Skills-displacing technological change and its impact on jobs: Challenging technological alarmism?

Seamus McGuinness, ESRI, Trinity College Dublin and IZA

Konstantinos Pouliakas, Cedefop and IZA

Paul Redmond, ESRI and Trinity College Dublin

Abstract

We use data from a new international dataset - the European Skills and Jobs Survey - to create a unique measure of skills-displacing technological change (SDT), defined as technological change that may render workers' skills obsolete. We find that 16 percent of adult workers in the EU are impacted by SDT, with significant variance across countries, ranging from a high of 28 percent in Estonia, to below seven percent in Bulgaria. Despite claims that technological change contributes to the deskilling of jobs, we present evidence that SDT is associated with dynamic upskilling of workers. The paper also presents the first direct micro-evidence of the reinstatement effect of automating technology, namely a positive contribution of automation to the task content and skills complexity of the jobs of incumbent workers. Despite the recent focus on the polarising impact of automation and associated reskilling needs of lower-skilled individuals, our evidence also draws attention to the fact that SDT predominantly affects higher-skilled workers, reinforcing inequalities in upskilling opportunities within workplaces. Workers affected by SDT also experience greater job insecurity.

JEL Codes: J24 ; O33 ; O31

Keywords: technological change, automation, skills, tasks, skill mismatch, skills obsolescence

1. Introduction

Recent years have seen an upsurge in the number of studies and policy reports focusing on the impact of technological change and automation on jobs and skills and overall consequences of the so-called 4th Industrial Revolution for the future of work (Brynjolfsson and McAfee, 2014; Bessen, 2015; Ford, 2015; World Economic Forum, 2016). Much of this literature has renewed interest in an old scientific research enquiry, namely whether innovation fosters technological unemployment and adverse distributional consequences for employment and wages. Characteristic of this literature has been the resurfacing of 'technological alarmism' (Autor, 2015, Mokyr et al., 2015), namely widespread concerns of technological change, in the form of robotics and artificial intelligence (AI), taking over peoples' jobs and livelihoods.

Some recent estimates have indicated that close to a half of all jobs in the US and UK are susceptible to replacement by machines (Frey and Osborne, 2013, 2017) and that technological progress and automation is a main driver of labour market polarisation (Autor et al., 2006; Goos et al., 2009). Most academic and policy attention has focused in recent years on the need to support medium- and lower-skilled workers with appropriate reskilling policies, so as to ensure their fast reintegration back to the labour market and/or foster job mobility (World Economic Forum, 2019; McKinsey Global Institute, 2017). Even though more recent estimates of the risk of automation, adopting a task-based approach, indicate a much lower risk of full job displacement by machines (Arntz et al., 2016; Nedelkoska and Quintini, 2018, Pouliakas, 2018), they too highlight that it is predominantly lower-educated workers who are most susceptible to job and incomes losses as a result of advancing automating technologies.

The above literature has focused on the substitution or displacement effect of technology. In doing so, it has generated and sustained a 'false dichotomy' about the impact of technological progress on labour market outcomes, in both popular press and academic circles (Acemoglu and Restrepo, 2018). In particular, it has side-tracked the debate from a fuller understanding of the impact of technological change on labour and skill demand and its associated effect on labour productivity. As acknowledged and recently modelled by Acemoglu and Restrepo (ibid, 2019a), the history of automation and technological change in the 19th and 20th centuries has been one of task (re)generation, whereby the task content of production has been expanded as a result of new or a broader range of tasks emerging.

Obtaining a satisfactory understanding of the manner in which technological progress affects labour and skill demand and its impact on productivity growth is hence dependent on whether such task reengineering - a so-called *reinstatement effect* – acts as a countervailing force to the displacement effect. But even if this net effect of innovation on jobs and skills is positive, the adjustment process of an economy to the introduction of new technologies is expected to be mediated and constrained by the extent to which automation may render workers' skills obsolete; and by the degree to which a mismatch is created between the requirements of new technologies and the tasks and skills of the existing workforce.

In this paper, we use novel data from the European Skills and Jobs Survey (ESJS) (Cedefop, 2015, 2018) to study the association between technological change, the task content of jobs and the skill formation and mismatch of EU adult workers. To our knowledge, this constitutes a first attempt to obtain insight on the underlying channels of the reinstatement effect at the micro/worker level. Acemoglu and Restrepo (2019a) have adopted a multi-sectoral, macro, approach that decomposes sources of labour demand growth in the US economy during the period 1947-2017. However, their measure of changing task content – the difference between the reinstatement and displacement effects – is obtained as a residual, or via relevant proxies such as the share of new job titles or emerging tasks within occupations. The ESJS data allows us instead to obtain direct measures of the skills intensity and task complexity of jobs and to relate these to the extent to which EU workers have been recently exposed to changing technologies that may have rendered their skills obsolete. Moreover, the data permit the measurement of the extent to which changing technologies are associated with skills mismatch among affected adult workers.

After first examining the association between exposure to technological change and skill mismatch of EU workers, the paper subsequently creates an indicator of employees' susceptibility to skill obsolescence caused by technological change, which we refer to as skills-displacing technological change (SDT). We consider this measure of SDT to offer unique insight as it captures occurrences of technological progress within workplaces that can automate or replace part of individuals' human capital, in contrast to skills-neutral technology. We examine the incidence of SDT across all 28 EU countries and investigate the characteristics of workers who experience SDT. We find that 16 percent of employees in the EU are affected by SDT. However, there is considerable variation across EU countries.

We subsequently look for the presence of reinstatement effects within workplaces, namely if SDT is associated with changing task content in workers' jobs and with dynamic skills erosion or upskilling among workers. The relationship between SDT and several labour market outcomes and proxies of labour productivity, namely employees' perceived job insecurity, job satisfaction and wages, is also investigated.

In addition to providing a unique, employee's perspective on the effect of technological change on skills, our paper contributes to the nascent literature on the potential impact of automating technology on the task/skills-complexity of jobs. Our analysis provides direct support to the hypothesis that skills-displacing technological change reinforces task variety and job-skill complexity and there is some evidence that it is associated with higher wages. SDT primarily affects workers with a higher stock of human capital and tends to be accompanied by greater provision of training and workplace learning, which also manifests in a greater incidence of dynamic upskilling. Therefore, despite the focus in literature on the negative impact of automating technologies on jobs, our evidence confirms that incumbent EU employees affected by changing technologies are far more likely to experience skills enhancement as opposed to skills erosion/deskilling (Braveman, 1974).

The impact of automation on jobs and workers is however not all positive; employees subject to SDT do experience greater job insecurity. This is perhaps not surprising given the claims often made in both media and policy debates, which typically focus on job destruction and skills displacement due to innovation. As such, even employees whose skills and career development may have benefitted from technological change in the past, may still be uncertain about the future.

2. Literature Review

2.1. Technological change and labour market outcomes

Concerns about new or changing technologies potentially fostering technological unemployment and the substitution of machines for labour have featured prominently in all industrial revolutions and ages (Keynes, 1933; Mokyr et al., 2015). *Skill-biased technological change (SBTC)* was espoused, for instance, as the leading theory to explain rising wage inequality in the early 1980s in most advanced economies (Berman et al., 1998; Katz and Autor, 1999)[1]. However, it failed to account for the non-linearities in the structure of employment growth observed across some economies, most notably the hollowing out of jobs at the middle of the occupational skills spectrum and associated job polarisation. Such an empirical regularity stimulated the alternative theory of *routine-biased technological* change (RBTC), which emphasises the disruptive effects of technical change on occupations heavily reliant on routine, non-complex tasks that can be easily codifiable by robotic or algorithmic processes (Autor et al., 2006; Autor and Dorn, 2013).

Consistent with this task approach to labour economics, many studies have sought to estimate the susceptibility of jobs to automation by correlating the mix of their task characteristics with their likelihood of substitution by robotic or algorithmic processing[2]. Frey and Osborne (2013) have hence argued that 47% of occupational categories in the US labour market are at high risk of automation.[3] However, Arntz et al. (2017) and more recently Nedelkoska and Quintini (2018) and Pouliakas (2018) have dismissed such high computerisation risk figures, on the grounds that they potentially exaggerate the extent to which occupations as a whole can be automated. Once task heterogeneity and varying skill demands within occupational groups is taken into account, a high risk of automation is only evident for about 9%-14% of jobs, although about one third of all jobs face some smaller degree of task transformation[4].

