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ABSTRACT

Determinants of Automation Risk in the EU Labour Market: A Skills-Needs Approach[1]

This paper focuses on identifying determinants of 'automatability risk', namely the propensity of EU employees being in jobs with high risk of substitutability by machines, robots or other algorithmic processes, and uncovers its impact on labour market outcomes. Using relevant data on tasks and skill needs in jobs, collected by the European skills and jobs survey (ESJS), jobs are bundled according to their estimated risk of automation. The paper builds on the methodology of previous studies that estimate the latent relationship between 'true' automatability and job tasks (Frey and Osborne, 2013, 2017; Arntz et al., 2016; Nedelkoska and Quintini, 2018) but utilises highly disaggregated job descriptions provided by a subsample of the ESJS, as well as information on jobs' skill requirements. About 14% of EU adult workers are found to face a very high risk of automation. The distribution of high automatability across industries and occupations is also found to be skewed towards routine jobs with low demand for transversal and social skills. The risk of job displacement by machines is higher among males and lower-skilled workers, with little evidence of polarisation. It is prevalent in private sector jobs that fail to provide remedial training to employees, accentuating the vulnerability of at-risk-workers and highlighting the need for stronger lifelong learning policies at EU level.

JEL Classification: J01, J21, J24

Keywords: automation, skills, technology, digitalisation, future of work, skill needs

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1. Introduction

Recent years have seen an upsurge in the number of new research and policy studies, and associated media attention, focusing on the impact of technological change on employment, reskilling needs and overall implications about the future world of work (Bessen, 2015; Ford, 2015; World Economic Forum, 2016). Such increasing attention has been a consequence of the acceleration in new technological advances linked to the so-called 'fourth industrial revolution' (Schwab, 2016), which is thought to have exerted marked effects on both advanced and emerging labour markets. Recently collected EU-wide data by the European Centre for the Development of Vocational Training (Cedefop) have revealed, for instance, that about 43% of adult employees in the EU labour market experienced changing technologies, such as new ICT systems or machinery, in their workplace in the past five years (Cedefop, 2017, 2018).

Most of the recent literature has alternated between what may be called 'doom and gloom' and 'boon' scenarios. On the one hand, some scholars have claimed that close to a half of jobs in advanced economies are 'susceptible' to automation by robots and new technologies (Frey and Osborne, 2013). Their arguments reflect the fact that economies and societies are said to be at a critical turning point, a 'second machine age', in which rapid technological advances associated with machine learning, artificial intelligence, 3D printing, visual-space perception, natural language processing, among others, are likely to cause an exponential or 'combinatorial' social transformation in the near future (Brynjolfsson and McAfee, 2014; 2017). On the other hand, advocates of the positive consequences of technical progress tend to highlight that embodied technical change is usually associated with a net employment and labour market balance (Vivarelli, 2014; Bessen, 2016; Autor, 2015).

The aim of this paper is to engage in an in-depth investigation of the determinants of 'automatability risk' in EU jobs, namely the propensity of EU employees to be in jobs with a high risk of substitutability by computers or other automation processes. Using relevant data on tasks and skill needs in jobs, collected as part of the European Skills and Jobs Survey - a survey of approximately 49,000 EU adult workers in the 28 EU Member States (Cedefop, 2015) - jobs are bundled according to their estimated risk of automation. The methodology builds on previous assessments of Frey and Osborne (2013) and Nedelkoska and Quintini (2018) and provides further insight by enabling estimation of the relationship between jobs' task/skill content and automatability risk using individual-level data with highly disaggregated job title information. Overall, the analysis confirms well-reported estimates of automatability risk across different industries and occupational categories, with marked consequences for labour market outcomes. It is also found that the risk of automation is particularly stark among men and lower-skilled workers and is associated with jobs in which employee training is not provided, hence accentuating the vulnerability of at-risk workers.

Section 2 engages in a brief review of the enormous literature that examines the relationship between technological change, innovation and the impact of automation on labour market outcomes, such as employment or wages. Section 3 describes the data and discusses the key variables used in the analysis. Section 4 subsequently outlines in detail the methodological process employed in order to estimate the latent relationship between automation risk and skill requirements/tasks in jobs and, hence, infer the mean automation probability in EU job markets. Section 5 subsequently investigates the determinants of automation risk by engaging in multivariate regression analysis, while it also explores its correlation with various labour market outcomes, including earnings, job satisfaction, job insecurity and skills obsolescence. Section 6 provides a conclusion.

