the text

Table I. Binomial logistic regression models explaining the risk of unemployment, layoff and dismissal across organizations with or without usage of robotics at work

		Risk of unemployment		Risk of layoff		Risk of dismissal	
Robust regression		0 Robots are not used at	1 Robots are used at work	0 Robots are not used at work	1 Robots are used at work	0 Robots are not used at work	1 Robots are used at work
Model		1a	1b	1a	1b	1a	1b
Occupational level (ref: managers/professionals)	Low skills occupations	0.813 (0.100)	1.069 (0.370)	1.288 (0.168)	1.392 (0.496)	0.817 (0.101)	0.759 (0.270)
Contract status (ref: permanent)	Temporary contract	6.248*** (0.812)	7.344*** (2.965)	0.927 (0.168)	0.753 (0.422)	1.832*** (0.282)	2.658* (1.187)
Working hours (ref: full-time)	Part-time	0.547** (0.125)	0.984 (0.583)	1.049 (0.274)	1.245 (0.845)	1.033 (0.264)	2.639 (2.033)
Gender (ref: male)	Female	1.218 (0.135)	1.721 (0.483)	0.829 (0.101)	0.875 (0.274)	1.028 (0.121)	1.786* (0.499)
Age group (ref: 15–29)	30-44	1.802*** (0.302)	2.536 (1.230)	1.670** (0.301)	1.658 (0.847)	1.533* (0.266)	2.087 (0.975)
	45-54	2.058*** (0.364)	2.034 (1.127)	1.729** (0.318)	2.156 (1.187)	1.796*** (0.322)	2.224 (1.150)
	55-64	1.695** (0.315)	2.097 (1.268)	1.350 (0.265)	3.224* (1.776)	1.518* (0.289)	2.992* (1.647)
Marital status (ref: single or divorced)	Married	0.863 (0.095)	0.995 (0.309)	0.841 (0.097)	1.092 (0.353)	0.880 (0.099)	0.930 (0.271)
Industry (ref: manufacturing)	Agriculture, forestry and fishing, mining and quarrying	0.868 (0.372)	0.313 (0.379)	1.568 (0.579)	0.563 (0.635)	0.810 (0.329)	0.512 (0.569)
	Construction, electricity, gas, steam and air conditioning supply, water supply and waste management	0.973 (0.225)	1.807 (1.178)	1.646* (0.342)	1.679 (1.238)	0.765 (0.175)	1.566 (1.032)
	Trade	0.717 (0.164)	0.358 (0.266)	0.558* (0.129)	0.424 (0.332)	0.749 (0.161)	0.508 (0.316)
	Transportation and storage	0.899 (0.240)	1.511 (0.970)	0.862 (0.216)	1.995 (1.032)	0.777 (0.204)	2.156 (1.248)
	Accommodation and food service activities	0.517 (0.189)	1.978 (2.207)	1.112 (0.343)	-	0.577 (0.193)	-
	Information and communication	1.231 (0.307)	2.638 (1.498)	0.808 (0.221)	0.504 (0.390)	1.296 (0.303)	1.206 (0.749)
	Financial and insurance activities, real estate activities	1.091 (0.325)	2.513 (1.485)	0.338** (0.134)	0.195 (0.213)	1.132 (0.311)	2.656 (1.497)