Another strand of the literature has examined whether job polarisation prevails by focusing on the impact of increasing robot exposure on labour market outcomes. Acemoglu and Restrepo (2019b) estimate non-trivial negative effects of increasing robot density on the US employment/population ratio (-0.18 to 0.34% for each additional robot per 1000 workers) and worker's wages (-0.25 to 0.5%) during the 1990-2007 period. Graetz and Michaels (2018) find that while the adoption of industrial robots increased both labour productivity and value added in a sample of 17 OECD countries, it reduced hours worked primarily for low-skilled workers, with a less pronounced decline for workers

[11] This theory was supported by a number of research studies that detected a positive association between the use of computer or other proxies of technology (e.g. R&D intensity) with skills upgrading (Katz and Murphy, 1992; Krueger, 1993; Machin and van Reenen, 1998; Autor et al., 1998).

[2] Felten et al. (2018) and Brynjolfsson et al. (2018) have similarly sought to assess the impact of AI and machine learning on occupations.

[3] At risk professions are mostly middle- and low-skilled (e.g. data entry clerks, telemarketers, transportation, librarians), but they also include a wide range of service/white-collar jobs, such as accountancy, logistics, legal works, translation and technical writing.

[4] The methodology used in these papers is however fallible, as it tends to extrapolate to all workers the prediction of the estimated automatability equation from a training sub-sample; automatable occupations are identified based on expert opinion; while matching information on tasks/skills at a very detailed occupational level is subject to data constraints and measurement error. More importantly, the assessments about future automation risk are static, as they are bound by the current task-set of occupations and fail to adequately acknowledge that automation may imply changing task content in jobs.

with middle skills. Dauth et al. (2017) find no evidence of total job losses among German manufacturing workers as a result of rising robot exposure, although they detect a shifting composition in aggregate employment towards additional service sector jobs and a wage squeeze among middle-skilled workers.

Related studies have also accounted for the full equilibrium relationship between innovation and employment or skills bias, taking into account various compensatory price, scale or income effects arising from greater product - as opposed to process - innovation[5] and other externalities and spillover effects across industries and occupations (Vivarelli, 2012). These studies have demonstrated that claims of negative consequences of technology are potentially exaggerated, as technological innovation is found to be historically associated with a positive net employment premium (Van Reenen, 1997; Vivarelli, 2015; Pellegrino et al., 2017; Piva and Vivarelli, 2017)[6]. There is also no significant evidence found of technology – by crowding out middle-skill, routine jobs - being the culprit for jobless recoveries in developed countries (Graetz and Michaels, 2017).

Our paper complements a recent literature that uses individual-level data to estimate the impact of new (digital) technologies on labour market outcomes. Bessen et al. (2019) detect greater job separation rates and cumulative wage losses due to fewer annual days worked (though no effect on wage rates) among incumbent Dutch workers affected by significant automation spikes in their firm. More recently, Fossen and Sorgner (2019) have investigated the heterogeneous effects of new digital technologies on individual-level employment and wage-dynamics in the U.S labour market. They find a significant impact of high computerisation risk on individuals' labour market transitions and deceleration in wage growth, although advances in AI are likely to improve an individual's job stability and wage growth. In contrast to job polarisation studies, which have focused on the displacing impact of automating technologies for middle-level skills, the authors highlight that the effect of new digital technologies is mostly concentrated on higher educated and older workers.

2.2. Technological change, tasks and skills mismatch

While there is an abundance of empirical studies of the impact of technological advances (notably digital technologies) on economic growth, employment and wage outcomes, fewer have focused on how such links are mediated by the impact of technology on job tasks and workers' upskilling and skills mismatch[7].

Both prominent theories of SBTC or RBTC imply a positive complementarity between new technologies and a higher level of required skills, a relation that has been confirmed by numerous empirical studies (Machin and van Reenen, 1998; Bessen, 2016). RBTC theory also implies a differential demand for specific skills, namely higher demand for skills complementary to non-

[5] For example, lower prices of high-tech consumer goods and new product markets that stimulate higher aggregate demand.

[6] As noted by Vivarelli (2014), "in general, the microeconometric literature, and particularly the most recent panel data analyses, tend to support a positive link between technology and employment, especially when R&D and/or product innovation are adopted as proxies of technological change and when high-tech sectors are the focus".

[7] In addition to changing task content of production (Acemoglu and Restrepo, 2019a), other channels through which technological change may translate into higher skill demand include higher internal R&D expenditures in firms and wider organisational changes associated with the purchase and use of new technologies (Caroli and van Reenen, 2001), including smarter organisational management (Breshanan and Yin, 2016).

routine, cognitive/analytical tasks but also elementary tasks, such as problem-solving, creativity, adaptability, communication and customer service skills (Goos, 2018).

Deming (2017) has shown that soft skills, in particular, have experienced rising wage premia in labour markets in recent years. It is often argued by a wide range of policy reports and organisations (Cedefop, 2018; OECD, 2019) that the aforementioned non-cognitive and soft skills, crucial for shielding individuals against the impending threat of job substitution and displacement by machines, are in short supply in EU labour forces. It has also been reported by the World Economic Forum's *Future of Jobs* study that by 2020 more than a third of the desired core skill sets of most occupations will be comprised of skills not yet considered crucial for the job today (World Economic Forum, 2016). Skill shortages (both current and anticipated), arising because of the wedge that is driven between new skill requirements as a result of advancing digital technologies and the skills of workers (McGuinness et al., 2018), may therefore inhibit the adoption and diffusion of new technologies, especially in the high-tech sector (Bennet and McGuinness, 2009), and prolong the adjustment period of economies to a new equilibrium (Acemoglu and Restrepo, 2018)[8].

New technologies tend to magnify skill gaps as well by placing a premium on some skills while devaluing and rendering others obsolete (van Loo et al., 2001). Economic skills obsolescence, in particular, is the most relevant form for this study as it captures the impact that technological change may have on depreciating the labour market value of a worker's skillset or of a 'human capital vintage' (Jansen and Backes-Gellner, 2009; De Grip and van Loo, 2002).

Technological trends can bring about a significant change in the core curriculum content of many academic disciplines, especially in high-tech oriented fields (Neuman and Weiss, 1995), with some finding an average 'half-life' of competencies acquired during tertiary education lying somewhere in the range of 10-15 years. Allen and van der Velden (2002), for instance, estimated from a sample of Dutch graduates that almost a third of their skills obtained during tertiary education had become obsolete seven years later. Deming and Noray (2018) find that the initially high economic return to applied STEM degrees declines by more than 50 percent in the first decade of working life. Allen and De Grip (2011) and Cedefop (2012) have showed that skills obsolescence is more prominent in technologically- and learning-intensive jobs and that adult workers affected by it are more likely to participate in training, hence lowering risk of job loss.

Deming and Noray (2018) seek to explain this life cycle pattern of returns to education, by highlighting the importance of technological change in terms of introducing new job tasks and rendering other obsolete. Acemoglu and Restrepo (2018, 2019a) highlight that even though most literature has focused on the job displacement potential of automation, the impact of technological change on the changing task content of production should account for a positive *reinstatement effect* that is often neglected.[9] The authors assert that one of the major channels through which

[8] Skill mismatch is identified by Acemoglu and Restrepo (2018) as one of the main channels making the adjustment period of labour markets towards a new equilibrium, following a technological shock, slow and painful. The others include the costly reallocation and matching process of workers to new jobs, as well as excessive automation due to perverse incentives.

[9] Most papers adopting the RBTC paradigm have used broad occupational clusters as proxies of 'routine work', due to marked difficulties in measuring 'job routinisation'. This is a significant deficiency given evidence of marked variance in job tasks within them (Autor and Handel, 2013) and since inter- and intra-occupational routinisation patterns over time may diverge (Eurofound, 2016).

automation affects labour markets is via the emergence of new or reengineered tasks. Braverman (1974), by contrast, had noted several decades ago that new technologies may standardise some job tasks and hence reduce the skills gradient of technologically-exposed jobs (the deskilling hypothesis). This in turn may feed into growing levels of overskilling, dissatisfaction and cognitive decline of workers in accordance with the so-called 'use it or lose it' hypothesis (de Grip et al., 2008).

3. Data and descriptive statistics

In this paper, we use data from Cedefop's European Skills and Jobs Survey (ESJS) (Cedefop, 2015, 2018)[10] to assess the impact of technological change on various labour market outcomes, mediated via its impact on job tasks and workers' skills development and mismatch. To do so we first construct our key measure of skill-displacing technological change (SDT), which seeks to capture the extent to which EU employees are affected by technological change that may displace part of their skillset.

We define skills-displacing technological change as a situation where a worker experiences changes in the technologies used in the job over the past five years and also anticipates a high likelihood of some of his/her skills becoming outdated in the next five years. The measure of SDT is hence a combination of responses to two relevant ESJS questions. The question relating to changes in technology asks an employee – with a binary yes or no question - whether there were any "*changes to the technologies you use (e.g. machinery, ICT systems)*" in the last five years (or since the start of the job, if newly recruited). The question relating to skills becoming outdated asks an employee to rank on a scale from 0 to 10, with 0 being very unlikely and 10 being very likely, whether "*several of my skills will become outdated in the next five years*". Therefore an employee is categorised as being at risk of SDT if they answer yes to the first question and respond above 6, the value corresponding to the upper quartile of the variable distribution, in the second question.