2. Literature Review

Concerns about changing technologies 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; Autor, 2015). Empirical studies of the impact of technological progress on economic and social outcomes therefore abound in the literature, including those that attribute rising wage inequality and returns to college education since the early 1980s to *skill-biased technological change (SBTC)* (Katz and Murphy, 1992; Berman et al., 1994; Katz and Autor, 1999), as evidenced by a positive association between computer use and other proxies of technology (e.g. R&D intensity) with skills upgrading (Krueger, 1993; Machin and van Reenen, 1998; Autor et al., 1998).

Such an explanation, however, fails to take into account the non-linearities in growth of the employment structure observed across some advanced economies, most notably the widening polarisation of the occupational distribution, which gave rise to theories of *routine-biased technological change (RBTC)*. Starting with Autor et al. (2003), these theories emphasised the potentially 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; Goos et al., 2009; Acemoglu and Autor, 2011; Handel, 2012).

Consistent with the RBTC hypothesis, recent studies have sought to estimate the susceptibility of occupations and jobs to automation. Such estimates are calculated on the basis that some professions are more frequently characterised by a set of 'conducive' task characteristics (e.g. routine or manual tasks, standardised job content, infrequent social interactions, precise physical or hand-arm movement) that can render them vulnerable to robotic processing or algorithimic coding/standardisation. These are in contrast to some tasks/skills that constitute 'engineering bottlenecks' to automation, including problem-solving or social intelligence, caring, perception and situational adaptability.

Applying this framework, Frey and Osborne (2013) estimated that 47% of occupational categories in the US labour market are at high risk of automation, mostly middle- and low-skilled professions (e.g. data entry clerks, telemarketers, transportation, librarians). Recent studies have also tended to demonstrate that increasing robotic adoption in advanced economies has exerted non-negligible effects on employment, wages (including a declining labour income share) and hours of work, though such negative impacts affect workers of different skill levels differently and are dependent on labour supply and demand elasticities and product market substitutability (including geographical proximity) (Graetz and Michaels, 2015; Acemoglu and Restrepo, 2016, 2017; Dauth et al. 2017).

Arntz et al. (2016) and more recently Nedelkoska and Quintini (2018) dismiss such high figures on the grounds that they potentially exaggerate the extent to which occupations as a whole can be automated. Accounting for the fact that workers who may be classified within the same occupational group may perform a different portfolio of tasks, about 9-14% of jobs are found to be at a high risk of being automated, defined as jobs where at least 70% of the tasks are automatable, though a large share (about one third) of all jobs face some smaller degree of automatability. Similar scepticism and reflection on 'why so many jobs exist today' have been expressed by Autor (2015), who notes that most of the pessimistic literature fails to adequately acknowledge the *Polanyi paradox* ('*we can know more than we can tell*') and since human judgement, adaptability and intuition (often beneath our conscious appreciation as they tend to be transmitted via culture, tradition and evolution) are features of jobs that cannot be easily automated.

Another strand of related literature, focussing on the relation between innovation and employment or skills bias (Vivarelli, 2014, 2015), further tends to argue that claims of negative consequences of technology are potentially exaggerated. Once one takes into account various compensatory price, scale or income effects arising from greater product (as opposed to process) innovation – such as lower prices of high-tech consumer goods and new product markets that stimulate higher aggregate demand – and other externalities and spillover effects across industries and occupations, technological innovation has been historically associated with a positive net employment premium (Van Reenen, 1997; Pantea et al., 2014; Vivarelli, 2015; Pellegrino et al., 2017; Piva and Vivarelli, 2017).

While historical evidence tends to dismiss widespread fears of robots and machines replacing human input, concerns about a jobless future of work are nevertheless sustained and have recently intensified (Hogarth, 2017). Part of the reason is that recent advancements in digital technology, such as machine and deep learning and mobile robotics, have raised the prospect of automation affecting a wider range of jobs dependent on cognitive/non-routine tasks (e.g. accountancy, logistics, legal works, transportation, translation, financial analysis, medical diagnostics, text writing), previously thought to be out of reach of computers (Frey and Osborne, 2017).