	Professional, scientific and technical activities	0.703 (0.185)	0.578 (0.421)	0.888 (0.228)	-	0.765 (0.190)	0.972 (0.704)
	Administrative and support service activities	1.047 (0.295)	6.158*** (3.292)	0.984 (0.276)	8.138*** (5.061)	1.244 (0.340)	6.826*** (4.057)
	Public administration and social security	0.396*** (0.105)	0.956 (0.596)	0.226*** (0.090)	0.361 (0.388)	0.355*** (0.104)	1.327 (0.802)
	Education	0.724 (0.158)	0.861 (0.474)	0.957 (0.217)	1.122 (0.709)	0.622* (0.140)	0.751 (0.459)
	Human health and social work activities	0.473*** (0.096)	0.391 (0.218)	0.516** (0.109)	0.307 (0.237)	0.506*** (0.102)	0.158* (0.123)
	Arts, entertainment and recreation	1.208 (0.384)	-	1.232 (0.468)	0.541 (0.555)	0.887 (0.337)	-
	Household service activities, other service activities	1.137 (0.337)	-	0.587 (0.237)	-	0.450* (0.166)	-
Routinisation of labour (ref: non-routine)	Routine	1.081 (0.154)	1.062 (0.357)	0.934 (0.139)	1.550 (0.497)	1.002 (0.145)	1.033 (0.337)
Demanding work (ref: non-demanding)	Physically demanding	1.048 (0.127)	0.647 (0.213)	1.090 (0.138)	0.610 (0.188)	1.169 (0.143)	0.751 (0.258)
Intercept		0.211*** (0.067)	0.068*** (0.057)	0.130*** (0.044)	0.069** (0.064)	0.153*** (0.050)	0.034*** (0.033)
Log pseudolikelihood empty model		-1601.2445	-263.53519	-1367.3031	-234.73501	-1453.5383	-250.74012
Log pseudolikelihood full model		-1433.6514	-225.97791	-1290.1952	-206.99958	-1396.5731	-223.62742
N		3506	521	3506	515	3505	519

Notes: Dependent variable: risks of unemployment (0 – no, 1 – yes). Indicated are odds ratios (SE in parentheses). The models have been adjusted to sampling weights – a weighting factor that corrects for data skew to match the structure of the target population by age, gender, socio-economic status, educational level and province.
***p < .001, ** p < .01, * p < .05.

7 – Appendix

Table AI. Summary statistics of individual-level variables.

		Percentage
Usage of robotics at work	Yes	13.0%
Risk of unemployment	Yes	17.0%
Risk of layoff	Yes	13.3%
Risk of dismissal	Yes	14.9%
Occupational level	Low skills occupations	44.9%
Contract status	Temporary contract	12.2%
Working time regime	Part-time	96.2%
Gender	Female	51.9%
Age group	15-29	14.4%
	30-44	35.5%
	45-54	27.5%
	55-64	22.4%
Marital status	Married	71.7%
Industry	Manufacturing	15.5%
	Agriculture, forestry and fishing, mining and quarrying	1.5%
	Construction, electricity, gas, steam and air conditioning supply, water supply and waste management	7.1%
	Trade	10.1%
	Transportation and storage	5.1%
	Accommodation and food service activities	2.7%
	Information and communication	5.0%
	Financial and insurance activities, real estate activities	3.6%
	Professional, scientific and technical activities	5.6%
	Administrative and support service activities	3.9%

	Public administration and social security	5.6%
	Education	9.7%
	Human health and social work activities	19.3%
	Arts, entertainment and recreation	2.1%
	Household service activities, other service activities	2.6%
Routinisation of labour	Routine	16.0%
Demanding work (ref: non-demanding)	Physically demanding	30.0%
	N	4110

Table AII. Summary statistics of macro-level variables

Variable	Obs	Mean	Std. Dev.	Min	Max
LP: contribution of ICT-capital intensity	4100	0.014	0.071	-0.159	0.337
LP: contribution of R&D- intensity	3879	-0.093	0.289	-0.652	0.630
LP: contribution of equipment and machinery- capital intensity	3991	0.079	0.124	-0.297	2.193
TFP: contribution of ICT- capital input	3991	0.066	0.184	-0.135	0.770
TFP: contribution of R&D- capital input	3879	-0.134	0.393	-0.999	0.425
TFP: contribution of machinery and equipment- capital input	3991	0.163	0.201	-0.144	2.193

Table AIII. Binomial regression models explaining the risk of unemployment across organizations with or without usage of robotics at works with macro-level economic factors.