Our approach is predicated on the reasonable assumption that not all exposure to new technologies is skills-displacing, but future obsolescence of some of workers' skills, especially technology-specific skills, is likely to be influenced by past job-related technological change (as well as future correlated technological developments). Ideally, we would prefer a single question that simultaneously relates future perceived skills obsolescence to emerging technologies, however, in the absence of such data, we believe that our measure represents a good alternative. Arguably, this is preferable to alternative approaches, based on subjective views of the exposure of occupations to future technologies, using a framework that does not account for variations in the impact of technology on different tasks and skills of workers within occupations.

We can provide some validation of our SDT measure by regressing expected skills obsolescence on the descriptor of exposure to past technological change. We find that, after controlling for a wide range of personal and job characteristics, employees in jobs impacted by technology in the past five years are more likely to expect their skills to become outdated in the next 5 years (see column 2 in Appendix Table A1). Therefore, our SDT measure appears to reflect perceived technologically-driven future skills displacement. We also regress a measure of skills mismatch obtained from the ESJS,

[10] The European skills and jobs survey (ESJS), carried out by the European Centre for the Development of Vocational Training (Cedefop) in 2014, is a unique dataset of about 49,000 EU adult paid employees, containing information on their skill formation and skill mismatches, workplace changes and other relevant demographic and socioeconomic characteristics. For further information see https://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

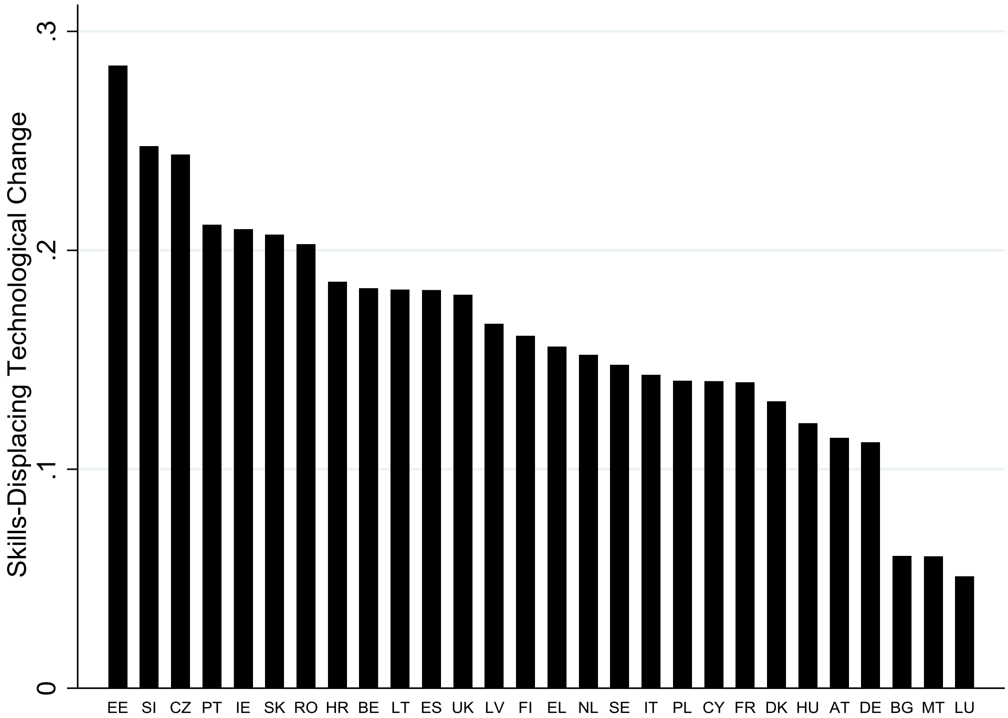
which indicates whether the employee has surplus or deficit skills for their current job, on recent changes to technology and find a positive and statistically significant impact (see column 1 in Appendix Table A1). This link between technological change and skills mismatch confirms that technology tends to initially drive a wedge between incumbent workers' skill sets and job requirements, prolonging the adjustment period before any positive impacts of technological change on job outcomes become apparent (Acemoglu and Restrepo, 2018).

The ESJS data reveal that 43% of EU adult employees experienced recent changes in the technologies they use. With respect to the obsolescence component of SDT, the data further indicates that 24 percent of adult employees in the EU labour market think that it is very likely, and 28 percent moderately likely, that several of their skills will become outdated in the next five years.[11] Approximately 36 percent of respondents working in the ICT services sector acknowledged that it is very likely to see their skills become outdated in the foreseeable future. Other sectors in which employees perceive a high risk of skills becoming outdated include financial, insurance and real estate services (27%); gas, electricity or mining services (25%); and professional, scientific or technical services (25%). The occupational breakdown suggests that perceived skill obsolescence is higher among high-skilled occupations, as opposed to occupations requiring low levels of education and high routinisation.

The incidence of SDT across the 28 EU countries is shown in Figure 1. Approximately 16 percent of EU employees are categorized as experiencing SDT, with the highest rates observed in Estonia (28%), Slovenia (25%), Czechia (24%), Portugal (21%) and Ireland (21%). Table 1 shows the occupations that are most susceptible to skills-displacing technological change and those that exhibit a relatively stable skills profile that is relatively unaffected by technology. It is evident that workers employed in ICT, health, managerial and engineering-related occupations are more likely to experience changing technologically-induced skills profiles in their jobs. On the other hand, employees in the primary sector and in elementary or personal service occupations are relatively insulated from technological innovation and do not feel their skills will become outdated in the near future. This finding runs contrary to job polarisation theory and the expert views of machine learning experts that underpin the widely cited Frey & Osborne (2013) study, namely that it is predominantly medium- or lower skilled occupations, involving routine tasks, that are (or will be) most highly exposed to the skill displacing impacts of technological change and automation.

([11]) We consider responses in the 7-10 range to indicate a very likely chance of anticipated skills obsolescence and those between 4-6 to indicate a moderately likely assessment.

Figure 1. Share of adult employees at risk of skills-displacing technological change, EU28



Notes: Ranking of countries based on incidence of SDT. Some caution is called for when interpreting the statistics for Malta, Luxembourg and Cyprus due to relatively small sample sizes of 498, 489 and 492 respectively.
Source: Cedefop European Skills and Jobs survey (ESJS) (http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey)

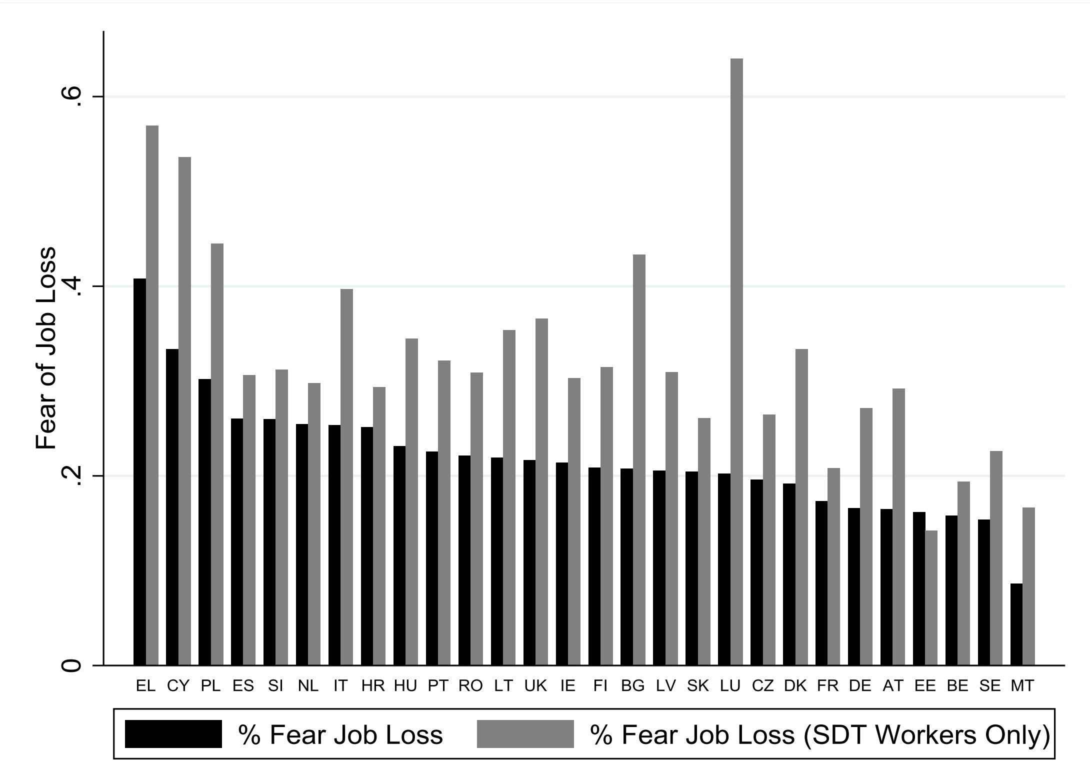
Table 1. **Skills-displacing technological change across occupations, EU28**