3. Data and descriptive statistics

3.1 The European skills and jobs survey

In this paper we use data from the European Skills and Jobs Survey (ESJS) to identify the risk of automation across a sample of EU employees as well as how such risk varies across different socioeconomic determinants and affects labour market outcomes. The ESJS is a state-of-the-art survey of adult employees (aged 24-65) carried out in the 28 member states of the European Union, collecting information on the match of their skills with the skill needs of their jobs.[2] It was financed and developed by the European Centre for the Development of Vocational Training (Cedefop), in collaboration with a network of experts, the OECD, and Eurofound (Cedefop, 2015). The aim of the survey is to help inform the development of European policies on initial and continuing education and training and employment policies. To do so, it seeks to understand how individuals' qualifications and skills are matched (or not) to the changing skill demands and task complexities of their jobs. The survey also examines the extent to which employees' skills are developed and used in their workplaces over time.

([2]) For full details of the survey and to download the microdata the reader is referred to: http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

A mixed online-telephone methodology ensured that the data collected provided a representative sample of the adult working age population in each of the EU28 member states.[3] The survey was carried out using quota sampling by the survey company Ipsos MORI and its network partners in each country between 7 March and 26 June 2014. In total, 48,676 respondents from different demographic groups took part either by telephone (9,154 employees) or online interviewing (39,522 employees). In most EU countries about 1,000-1,500 employees were effectively interviewed, although the sample varies between countries. The sample was augmented to 4,000 observations in the case of five large EU labour markets (Germany, France, Poland, UK, and Spain), 3,000 cases for Italy, and 2,000 cases in Greece and Finland, while 500 individuals were surveyed by telephone in each of the three smallest countries (Malta, Cyprus and Luxembourg).[4]

3.2 Sample and key variables

To estimate the risk of automation affecting European workers' jobs, the analysis adopts a similar methodology to that of previous approaches that have moved beyond the occupational level of analysis used by Frey and Osborne (2013, 2017). In particular, Arntz et al. (2016) and Nedelkoska and Quintini (2018) exploit the unique data on tasks available in the OECD's Survey of Adult Skills (PIAAC), to estimate the micro relationship between workers' job tasks and the risk of automatability. As discussed above, such an approach accounts for the marked variation in tasks that exists within occupations.

The use of the ESJS data in this paper enables the replication of the aforementioned approach, albeit it exploits a key value-added of the new survey, namely it contains information on a series of different skill sets needed in EU employees' jobs. Specifically, the survey asked respondents to assess the importance of a set of eleven different skills needed for their jobs.[5] It also collected information on the frequency of engaging in routine, autonomous or learning tasks at work. The ESJS also contains important contextual information, such as a standard set of control vairables capturing demographic, socioeconomic and job characteristics of the EU employee workforce (age, gender, level of education, native status, firm size, type of contract, economic sector, occupation etc.).

Of specific relevance for the paper's analysis is the fact that information at the one- and two-digit international standard classification of occupations was collected for all ESJS respondents. Individuals in the online part of the survey were asked to identify their broad one- and two-digit occupation based on pre-existing drop-down lists, which contained detailed examples of four-digit occupations. For those who had difficulty identifying their broad occupational group, a follow-up

([3]) According to Forth, J. (2016) *Evaluation of Design Effects in the European Skills and Jobs Survey*, NIESR, UK, minimisation of design effects can be achieved in the ESJS by treating its sample design as akin to that of stratified cluster sampling. Furthermore, Cedefop (2015) demonstrates that the ESJS sample produces comparable survey estimates with those originating from other random probability surveys (ESWC, PIAAC) on similarly-defined survey items.

([4]) The questionnaire was translated into the national languages of the EU countries using a strict translation protocol, managed by Ipsos MORI. Prior to administering the survey, extensive cognitive and pilot tests took place to validate the content and validity of the survey instrument. For details, see Cedefop (2015).

([5]) The set of skills assessed in the ESJS included the level and importance of literacy, numeracy and ICT skills, as well as the degree of importance of technical, communication, team-working, foreign-language, customer-handling, problem-solving, learning and planning/organisational skills. Respondents were asked to assess '*On a scale from 0 to 10, where 0 means not at all important, 5 means moderately important and 10 means essential, how important are the following for doing your job?* '.

question asked them to identify the name and title of their jobs. In the telephone interviews, all individuals were also asked to describe 'what kind of work they do most of the time' and this detailed job description was subsequently coded back to the broader one- and two-digit ISCO groupings by the survey company Ipsos MORI. Together, about 14,097 respondents (circa 29% of the total ESJS sample) provided detailed information about their job title/work description. In section 5 below we exploit this uniquely detailed level of occupational information to engage in estimation of the risk of automation in EU job markets.