	Robots are not used at works						Robots are used at works					
Model	2a	2b	2c	2d	2e	2f	3a	3b	3c	3d	3e	3f
Individual-level variable												
Industry (ref: manufacturing)												
Other than manufacturing	0.791 (0.132)	0.887 (0.286)	0.759 (0.125)	0.744 (0.123)	0.512 (0.339)	0.796 (0.131)	1.096 (0.322)	0.751 (0.510)	0.975 (0.292)	1.008 (0.301)	0.196 (0.270)	1.160 (0.327)
Contract status (ref: permanent)												
Temporary contract	5.804*** (0.725)	5.929*** (0.779)	5.781*** (0.750)	5.946*** (0.774)	5.919*** (0.779)	5.811*** (0.751)	5.269*** (1.917)	4.955*** (1.812)	5.349*** (2.024)	5.610*** (2.077)	4.947*** (1.811)	5.169*** (1.879)
Macro-level variables												
LP: contribution of ICT-capital intensity	1.080 (0.825)						0.273 (0.547)					

LP: contribution of R&D- intensity		0.843 (0.358)						1.885 (1.706)				
LP: contribution of equipment and machinery- capital intensity			0.427 (0.197)						0.033** (0.044)			
TFP: contribution of ICT- capital input				2.133** (0.547)						4.528* (3.066)		
TFP: contribution of R&D- capital input					1.531 (0.955)						5.401 (6.938)	
TFP: contribution of machinery and equipment- capital input						1.170 (0.315)						0.821 (0.507)
Intercept	0.239*** (0.075)	0.222*** (0.094)	0.257*** (0.080)	0.226*** (0.071)	0.375 (0.256)	0.237*** (0.074)	0.083*** (0.068)	0.110* (0.098)	0.094** (0.077)	0.067*** (0.053)	0.362 (0.484)	0.076*** (0.060)
Log pseudolikelihood	-1455.0746	-1354.806	-1396.2284	-1393.6786	-1354.6329	-1398.102	-241.66872	-240.48466	-237.26234	-239.36089	-239.88041	-241.67242
N	3506	3289	3398	3398	3289	3398	531	528	530	530	528	530

Notes: Model includes all variables as in Model 1 in Table 1. Dependent variable: risks of unemployment (0 – no, 1 – yes). Macro-level variables have been mean-centered. Indicated are odds ratios (SE in parentheses). The models have been adjusted to sampling weights – a weighting factor that corrects for data skew to match the structure of the target population by age, gender, socio-economic status, educational level and province. ***p < .001, ** p < .01, * p < .05.

Table AIV. Binomial regression models explaining the risk of layoff across organizations with or without usage of robotics at works with macro-level economic factors.

	Robots are not used at works						Robots are used at works					
Model	4a	4b	4c	4d	4e	4f	5a	5b	5c	5d	5e	5f
Individual-level variable												
Industry (ref: manufacturing)												
Other than manufacturing	0.857 (0.142)	1.549 (0.439)	0.869 (0.140)	0.870 (0.141)	3.491 (2.435)	0.896 (0.144)	0.695 (0.240)	1.877 (1.044)	0.966 (0.288)	1.061 (0.310)	7.809 (12.041)	1.018 (0.294)
Contract status (ref: permanent)												
Temporary contract	0.907 (0.160)	0.863 (0.161)	0.857 (0.157)	0.857 (0.157)	0.866 (0.162)	0.860 (0.158)	0.709 (0.375)	0.705 (0.369)	0.679 (0.351)	0.668 (0.348)	0.714 (0.374)	0.662 (0.351)
Macro-level variables												
LP: contribution of ICT-capital intensity	0.980 (0.766)						0.004* (0.010)					
LP: contribution of R&D- intensity		0.401* (0.145)						0.393 (0.286)				