• ICT Associate Professionals • ICT Professionals • Production or specialist services managers • Electronic and electronic trades workers • Teaching professionals • Administrative or commercial managers • Science and engineering professionals/associate professionals • Health professionals	• Subsistence farmers, fishers or hunters • Cleaners or helpers • Food preparation assistants • Personal services workers • Personal care workers • Labourer in mining, construction, manufacturing • Driver or mobile plant operator • Agriculture, forestry and fishery labourer • Protective services worker

Notes: Ranking of occupations based on SDT.
Source: Cedefop European skills and jobs survey (ESJS)

While 16 percent of jobs across Europe have been identified as being susceptible to SDT, it is not clear to what extent these technological changes are threatening the existence of particular jobs, as opposed to merely altering their task content. To explore the matter further, Figure 2 graphs the percentage of workers who believe that it is likely that they will lose their jobs in the next year.[12] The percentage of workers fearing job loss is shown for all employees in the data, and separately for SDT employees. This enables us to evaluate the extent to which workers affected by SDT also experience higher levels of job insecurity. It should be noted that the variable will only capture the relationship between SDT and the immediate risk of job loss (over the next year). However, it may be that some workers view the risks to job loss arising from technological change to be more long term in nature. Nevertheless, the variable does provide an indicator of the degree to which SDT is impacting worker perceptions of job security.

Figure 2: Percentage of adult employees who fear losing their job, EU28



Notes: The graph displays the share of adult workers (in the total sample and only among those affected by SDT) per EU country with high responses (above 6 on a 0-10 scale) to the question: *How likely or unlikely do you think it is that "I will lose my job in the next year"? Please use a scale of from 0 to 10, where 0 means very unlikely and 10 very likely.* Some caution is called for when interpreting the statistics for Malta, Luxembourg and Cyprus due to relatively small sample sizes of 498, 489 and 492 respectively.
Source: Cedefop European skills and jobs survey (ESJS)

[12] In the ESJS respondents rank the following statement on a scale of 0 to 10 with 0 being very unlikely and 10 very likely – *"I will lose my job in the next year"*. We categorized those with a value above 6 as believing it is likely they will lose their job in the next year.

On average, 23 percent of all employees believe that it is likely that they will lose their jobs over the next 12 months, with incidences ranging from 30-40 per cent in Greece, Cyprus and Poland to 9-16 percent in Malta, Sweden and Belgium. Figure 2 also shows the rates of job insecurity for SDT workers only. On average, the incidence of job insecurity is 10 percentage points higher for SDT workers than for the full sample of employees, implying that about 5% of EU workers face a contemporary risk of SDT facilitating job loss. Over half of SDT employees in Luxemburg, Greece and Cyprus think it is likely they will lose their job in the next 12 months. Therefore, the data on job security does provide preliminary descriptive evidence to support the hypothesis that SDT is perceived as a threat to the existence of some jobs.

4. Empirical Approach

We begin by investigating whether SDT employees possess different characteristics to non-SDT employees, by estimating the following regression,

$$SDT_{i,c} = \alpha + Individual_{i,c}'\beta_P + Job_{i,c}'\beta_J + Occupation_{i,c}'\beta_O + \epsilon_{i,c} \quad (1)$$

Our dependent variable, $SDT_{i,c}$, is a dummy variable which equals one if employee *i* in country *c* is affected by SDT and zero otherwise. $Individual_{i,c}$ is a vector of employee characteristics, including age, gender and education level. $Job_{i,c}$ is a vector consisting of the following characteristics of a person's job: sector (public / private); employment tenure (in years); a dummy variable for whether the firm has multiple workplaces (branches / local units); a firm size dummy variable indicating whether the firm has less than 50 employees; contract type (temporary / permanent); a dummy variable to indicate whether the person has been promoted by their current employer; and dummy variables to indicate whether the person's job involves teamwork, non-routine tasks, learning on the job and autonomy. $Occupation_{i,c}$ is a vector of eight occupation dummies, consisting of managerial, professional, associate professional, sales, clerical, agriculture, building and elementary occupations. We estimate equation (1) using a probit model.

It may also be the case that SDT is associated with different measures of job quality compared to non-SDT jobs. If it is the case that SDT is eliminating the need for human capital or depreciating its value within particular jobs, or that workers affected by automating technology may lose part of their bargaining power, then we could expect to observe individuals in such jobs experiencing lower earnings compared to their counterparts where SDT is not a factor. This would reflect the lower productivity contribution to firm output among SDT employees. Additional impacts of SDT, consistent with a pattern of job destruction or deskilling, would include lower job complexity, a lower variety of tasks within jobs, lower job satisfaction due to the fall in the intrinsic value of job tasks, a depreciation of existing skills and increased job insecurity relative to comparable workers in positions not susceptible to SDT. To investigate this, we estimate the following regression,

$$Outcome_{i,c} = \alpha + SDT_{i,c}'\beta_T + Individual_{i,c}'\beta_P + Job_{i,c}'\beta_J + Occupation_{i,c}'\beta_O + \epsilon_{i,c} \quad (2)$$

We estimate this model using the following labour market outcomes as dependent variables: earnings, job satisfaction, job insecurity, job-task variety, job complexity, skill depreciation/improvement and the likelihood of receiving training. We are interested in examining the association between the various outcomes and the SDT dummy variable. Therefore the coefficient of interest is β_T. It could be argued that rather than being an outcome, the task variety/complexity variables could instead be considered as a job characteristic in equation (2). However, given the dearth of empirical evidence on the effect of technology on changing task content of jobs, and since previous studies have been forced to use residuals or occupation-based proxies of changing or emerging tasks in jobs (Acemoglu and Restrepo, 2019a), we examine this as an outcome variable. Furthermore, fully disentangling the directionality of causation in this area is extremely challenging. Our interest therefore lies in examining how SDT is associated with various potential job outcomes, and as such we refrain from making strong causal claims.

Job complexity is measured on the basis that respondents were asked to rank, on a scale from 0 to 10, the degree to which eight skill[13] areas were required in their current job. A response of 0 means not at all important while a response of 10 indicates that the skill is essential. Therefore, the job complexity measure ranges from a minimum of 0 to a maximum of 80. The task variety measure is based instead on an ESJS question which asks "*since you started your job, has there been a change in the variety of tasks in your job*". The employee answers on a 0-10 scale, where 0 indicates the tasks have decreased a lot, 5 indicates the tasks stayed the same and 10 indicates they increased a lot. We generate a dummy variable which indicates whether task variety has increased over an individual's job tenure, which equals one if employees responded 6-10, and zero otherwise.

It is important to consider the possibility that individuals experiencing SDT may be systematically more likely to have certain types of observable characteristics (such as education levels, tenure and occupation) that collectively influence the outcome variables (earnings, job satisfaction etc.). Therefore, it is possible that the impacts of SDT may be confounded with systematic differences associated with SDT affected employees or jobs, leading to potentially biased estimates. To overcome this selection problem, we augment the estimates from our baseline probit models with those generated using propensity score matching (PSM) methods. The PSM approach is a two-step procedure. In step one, each individual's probability (or propensity score) of being impacted by SDT is assessed conditional on a set of explanatory variables. Treatment and control group individuals are then matched on the basis of their propensity scores, which is equivalent to matching on the key characteristics of the SDT (treatment) group. In the second step, the average outcome measures of the treatment and control groups are compared. In the absence of selection bias the PSM estimates should align with those of the probit models.

More formally, the propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics,

$$p(X) = \Pr(D = 1|X) = E(D|X) \qquad (3)$$

where D is a binary term indicating exposure to the treatment, in this case SDT, and X is a vector of determining characteristics. Rosenbaum and Ruben (1983) show that matching individuals on the basis of propensity scores is equivalent to matching on actual characteristics. In terms of the matching technique adopted, we apply nearest neighbour with replacement. An additional benefit of the PSM approach is that we can implement post-estimation checks to measure the degree to which the PSM estimates are robust to the influence of unobserved heterogeneity. Becker and

[13] Technical skills, communication skills, team-working skills, foreign language skills, customer handling skills, problem solving skills, learning skills, planning and organisational skills. These eight skills descriptors were integrated in the ESJS on the basis that numerous other detailed skill-requirements at work load onto them as principal component vectors (Cedefop, 2015).