4. Empirical methodology

4.1. The skills/tasks-occupational approach

In order to calculate the share of EU jobs susceptible to automation, namely those whose majority of tasks may be codified using state-of-the-art computer equipment and machine learning (ML) and artificial intelligence (AI) methods (conditional on the availability of big data), this paper adopts the standard methodology used in previous literature. In particular, information on the "true" likelihood of automation from a selected set of 70 detailed (4-digit) occupations is used (the so-called 'training dataset'), as collected by Frey and Osborne (hereby FO) on the basis of expert opinions. FO subsequently relied on the views of ML specialists to identify three so-called 'engineering bottlenecks' (corresponding to nine O*NET variables), namely tasks which, given the current state of art of technology, are difficult to automate. By modelling the underlying latent probability of "true" automation as a function of the feature vector of nine bottleneck variables, FO extend their out-of-sample prediction of automation risk to about 702 occupations.

In this study, corresponding information on tasks and skill needs in the ESJS dataset is used that can be mapped or proxy for the engineering bottlenecks of FO, albeit in some cases imperfectly. The aim is to unearth the underlying latent empirical relationship between the variance in skill needs within occupations and the probability of automation, the latter inferred by the FO training dataset, in a similar manner to the task-based methodology employed by Arntz et al. (2016) and Nedelkoska and Quintini (2018).

Table 1 below illustrates the correspondence between ESJS-related variables and FO's 'engineering bottlenecks'.[6] It is clear that while on most occasions there is reasonable connection between the two, for some, most notably those descriptive of work posture and the provision of care for others, there is a poor or absent link. Nevertheless, it can be confirmed that the ESJS variables can be broadly mapped to the main matrix of descriptors identified in the task-based literature, namely routine-cognitive-interactive-manual tasks (Acemoglu and Autor, 2011; Autor, 2013).

([6]) The ESJS data also enables exploration of additional features conducive to job automation, not explicitly accounted for in the FO approach, namely the degree of 'standardisation' and 'digitisation' of job content. In particular, ESJS respondents were asked to assess the level of numeracy and ICT skills needed in their jobs. A priori, it is expected that jobs dependent on advanced numerical skills (defined in the ESJS as '*calculations using advanced mathematical or statistical procedures*') or advanced digital skills (defined as '*developing software, applications or programming; use computer syntax or statistical analysis packages*') will be more susceptible to automation, given that tasks in such jobs should be more easily specified to be performed by advanced machine learning techniques.

Table 1 **ESJS variables corresponding to FO identified engineering bottlenecks**

Bottleneck	*FO O*NET Variable*	*O*NET definition*	*ESJS variable*	*ESJS definition*
Perception manipulation	Finger dexterity	*The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate or assemble very small objects*	*Technical skills*	*Specialist knowledge needed to perform job duties; Knowledge of particular products or services; Ability of operating specialised technical equipment*
	Manual dexterity	*The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate or assemble objects*		
	Cramped work space, awkward positions	*How often does this job require working in cramped work spaces that requires getting into awkward positions?*	NA	
Creative intelligence	Originality	*The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem*	*Problem solving skills*	*Thinking of solutions to problems; Spotting and working out the cause of problems*
			Learning skills	*Learning and applying new methods and techniques in your job; adapting to new technology, equipment or materials; Engaging in own learning*
			Learning tasks	*How often, if at all, does your job involve 'learning new things'?*
			Non-routine tasks	*How often, if at all, does your job involve 'responding to non-routine situations during the course of your daily work'?*
			Autonomous tasks	*How often, if at all, does your job involve 'choosing yourself the way in which you do your work'?*
	Fine arts	*Knowledge of theory and techniques required to compose, produce and perform works of music, dance, visual arts, drama and sculpture.*	NA	
Social intelligence	Social perceptiveness	*Being aware of others' reaction and understanding why they react as they do.*	*Team working skills*	*Cooperating and interacting with co-workers; dealing and negotiating with people*
	Negotiation	*Bringing others together and trying to reconcile differences.*	*Planning and organisation skills*	*Setting up plans and managing duties according to plans; Planning the activities of others; Delegating tasks; Organising own or other's work time*
	Persuasion	*Persuading others to change their minds or behaviour.*	*Foreign language skills*	*Using a language other than your mother tongue to perform job duties*
			Communication skills	*Sharing information with co-workers/clients; Teaching and instructing people; Making speeches or presentations*
	Assisting and caring for others	*Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers or patients.*	*Customer handling skills*	*Selling a product/service; Dealing with people; Counselling, advising or caring for customers or clients*