LP: contribution of equipment and machinery-capital intensity			1.005 (0.405)						0.381 (0.410)			
TFP: contribution of ICT- capital input				0.989 (0.284)						0.344 (0.318)		
TFP: contribution of R&D- capital input					0.251* (0.167)						0.138 (0.203)	
TFP: contribution of machinery and equipment-capital input						2.034** (0.466)						2.691* (1.313)
Intercept	0.149*** (0.051)	0.081*** (0.034)	0.156*** (0.053)	0.157*** (0.053)	0.039*** (0.029)	0.141*** (0.048)	0.117* (0.104)	0.040*** (0.036)	0.078*** (0.066)	0.074*** (0.064)	0.010** (0.016)	0.051*** (0.045)
Log pseudolikelihood	- 1323.8411	- 1229.2662	- 1290.6683	- 1290.6677	- 1229.9658	- 1286.3422	- 220.92112	- 223.50962	- 224.03022	- 223.68389	- 223.31563	- 222.82282
N	3506	3289	3398	3398	3289	3398	532	529	531	531	529	531

Notes: Model includes all variables as in Model 1 in Table 1. Dependent variable: risks of layoff (0 – no, 1 – yes). Macro-level variables have been mean-centered. Indicated are odds ratios (SE in parentheses). The models have been adjusted to sampling weights – a weighting factor that corrects for data skew to match the structure of the target population by age, gender, socio-economic status, educational level and province.
***p < .001, ** p < .01, * p < .05.

Table AV. Binomial regression models explaining the risk of dismissal across organizations with or without usage of robotics at works with macro-level economic factors.

	Robots are not used at works						Robots are used at works					
Model	6a	6b	6c	6d	6e	6f	7a	7b	7c	7d	7e	7f
Individual-level variable												
Industry (ref: manufacturing)												
Other than manufacturing	0.758 (0.120)	0.836 (0.257)	0.725* (0.114)	0.713* (0.112)	0.445 (0.274)	0.764 (0.119)	0.994 (0.302)	0.475 (0.298)	1.039 (0.309)	1.080 (0.327)	0.103 (0.135)	1.175 (0.336)
Contract status (ref: permanent)												
Temporary contract	1.681*** (0.244)	1.708*** (0.258)	1.737*** (0.258)	1.792*** (0.268)	1.704*** (0.257)	1.751*** (0.259)	1.934 (0.798)	1.951 (0.809)	1.887 (0.784)	1.949 (0.805)	1.939 (0.804)	1.890 (0.771)
Macro-level variables												
LP: contribution of ICT-capital intensity	1.164 (0.904)						0.063 (0.127)					
LP: contribution of R&D- intensity		0.881 (0.361)						3.727 (2.981)				
LP: contribution of equipment and			0.322* (0.153)						0.122 (0.149)			

machinery- capital intensity												
TFP: contribution of ICT- capital input				2.362*** (0.580)						2.105 (1.448)		
TFP: contribution of R&D- capital input					1.703 (0.989)						10.068 (12.213)	
TFP: contribution of machinery and equipment- capital input						1.059 (0.294)						1.348 (0.747)
Intercept	0.165*** (0.053)	0.166*** (0.070)	0.181*** (0.058)	0.155*** (0.050)	0.301 (0.196)	0.166*** (0.053)	0.052** (0.049)	0.082** (0.079)	0.048*** (0.044)	0.039*** (0.035)	0.324 (0.438)	0.038*** (0.034)
Log pseudolikelihood	-1415.6546	-1338.4565	-1376.3707	-1373.8113	-1338.0575	-1379.8512	-241.17186	-239.88111	-240.31181	-241.52652	-239.56628	-241.9475
N	3505	3288	3397	3397	3288	3397	531	528	530	530	528	530

Notes: Model includes all variables as in Model 1 in Table 1. Dependent variable: risks of dismissal (0 – no, 1 – yes). Macro-level variables have been mean-centered. Indicated are odds ratios (SE in parentheses). The models have been adjusted to sampling weights – a weighting factor that corrects for data skew to match the structure of the target population by age, gender, socio-economic status, educational level and province.
***p < .001, ** p < .01, * p < .05.