Caliendo (2007) outline a sensitivity check which allows the researcher to determine how strongly unobserved effects must influence the selection process to undermine the propensity score matching results. This can be implemented using their *mhbounds* Stata command.[14]

5. Results

5.1 Determinants of SDT

In Table 2 we evaluate the characteristics that are more likely to be observed among SDT affected employees, by estimating equation (1). Our comparison group are non-SDT employees who have neither been affected by technological change in the past five years, nor expect their skills to become outdated in the next five years. Some employees report having experienced one of the two SDT related attributes. For example, a worker may indicate that they have experienced technological change in the last five years but do not expect their skills to become outdated in the next five years. We exclude such workers from our comparison group. We also exclude workers who have not experienced technological change but feel they will experience skill obsolescence in the future.[15] Thus, our reference group consists of workers who have not experienced either of the two components of SDT.

The estimates are shown in the first column of Table 2, entitled "SDT". Relative to the reference group, workers experiencing SDT are more likely to be male, have higher levels of education and tenure, are more likely to be employed in the private sector and to have been promoted by their current employer. In addition, SDT workers are also more likely to undertake non-routine tasks in their job, work in teams and experience on-the-job learning. They are less likely to have temporary contracts, work in small firms (under 50 employees), and experience autonomy in their jobs compared to non-SDT workers.[16] With regard to occupation, workers who experience SDT are more likely to be in higher skilled occupations, such as managers, professionals and associate professionals, compared to non-SDT employees. While much of the narrative regarding the impact of technology and automation on employment often focuses on the displacement of routine tasks in medium- and low-skilled jobs and the potential negative consequences, our analysis indicates that it is better educated individuals in high-skilled occupations who face a higher likelihood of being affected by skills-displacing technological change[17]. However, the results suggest that while technology may create a dynamic skills environment, with changing skill requirements, it may also be enhancing upskilling and career opportunities for employees. This is supported by the fact that SDT employees are far more likely to have been promoted at work, tend to work in permanent jobs and engage in non-routine tasks involving learning on the job.

[14] See Becker and Caliendo (2007) for a detailed exposition of this sensitivity check.

[15] There are 8329 workers (18% of the total sample) who have not experienced technological change but expect future skill obsolescence and there are 14023 workers who experienced technological change but do not expect future skill obsolescence (29%). Our comparison group consists of 17951 employees (37%) who experienced neither technological change nor expect future obsolescence.

[16] Regarding autonomy, workers are asked how often they can choose the way in which they do their work: always, usually, sometimes or never. We generate an indicator variable which equals one for those who always experience autonomy and zero otherwise. Our results are similar if we include workers who "usually" experience autonomy in the same category as those who "always" experience it.

[17] We acknowledge however that there is likely to be selectivity bias in our sample of 'surviving' workers, given that SDT that has replaced routine work and facilitated job loss would have resulted in unemployment or inactivity.

Table 2: Characteristics of workers susceptible to SDT: Probit estimates (Marginal Effects)

VARIABLES	SDT	Downskill	Upskill	No skill change
Age	0.0001	0.0001	-0.0003	0.0006***
	(0.0004)	(0.0001)	(0.0003)	(0.0001)
Male	0.0426***	0.0031**	0.0384***	0.0089***
	(0.0063)	(0.0013)	(0.0061)	(0.0022)
Education (ref: low ed)				
Med isced	0.0579***	0.0029	0.0524***	0.0111***
	(0.0106)	(0.0026)	(0.0105)	(0.0039)
High isced	0.0736***	0.0095***	0.0632***	0.0142***
	(0.0116)	(0.0031)	(0.0114)	(0.0045)
Part-time	-0.0002	-0.0000	-0.0002	0.0000
	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Private sector	0.0244***	0.0004	0.0238***	0.0016
	(0.0064)	(0.0013)	(0.0063)	(0.0023)
Tenure	0.0078***	0.0003***	0.0078***	-0.0002
	(0.0004)	(0.0001)	(0.0004)	(0.0001)
Multiple workplaces	0.0493***	0.0048***	0.0475***	0.0014
	(0.0062)	(0.0013)	(0.0061)	(0.0022)
Small firm	-0.0520***	-0.0016	-0.0496***	-0.0061***
	(0.0063)	(0.0014)	(0.0062)	(0.0023)
Temporary contract	-0.0299***	-0.0050***	-0.0333***	0.0035
	(0.0093)	(0.0015)	(0.0091)	(0.0034)
Promoted	0.0602***	-0.0044***	0.0682***	-0.0064***
	(0.0073)	(0.0013)	(0.0072)	(0.0025)
Non-routine job	0.0377***	0.0020	0.0352***	0.0061**
	(0.0075)	(0.0018)	(0.0074)	(0.0030)
Learning in job	0.0753***	-0.0001	0.0778***	0.0031
	(0.0084)	(0.0019)	(0.0083)	(0.0032)
Autonomy	-0.0543***	-0.0056***	-0.0486***	-0.0066***
	(0.0066)	(0.0013)	(0.0064)	(0.0023)
Teamwork	0.0207***	-0.0044***	0.0243***	-0.0011
	(0.0063)	(0.0013)	(0.0062)	(0.0022)
Occupation (ref: elementary)				
Managers	0.1226***	0.0022	0.1523***	-0.0068
	(0.0218)	(0.0052)	(0.0233)	(0.0046)
Professionals	0.1659***	0.0058	0.1950***	-0.0065
	(0.0194)	(0.0052)	(0.0207)	(0.0043)
Assoc professionals	0.2054***	0.0128*	0.2326***	-0.0041
	(0.0198)	(0.0072)	(0.0212)	(0.0045)
Sales	0.0260	0.0003	0.0525***	-0.0125***
	(0.0179)	(0.0040)	(0.0192)	(0.0035)
Clerical	0.1424***	0.0038	0.1632***	-0.0012
	(0.0186)	(0.0045)	(0.0199)	(0.0046)
Agriculture	0.0248		0.0406	0.0018
	(0.0417)		(0.0435)	(0.0117)
Building	0.0964***	0.0008	0.1262***	-0.0065
	(0.0210)	(0.0047)	(0.0225)	(0.0043)
Machine operative	0.0670***	-0.0011	0.0851***	-0.0057
	(0.0209)	(0.0041)	(0.0222)	(0.0044)
Country f.e.	yes	yes	yes	yes
Observations	25,538	17,287	24,615	18,311

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: Cedefop European skills and jobs survey (ESJS)

5.2 *Impact of SDT on skills*

To further investigate the impact of SDT on skills, we divide our SDT employees into subsamples based on whether they experienced a skills improvement (upskilling) or a skills decline (deskilling) within their current job. Specifically, the ESJS asks respondents the following question, "*compared to when you started the job with your current employer, would you say your skills have worsened, improved or stayed the same*?" The question has a response scale from 0 to 10, where 0 indicates that "skills have worsened a lot", 5 indicates that "skills have stayed the same", and 10 that "skills have improved a lot". We have classified responses from 0 to 4 as dynamic downskilling and from 6 to 10 as dynamic upskilling. Individuals providing a response of 5 are deemed to have constant skills. In Table 3 we report the incidence of each of the three scenarios for SDT and non-SDT employees. We see that, while the vast majority of both types of worker report that their skills have improved since starting their current job, the rate of dynamic upskilling among SDT employees (90 percent) is greater than non-SDT employees (82 percent). Therefore, this descriptive evidence is supportive of the fact that workers affected by SDT are in jobs that enable their continuing skills augmentation. It is also reasonable to assume that employers deciding to adopt new technological solutions at their businesses will entrust their most highly skilled personnel in using them, reinforcing a virtual cycle between technology adoption and skills development.

Table 3: Incidence of dynamic upskilling and dynamic downskilling

	SDT	Non SDT
Upskilling	90	82
Downskilling	3	3
No change	6	15

Notes: Upskilling is defined by the share of adult workers who stated that compared to when they started their job with their current employer, their skills have now improved (above 5 on a 0-10 scale, where 0 means workers' skills have worsened a lot, 5 means they have stayed the same and 10 means they have improved a lot); Downskilling is the share of those whose skills have worsened (below 5).