4.2. Estimating the latent automatability-skill needs relation

A key challenge of the above exercise is to find a match between the 70 detailed occupations in the FO training dataset, derived from the US Bureau of Labor Statistics Standard Occupational Classification System, with corresponding occupational classes in the ESJS. Obtaining an exact identification is however difficult given that most micro datasets, including the ESJS, typically contain information at reasonable levels of sample accuracy for broader occupational levels. A similar assignment problem has been faced by Arntz et al. (2016), who use a multiple imputation approach to match the FO automatability indicator to the US PIAAC sample data based on available 2-digit ISCO codes. Nedelkoska and Quintini (2018), by contrast, achieve a closer correspondence between the 70 hand labelled occupations in FO's training data and a subset of 4-digit occupational classes. To do so, however, they have had to rely only on the Canadian sample of the PIAAC dataset, which has a substantially larger sample size than any other country in the international OECD survey.

This study exploits the uniquely detailed information on workers' job descriptions available in the ESJS to estimate automation risk in EU job markets. In particular, the analysis exploits the fact that the ESJS microdata contains detailed job titles and work descriptions for about 14,097 respondents[7] from all EU28 countries[8] (circa 29% of the total ESJS sample) and has engaged in (quasi) text mining analysis, involving information and concept/entity extraction as well as text clustering. In particular, the detailed job descriptions have been matched, using a reasonable proximity of keywords, with the occupations in the FO training dataset. To achieve a good match, appropriate keywords, clues and recurrent grammatical and syntactical structures have been used that constitute 'close descriptors' of the minor FO training occupations, as described in the relevant US SOC and ISCO-08 taxonomies. As an additional quality control check, it has been ensured that the identified detailed job descriptions from the ESJS are loosely constrained to the broader 2-digit ISCO-08 group(s) containing the FO 4-digit training occupations.[9]

As an example of the abovementioned process, to match the ESJS job title string variable to a detailed FO occupational group, say 'cashiers', keywords such as 'cashier', 'checkout assistant' and 'checkout attendant' were used, together with clues ('cash register', 'cash') and relevant descriptive syntax ('ticket issuing'). These keywords were derived from the descriptions of the respective occupation in either the US Bureau of Labor Statistics (BLS) SOC system or the International Labour

([7]) The final number of cases with valid detailed job descriptions has been derived after a number of steps made to 'clean' the respective variable; in particular, all entries were first made upper case, multiple blank spaces were made visible and amended, while missing values (including anomalous entries such as '??', "…", "") were made visible and dropped. Several redundant answers (such as 'NULL', 'NULL.', 'NO', 'NONE OF YOUR BUSINESS', 'NO COMMENT', 'I DON'T KNOW', 'NOTHING, 'I DON'T WANT TO DISCLOSE', 'NA', 'NOT APPLICABLE' etc.) were identified and deleted.

([8]) A notable feature of this detailed data capturing adult workers' job profiles is that the survey company Ipsos MORI used national linguists to translate the information from the respective national language of each respondent into English.

([9]) For instance, the identified matched job descriptions for 'Civil engineers' have been constrained to match only cases consistent with the group ISCO-08 21 'Science and engineering professionals', whereas the cluster linked to 'Civil engineering technicians' was restricted only to cases within the broader group ISCO-08 31 'Science and engineering associate professionals'.