Source: Cedefop European skills and jobs survey (ESJS)

We estimate equation (1) on these three subsamples of SDT employees (dynamic downskillers, dynamic upskillers and those with no change) and show the results in columns 2 to 4 of Table 2.[18] Given that the vast majority of SDT workers fall into the category of dynamic upskilling, it is not surprising that the results for the SDT upskillers (column 3) are very similar to the results for the general SDT population (column 1) which are discussed above. However, differences emerge when looking at the subgroup of SDT employees who experienced skills erosion (the downskillers). Most notably, this group were less likely to have been promoted by their current employer compared to workers unaffected by SDT, and were less likely to be involved in teamwork.

Similar to the SDT workers who experienced skills erosion, the SDT workers who experienced no skills change (column 4 of Table 2) were also less likely to have been promoted by their employer than non-SDT workers. Furthermore, the SDT group with no skills change are older than non-SDT workers. With regard to their other characteristics, they tend to be better educated than workers

[18] The reference group remains unchanged, i.e., employees who experienced neither of the two SDT components.

who are completely unaffected by technology, however, the marginal effects are not as strong as the effects observed among SDT workers who saw skill enhancement.

5.3 Impact of SDT on job quality

Table 4 reports results for the impact of SDT on key job quality outcome measures. Equation (2) is estimated using probit models for the binary outcome measures and OLS for the continuous variables. We also report results from the PSM estimation procedure. We use the full model specification which includes all covariates outlined in equation (2). However, for brevity, we focus on the SDT coefficient given that this is our primary variable of interest. As before, we split the SDT workers into additional subsamples based on whether they experienced dynamic upskilling or dynamic downskilling.

For the full SDT sample (column 1 of Table 4), we observe that SDT is associated with greater job-skill complexity and an 8 percentage point higher likelihood of workers experiencing increasing task variety over their job tenure, relative to non-SDT workers. SDT employees also have a 4-5 percentage point higher likelihood of skills enhancement and 11 percentage point greater chances of receiving training.

It should be noted that the coefficient on downskilling is also positive, however the magnitude is small compared to upskilling. In addition, SDT is associated with a five percentage point reduction in the likelihood of experiencing unchanging skills, compared to non-SDT employees. This reflects the fact that we are comparing employees in a dynamic skills environment, the SDT group, with employees in a more stagnant skills environment who experience no technological change. Invariably, there will be a higher likelihood of skills change, both positive and negative, among SDT employees, however the key point is that the magnitude of skills enhancement greatly outweighs the magnitude of skills erosion.

The greater degree of skills development among workers affected by SDT may also underline their higher earnings of about 2%, although this positive effect is not statistically significant in the PSM specification. SDT employment is also associated with lower job satisfaction and markedly increased job insecurity, relative to those adult workers insulated from technological change that can impact their skills. All other things equal, SDT workers have a significantly higher fear of imminent job loss (by about 20 percentage points) than equivalent non-SDT employees.

Further insights emerge when we separately examine the job quality outcome measures for the SDT upskillers and SDT downskillers. In particular, we see that the negative job satisfaction effect observed among the full sample of SDT employees appears to be driven entirely by the SDT downskillers. For upskillers, there is no statistically significant job satisfaction impact. However, SDT downskillers experience a 30-40 percentage point reduction in job satisfaction, relative to non-SDT employees. Other notable results emerge when looking at job-skill complexity and earnings. SDT accompanied by downskilling is associated with lower job complexity compared to non-SDT employment. This is in contrast to greater job complexity for SDT upskillers. In a similar vein, increased task variety is approximately 10 percentage points more likely among upskillers but over 20 percent less likely among downskillers. There is also evidence that SDT accompanied by upskilling is associated with increased earnings, although we only observe a significant estimate in the OLS specification. Finally, SDT upskilling is associated with an increased probability of receiving training, whereas SDT downskillers are less likely to have received training.

Overall, the results shown in Table 4 suggest that SDT is associated with better quality jobs, which are more complex, have rising task variety, involve more training and have higher wages. While SDT employees, by definition, feel that some of their skills will become outdated in the next five years, the fact that they have experienced greater levels of upskilling compared to non-SDT employees suggests that SDT workers are capable of adapting to a changing skills environment by continuously updating their skills. In this sense, technological may be eroding existing skills-sets making them obsolete as time progresses, but ultimately our evidence suggests that this will transpire into better quality employment outcomes if employees have opportunities to update the obsolete skills with a new and improved skillset.

Table 4: Job Quality Outcome Measures: Probit and PSM Estimates

VARIABLES	Full sample SDT	SDT Upskillers	SDT Downskillers
Job Complexity			
OLS	3.390***	3.986***	-1.523*
PSM	3.487***	3.889***	-2.256*
Upskilling			
Probit	0.042***	n/a	n/a
PSM	0.046***	n/a	n/a
Downskilling			
Probit	0.009***	n/a	n/a
PSM	0.007**	n/a	n/a
Skills Unchanged			
Probit	-0.051***	n/a	n/a
PSM	-0.052***	n/a	n/a
Earnings			
OLS	0.024***	0.029***	-0.016
PSM	0.025	0.028	0.007
Job Satisfaction			
Probit	-0.023***	0.009	-0.331***
PSM	-0.020***	0.009	-0.381***
Job Insecurity			
Probit	0.207***	0.201***	0.231***
PSM	0.189***	0.180***	0.201***
Training			
Probit	0.111***	0.128***	-0.054*
PSM	0.109***	0.124***	-0.041

Task Variety			
Probit	0.085***	0.122***	-0.258***
PSM	0.071***	0.107***	-0.230***

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: Cedefop European skills and jobs survey (ESJS)

5.4 Robustness and sensitivity tests

While the results shown in Table 4 for SDT employees are revealing, we cannot be sure that these job outcome measures developed in parallel with job-related technological change. This is because the question relating to technological change specifically asks the employee whether this has occurred in the last five years. However, many employees will be working in their current job for more than five years. In order to account for this, we re-estimate equation (2), restricting our sample to workers with less than 5 years of tenure. By restricting our sample in this way, we can be certain that the job outcome measures of SDT employees evolved contemporaneously with recent technological change. The results from the tenure restricted models are detailed in Table 5. While the results are similar to the baseline estimates, a number of important differences emerge. For the sample of all SDT workers (column 1 of Table 5) in this tenure restricted model, there is no longer strong evidence that SDT is associated with a higher likelihood of downskilling, as the PSM estimate is not statistically significant. There are also notable results around job satisfaction. Table 5 shows that SDT employees, generally, do not experience lower job satisfaction. SDT upskillers actually experience greater job satisfaction in this tenure restricted specification. Finally, the reduction in job complexity associated with SDT downskillers is more pronounced in this tenure restricted model, as seen in column (3) of Table 5.

We next address issues related to potential unobserved heterogeneity, focusing on the tenure restricted sample in Table 5. The reliability of any propensity score matching estimate rests upon the Conditional Independence Assumption (CIA) being met. For the CIA to hold, all variables that simultaneously impact both the treatment and outcome variable should be observed in the data. Given that the ESJS contains an extensive range of information on personal, job and background characteristics (included in our first stage PSM models), we can be relatively confident that the data sufficiently incorporate all key aspects of the allocation to treatment processes. Nevertheless, despite this, we cannot completely rule out the possibility that our estimates are affected by one or more unobserved effects that simultaneously influence both the treatment and outcome variables.

We can test the sensitivity of our estimated treatment effects to the existence of such hidden bias. We apply the “mhbounds” sensitivity test proposed by Becker and Caliendo (2007).[19] This measures the extent to which an unobserved factor would have to influence the odds of being allocated to the treatment group before the estimated treatment effect becomes statistically unreliable. Specifically, the methodology examines the impact of unobservables that increase the odds of allocation to the treatment and are simultaneously associated with higher (termed positive selection bias) or lower (termed negative selection bias) levels of the outcome variable. Effectively, the sensitivity test measures the extent to which an unobserved factor must influence the odds of being allocated to the treatment group, under the assumptions of either positive or negative selection bias, before the estimated treatment effect becomes unreliable. The test does not demonstrate bias per se, but gives

[19] We use the rbounds procedure in the case of earnings where the outcome variable is continuous.

us a sense to which the statistical significance of our estimates are sensitive to the presence of unobserved influences. In the case of all of our outcome variables, we are concerned about the possibility of positive selection bias. We run the tests only on the statistically significant outcome variables from the models estimated on the tenure restricted SDT sample from Table 5.

Table 5: Job Quality Outcome Measures (Tenure of 5 Years or Less): Probit and PSM Estimates

VARIABLES	Full sample SDT	SDT Upskillers	SDT Downskillers
Skill Level of Job			
OLS	3.134***	3.926***	-3.972***
PSM	2.836***	4.551***	-6.000***
Upskilling			
Probit	0.042***	n/a	n/a
PSM	0.030***	n/a	n/a
Downskilling			
Probit	0.011**	n/a	n/a
PSM	0.005	n/a	n/a
Skills unchanged			
Probit	-0.053***	n/a	n/a
PSM	-0.035***	n/a	n/a
Earnings			
OLS	0.024	0.029*	-0.069
PSM	0.028	0.045	-0.212
Job Satisfaction			
Probit	-0.013	0.030***	-0.281***
PSM	-0.009	0.027*	-0.381***
Job Insecurity			
Probit	0.232***	0.220***	0.306***
PSM	0.206***	0.195***	0.230***
Training			
Probit	0.126***	0.149***	-0.007
PSM	0.114***	0.115***	-0.023
Task Variety			
Probit	0.101***	0.154***	-0.192***
PSM	0.083***	0.135***	-0.241***

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: Cedefop European skills and jobs survey (ESJS)

The results from the tests (Appendix Table A2) indicate that the estimated impacts of SDT on job complexity, task variety, job insecurity and training, are robust and would remain statistically reliable even in the presence of an unobserved variable that would cause the odds ratio of treatment assignment to increase by a factor of 1.5. More caution is required when interpreting the coefficient measuring the impact of SDT on dynamic upskilling, given that the test indicates that the results will lose statistical significance in the case of an unobserved variable which changes the odds of assignment to the treatment by a factor of 1.2. Nevertheless, the result for dynamic upskilling does not demonstrate bias, merely that the result would be questionable in the presence of unobserved heterogeneity.

6. Conclusion

Much has been written regarding the potential impact of technology on the future of jobs, with some studies suggesting that almost half the jobs that currently exist in advanced labour markets could be replaced, or automated, at some point in the future. A good deal of the existing debate in this area relies on empirical approaches which attempt to identify jobs, or tasks, which may be at risk of automation, mostly relying on the subjective views of experts. To date, little account has been taken of the views of workers themselves. This study considers the potential impact of technological change on jobs, adopting an approach that is centred on employee expectations and experiences regarding the influence of technology on their skills. We do this by creating a measure that captures the part of technological change that may have an impact on the demand and value of workers' skills-sets, which we term skills displacing technological change (SDT).

It is increasingly documented that automation and technological change have the potential to destroy jobs, as well as to enhance and improve existing jobs by creating new tasks and roles that did not exist in the past. While predicting the exact impacts of technology on the labour market is virtually impossible due to the uncertainty involved, our research emphasises the positive effects of technological change. Firstly, the share of workers affected by SDT appears low in light of some of the existing research that has spurred much technological alarmism in the recent research and policy discourse. We find that just 16 percent of EU employees experience SDT and a markedly lower share of affected workers (5 percent) are fearful it will lead to imminent job loss. It is notable that, of these SDT employees, the vast majority (90 percent) report that their skills have improved within their current employment. This is greater than the incidence of skills enhancement among non-SDT workers (82 percent). With regard to the characteristics of SDT employees, they have higher levels of education and are more likely to have been promoted by their current employer compared to non-SDT workers. In addition, they are more likely to work in larger organisations and in roles that involve teamwork, on-the-job learning and non-routine tasks. The highest incidence of SDT is also observed among higher-skilled occupations. This finding runs contrary to the widely heard predictions of job polarisation or recent risk of automation studies that mainly routine-, medium- and lower-skilled occupations will be most exposed to the displacing impacts of technological change.

We also investigate the link between SDT and various job quality measures. Confirming, for the first time using individual-level data, the reinstatement effect of automation, as espoused by Acemoglu and Restrepo (2018, 2019a), we find that employees subject to SDT have greater job complexity and are more likely to experience an increase in task variety within their current job, compared to employees unaffected by technological change. There is also some evidence of higher wages among SDT workers who have opportunities to upskill in their jobs. However, SDT employees do experience greater job insecurity. This is perhaps unsurprising given the uncertainty involved, coupled with claims made in the popular media and policy debates which typically expound the potential negative aspect of technology on jobs. As such, even workers who have benefited positively from technological change in the past may fear for their jobs in the future.

References

Acemoglu, D. and Restrepo. P. (2018). "Artificial Intelligence, Automation and Work", NBER Working Paper No. 24196.

Acemoglu, D. and Restrepo. P. (2019b). "Robots and jobs: Evidence from US labour markets", *Journal of Political Economy*, forthcoming.

Acemoglu, D. and Restrepo. P. (2019a). "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives*, 33 (2): Vol. 33, No.2, pp. 3-30.

Allen, J. and de Grip, A. (2012). "Does skill obsolescence increase the risk of employment loss?" *Applied Economics*, Vol. 44, No.25, pp. 3237-3245

Allen, J. and van der Velden, R. (2002), "When do skills become obsolete, and when does it matter?", de Grip, A., van Loo, J. and Mayhew, K. (Ed.) *The Economics of Skills Obsolescence* (*Research in Labor Economics, Vol. 21*), Emerald Group Publishing Limited, Bingley, pp. 27-50.

Arntz, M., Gregory, T. and Zierahn, U. (2016), "The Risk of Automation for Jobs in OECD Countries", *OECD Social, Employment and Migration Working. Papers, No. 189*, OECD Publishing, Paris.

Arntz, M., Gregory, T. and Zierahn, U. (2017). "Revisiting the Risk of Automation". *Economics Letters*, Vol. 159, pp. 157-160.

Autor, D.H, Katz, L. and Kearney, M. (2006). "The Polarization of the US Labor Market", *American Economic Review*, Vol. 96, No. 2, pp. 189-194

Autor, D.H, Levy, F., Murnane, R.J. (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, Vol.118, No.4, November 2003, pp. 1279-1334.

Autor, D.H. (2015), "Why are there still so many jobs? The history and future of workplace automation", *The Journal of Economic Perspectives*, Vol. 29, No. 3, pp. 3–30.

Autor, D.H. and D. Dorn (2013), "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market", *American Economic Review*, Vol. 103, pp. 1553-1597.

Autor, D.H. and Handel, M. (2013). "Putting tasks to the test: Human capital, jobs and wages", *Journal of Labor Economics*, Vol. 31, No. S1 ,pp. S59-S96.

Autor, D.H. Katz, L.F., Krueger, A.B. (1998). "Computing inequality: have computers changed the labor market?" *Quarterly Journal of Economics*. Vol.113, No. 4, pp. 1169–1213.

Autor, David H. (2015). "Why Are There Still So Many Jobs? The History and Future of Workplace Automation", *Journal of Economic Perspectives*, Vol. 29, No. 3, pp. 3-30.

Becker, S.O. and Caliendo, M. (2007). *Sensitivity Analysis for Average Treatment Effects*, *Stata Journal*, 7(1), 71-83

Bennett, J., and McGuinness, S. (2009). "Assessing the Impact of Skill Shortages on the Productivity Performance of High-Tech Firms in Northern Ireland". *Applied Economics*, Vol. 41, No. 6, pp. 727-737

Berman, E., Bound, J., and Machin, S. (1998). "Implications of skill-biased technological change: international evidence". Q*uarterly Journal of Economics*, Vol.113, No. 4, pp. 1245-1279.

Bessen, J.E. (2015). *Learning by Doing: The Real connection between Innovation, Wages and Wealth*, Yale University Press.

Bessen, J.E. (2016). "How Computer Automation Affects Occupations: Technology, Jobs, and Skills". Boston Univ. School of Law, Law and Economics Research Paper No. 15-49.

Bessen, J.E. et al. (2019). "Automation reaction – what happens to workers at firms that automate?" CPD Discussion paper, February.

Braveman, H. (1974). *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century, New York: Monthly review Press.*

Breshanan, T. and Yin, P-L. (2016). Adoption of new information and communication technologies in the workplace today, NBER Working Paper No. 22346.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. New York: WW Norton & Company.

Brynjolfsson, E., Mitchell, T. and Rock, D. (2018). "What Can Machines Learn, and What Does It Mean for Occupations and the Economy?", *AEA Papers and Proceedings*, pp. 43–47.

Cedefop (2012). *Preventing skills obsolescence*, Briefing note 9070, Thessaloniki. https://www.cedefop.europa.eu/en/publications-and-resources/publications/9070

Cedefop (2015). *Skills, qualifications and jobs in the EU: the making of a perfect match? Evidence from Cedefop's European skills and jobs survey*. Luxembourg: Publications Office. Cedefop reference series; No 103. http://www.cedefop.europa.eu/en/publications-and-resources/publications/3072

Cedefop (2018). *Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey*. Luxembourg: Publications Office. Cedefop reference series; No 106. http://www.cedefop.europa.eu/en/publications-and-resources/publications/3075

Dauth, W. et al. (2017), "German robots-the impact of industrial robots on workers", IAB DP 30/2017.