Organisations' (ILO) ISCO-08 group definitions.[10] A similar process has been employed for the remaining 67 occupations in the training dataset.[11]

As an outcome of this analysis, approximately 3,471 matches were achieved with 68 of the original FO training occupations, corresponding to 7% of the total ESJS sample (and 25% of the subsample with non-missing job descriptions). As can be seen in Annex Figure A1, a majority of matches were realised for some common occupations (accountants, maids and housekeeping cleaners, cashiers, chefs/chief cooks, waiters, nurses, industrial truck and tractor operators), while other narrower or more specific occupations were characterised by weaker filtering outcomes (e.g. paralegals/legal assistants, physicists, technical writers, parking lot attendants, zoologists). Nevertheless, the fact that the ESJS data have allowed for such detailed matching of the FO occupational list with specific job titles of employees from different EU countries constitutes a value-added in the literature. In particular, it enables estimation of the underlying function between the "true" automatability risk and skill needs of jobs based on a pooled sample of all EU countries, as opposed to relying on only one country (which may be characterised by a specific industrial structure, global value chain position and labour market institutions) or inputting the match at a broader (e.g. two-digit) occupational level.

More formally, a logistic regression can be used to estimate the latent function of the "true" automatability of occupations, as extracted from the FO training data, and individual-level information on skill needs at work, as follows:

$$P(y^{*} = 1|s) = \frac{1}{1+\mathrm{e}^{-(\beta 0+\beta 1 s+\beta 2 C_{f})}} \qquad [1]$$

where $y \in \{0,1\}$ is a (68 x 1) vector of the occupational automatability assessment and s is a matrix of ESJS skill-requirements variables (as shown in Table 1 above). The coefficients β are estimated on a pooled cross-section of employees from all EU28 countries after taking into account country fixed effects (C_f).

Having estimated the latent relationship between the risk of automation in the training occupational subsample and the ESJS skill needs variables, the coefficients of the model are subsequently applied to all other individuals in the 28 EU countries, to obtain an out-of-sample prediction of the individual risk of automation. The analysis also subsequently seeks to detect the underlying relationship between automation risk and various individual and job characteristics, and relates the former to several labour market outcomes (e.g. wages, job security, job satisfaction, skills obsolescence).

Despite the fact that estimation of automation risk using the detailed ESJS job descriptions is based on more precisely defined occupational matches with FO's original training dataset, the approach has important methodological limitations.

([10]) The BLS SOC system is available at the following link: https://www.bls.gov/soc/2018/major_groups.htm#13-0000; while the ILO ISCO-08 group definitions are available at: http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm

([11]) Two occupations in the FO list, namely 'credit and loan officers' and 'credit authorisers, checkers and clerks', have been captured under one list, given their marked similarity in job descriptions. It has also not been possible to match any entries in the ESJS with the FO occupations 'hunters and trappers' and 'farm labour contractors'. See Annex Table A1 for further examples.

Most notably, while a non-trivial 29% of the total number of respondents provided a detailed job description, it is reasonable to expect some bias in the distribution of respondents who provided such information, especially among online respondents. This is because it was only requested in the survey conditional on individuals being unable to accurately identify their one- or two-digit occupational group in prior questions.[12]

Furthermore, there is an imperfect correspondence between the US occupational classification used by FO and the ISCO classes and definitions used by the ESJS.[13] While it is also important to acknowledge that even though all efforts were made to exhaust the list of possible keywords used for matching the detailed ESJS job descriptions to the FO list, it is likely that several relevant entries may have not been identified. However, in order to ensure that the ESJS job descriptions mirror as closely as possible the respective FO occupations, the entity extraction process has been deliberately kept stringent.[14]

In addition, the underlying estimated model (1) connecting job tasks/skill needs to automatability risk is assumed to be fixed across countries in the EU job market, which is a generous assumption considering that EU economies are characterised by different industrial structures, development levels and position in global value chains, labour market institutions and incentives for capital-labour substitution.

5. Multivariate analysis

5.1. Risk of automation in EU job markets

Following implementation of the methodological steps outlined above, a "training dataset" denoted as $D = (\boldsymbol{s}, \boldsymbol{y})$, comprising of the approximately 3,500 matched cases has been retained, containing information on whether an individual's occupation is automatable or not, along with descriptions of his/her job tasks and required skills intensities for the job. In this dataset about 55% of employees (1,899 cases), labelled as $\boldsymbol{y}$=1, belong to occupations whose tasks/skills, according to FO, can be automated, while the remaining 45% (1,572 cases), taking the value $\boldsymbol{y}$=0, are employed in jobs that cannot (or can only partially) be replaced by machines.