De Grip, A. and Van Loo, J. (2002), "The economics of skills obsolescence: A review", de Grip, A., van Loo, J. and Mayhew, K. (Ed.) *The Economics of Skills Obsolescence* (*Research in Labor Economics, Vol. 21*), Emerald Group Publishing Limited, Bingley, pp. 1-26.

De Grip, A., et al. (2008). "Job-worker mismatch and cognitive decline," *Oxford Economic Papers*, Oxford University Press, Vol. 60, No. 2, pp. 237-253.

Deming, D.J. (2017): The Growing Importance of Social Skills in the Labor Market. *The Quarterly Journal of Economics*, Vol. 132, No. 4, pp. 1593-1640

Deming, D.J. and Noray, K.L. (2018). "STEM careers and technological change", NBER Working paper No. 25065.

Eurofound (2016). *What do Europeans do at work? A task-based analysis*, Luxembourg: Publications Office of the European Union.

Felten, E.W., M. Raj, and R. Seamans (2018). "A Method to Link Advances in Artificial Intelligence to Occupational Abilities". *AEA Papers and Proceedings*, Vol. 108, pp. 54–57.

Ford, M. (2015). *Rise of the robots: technology and the threat of a jobless future*, Basic books: New York.

Fossen, F.M. and Sorgner, A. (2019). "New Digital Technologies and Heterogeneous Employment and Wage Dynamics in the United States: Evidence from Individual-Level Data", IZA DP. No. 12242.

Frey, C. and Osborne, M. (2013), *The future of employment: how susceptible are jobs to computerisation*, University of Oxford.

Frey, C. and Osborne, M. (2017), "*The future of employment: how susceptible are jobs to computerisation"*, *Technological Forecasting & Social Change*, Vol. 114 (2017), pp. 254–280.

Goos, M. (2018). "The impact of technological progress on labour markets: policy challenges"**,** *Oxford Review of Economic Policy*, Volume 34, Number 3, pp. 362–375

Goos, M., Manning, A., Salomons, A. (2009). "Job polarization in Europe", *American Economic Review*, Vol. 99, No. 2, pp. 58–63.

Graetz, G. and Michaels, G. (2018). "Robots at Work", *The Review of Economics and Statistics*, Vol.100, No. 5, pp. 753-768.

Graetz, G. and Michaels, G. (2017). "Is Modern Technology Responsible for Jobless Recoveries?", *American Economic Review*, Vol.107, No. 5, pp. 168-73.

Janssen, S. and Backes-Gellner, U. (2009), "Skill Obsolescence, Vintage Effects and Changing Tasks", *Applied Economics Quarterly*, Vol.55, No. 1, pp. 83-103.

Katz, L. and Autor, D.H. (1999), "Changes in the Wage Structure and Earnings Inequality", in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, Vol. 3A, pp. 1463-1555

Katz, L. F., and Murphy, K. M. (1992). "Changes in relative wages, 1963–1987: supply and demand factors". Q*uarterly journal of economics*, Vol. 107(1), pp. 35-78.

Keynes, J.M., 1933. *Economic possibilities for our grandchildren* (1930). Essays in persuasion. pp. 358–373

Krueger, A. B. (1993). "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989". *Quarterly Journal of Economics*, Vol. 108, pp. 33-60.

Machin, S., and Van Reenen, J. (1998). "Technology and changes in skill structure: evidence from seven OECD countries". *Quarterly Journal of Economics*, Vol. 113(4), pp. 1215-1244.

McGuinness, S., Pouliakas, K. and Redmond, P. (2018). "Skill mismatch: concepts, measurement and policy approaches", *Journal of Economic Surveys*, Vol. 32, No. 4, pp.985-1015.

McKinsey Global Institute (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*, November.

Mokyr, J., C. Vickers and N. Ziebarth (2015). "The History of Technological Anxiety and the Future of Economic Growth: Is this Time Different?" *Journal of Economic Perspectives*, Vol. 29, pp. 31-50

Neuman, S. and Weiss, A. (1995). "On the effects of schooling vintage on experience-earnings profiles: Theory and evidence", European Economic Review, Volume 39, No. 5, pp. 943-955.

OECD (2019). "Digitalisation and productivity: a story of complementarities" Ch. 2 in *OECD Economic Outlook*, Issue 1, Paris.

Pellegrino, G., Piva, M. and Vivarelli, M. (2017). 'Are robots stealing our jobs?", IZA DP. No. 10540.

Caroli, E. and Van Reenen, J. (2001). "Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments", *The Quarterly Journal of Economics*, Volume 116, Issue 4, pp. 1449–1492.

Piva, M. and Vivarelli, M. (2017), "Is R&D good for employment? Microeconometric evidence from the EU", IZA DP. No 10581.

Pouliakas, K. (2018). "Automation risk in the EU labour market: a skill-needs approach", in Hogarth, T. (ed) *Economy, employment and skills: European, regional and global perspectives in an age of uncertainty*, *Quaderni* series of Fondazione Giacomo Brodolini, Rome.

Van Loo, J., De Grip, A. and de Steur, M. (2001). "Skills Obsolescence: Causes and Cures". *International Journal of Manpower*. Vol. 22. pp. 121-138.

Van Reenen, J. (1997), "Employment and technological innovation: Evidence from U.K. manufacturing firms", *Journal of Labor Economics*, Vol. 15, pp. 255-284.

Vivarelli, M. (2014). "Innovation, employment and skills in advanced and developing countries: a survey of the literature", *Journal of Economic Issues*, Vol. 48 (1), pp. 123-154.

Vivarelli, M. (2015). "Innovation and employment", *IZA World of Labor*, Vol. 154.

World Economic Forum (2016). *The future of jobs: employment, skills and workforce strategy for the fourth industrial revolution*, Geneva.

World Economic Forum (2018). *Towards a reskilling revolution: industry-led action for the future of work*, Geneva.

Appendix

Table A1: Impact of technological change on skills mismatch and obsolescence

VARIABLES	(1) Skills mismatch	(2) Skills obsolescence
Tech change	0.010**	0.040***
	(0.005)	(0.004)
Age	0.000*	0.001***
	(0.000)	(0.000)
Male	0.041***	0.012***
	(0.005)	(0.005)
Education (ref: low ed)		
Med isced	0.078***	0.004
	(0.008)	(0.007)
High isced	0.168***	0.016*
	(0.009)	(0.008)
Part-time	0.000*	0.000**
	(0.000)	(0.000)
Private sector	0.001	0.017***
	(0.005)	(0.005)
Tenure	-0.004***	0.000
	(0.000)	(0.000)
Multiple workplaces	0.036***	0.008*
	(0.005)	(0.005)
Small firm	-0.005	-0.023***
	(0.005)	(0.005)
Temporary contract	0.004	0.054***
	(0.007)	(0.007)
Promoted	-0.014***	-0.013***
	(0.005)	(0.005)
Non-routine job	0.039***	0.020***
	(0.006)	(0.005)
Learning in job	-0.025***	0.031***
	(0.006)	(0.006)
Autonomy	0.026***	-0.046***
	(0.005)	(0.005)
Teamwork	-0.032***	-0.011**
	(0.005)	(0.005)
Occupation (ref: elementary)		
Managers	-0.154***	-0.033**
	(0.014)	(0.013)
Professionals	-0.200***	-0.017
	(0.013)	(0.012)
Assoc professionals	-0.164***	-0.005
	(0.012)	(0.012)
Sales	-0.073***	-0.021*
	(0.012)	(0.012)
Clerical	-0.096***	0.021*
	(0.012)	(0.011)
Agriculture	-0.106***	-0.054**
	(0.028)	(0.026)
Building	-0.142***	-0.044***
	(0.014)	(0.013)
Machine operative	-0.068***	-0.067***

	(0.014)	(0.013)
Country F.E.	Yes	Yes
Constant	0.412***	0.309***
	(0.023)	(0.022)
Observations	47,730	47,730
R-squared	0.047	0.031

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Cedefop European skills and jobs survey (ESJS)

Table A2: Mhbounds and Rbounds – 5 year tenure restriction estimates

	Skill level		Job Insecurity		Dynamic Upskilling		Training		Task Variety	
	p+	**p-**	**p+**	**p-**	**p+**	**p-**	**p+**	**p-**	**p+**	**p-**
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.1	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
1.15	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00
1.2	0.02	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00
1.25	0.10	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00
1.3	0.31	0.00	0.00	0.00	0.39	0.00	0.00	0.00	0.00	0.00
1.35	0.52	0.00	0.00	0.00	0.47	0.00	0.00	0.00	0.00	0.00
1.4	0.59	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.02	0.00
1.45	0.83	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.05	0.00
1.5	0.94	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.12	0.00

Notes: The methodology is based on Becker and Caliendo (2007)

Source: Cedefop European skills and jobs survey (ESJS)