For the purposes of estimation of equation (1) four distinct set of variables, descriptive of the skill needs of employees' jobs, have been identified, as implied by factor analysis, as follows:

([12]) Indeed, it is confirmed by the descriptive statistics that the subgroup of individuals providing detailed job descriptions, as well as those with matched cases, is more prone, on average, to be females, older-aged and less educated. A significantly lower incidence of workers undertaking clerical support and market and sales duties and more of those carrying out lower-skilled occupations were inclined to disclose their job title and kind of work.

([13]) This imperfect correspondence is more severe for some occupations than others; for instance, 'Compliance Officers' in the BLS SOC system are classified under the broad ISCO-08 title 'Business and Financial Operations Occupations', while in the ISCO-08 taxonomy the closest matched occupation is 'Process control technicians, other'. See Table A.1. Annex A in Nedelkoska and Quintini (2018) for a suggested correspondence table between FO occupations and ISCO-08.

([14]) For example, including the keyword 'chief' to match the ESJS entries to the FO occupation 'Chief executives' would augment the number of matched cases, albeit at a cost of greater imprecision. This would be the case because it is not absolutely clear whether a person describing his/her job duties as 'chief' is actually a company director/executive, while a number of erroneous cases (such as 'police chief officer' or 'political chief of staff') would also be selected.

- *Transversal skills i.e.* the degree of importance of learning skills, problem-solving skills, communication skills, team working skills and planning/organisation skills for the job – indicative of a job's reliance on the so-called "four C's", namely creativity (learning), critical-thinking, communication and collaboration;
- *Foundation skills i.e.* the extent to which a job requires advanced literacy, numeracy or digital skills;
- *Selling or customer-serving skills i.e.* the importance of foreign language skills and customer-handling skills in the job - descriptive of a job's need to cater to a domestic and/or international clientele;
- *Technical skills i.e.* the degree to which a job is reliant on specialised or job-specific skills.

To further facilitate efficiency in the estimation, given the potential collinearity in the repeated and similarly-measured skill intensity survey items of the ESJS, the variables included in the transversal and customer-serving skills sets have been reduced to two summative variables. These have been derived using Cronbach's α statistic, and their internal consistency was verified.[15]

Estimation of the underlying latent 'true' probability of automation as a function of the aforementioned skill needs constructs and tasks characterising workers' jobs reveals estimates in accordance with the task-based literature. The empirical logit coefficients[16] shown in Table 2 indicate that there is a strong positive association between a job's routinisation frequency and propensity towards automatability. Jobs that demand advanced numeracy and at least some digital skills and those that have greater reliance on specialised skills are also more likely to belong to FO's list of automatable occupations. By contrast, the probability of automation is significantly lower for employees whose jobs facilitate their autonomy and which demand a higher degree of transversal[17] as well as selling skills.

An associated analysis of variance (ANOVA) decomposition further shows that most of the variance in automatability is accounted for by the variables planning, advanced numeracy and team working skills, whereas communication, problem-solving and foreign-language skills explain a small, insignificant, part of the explained sum of squares.

<Insert Table 2 here>

To obtain an out-of-sample prediction of the EU-wide individual risk of automation, the implied relationship between automatability and job tasks/skill needs as estimated above is extended to all other individuals in the ESJS sample. This analysis hence reveals that the median EU employee faces

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([15]) Details of the factor analysis and derivation of the Cronbach alpha scales are available in the Annex Table A2.

([16]) Estimation of equation (1) has also been carried out using a multilevel (mixed-effects) logistic model, which estimates the two moments of the country intercept and hence saves on degrees of freedom, relative to the inclusion of 28 country dummies in the logistic regression. The estimation confirms the statistically significant dispersion of automatability across EU countries – $\widehat{var}(\beta_0) = 0.11$ (robust s.e. = 0.054). Importantly, the estimated size and significance of the main skill needs coefficients are equivalent to those shown in Table 2. Results are available from the author upon request.

([17]) Although most skill needs variables are consistent with *a priori* expectations regarding their association with the risk of automation, a notable exception is learning skills, found to be positively related to automatable occupations. Nevertheless, it may be reasonably posited that jobs facing a higher degree of substitutability by technology may also entail a greater '*need for learning and applying new methods and techniques*' and for '*adapting to new technology*' by '*engaging in own learning*'.

a 51% probability of being in a job that may be automated.[18] Following FO's approach, it is hence found that about 14% of EU adult employees are in jobs that face a very high risk of automation (i.e. the median automation probability exceeds 70%). Similarly, 40% have a non-trivial chance of automation (between 50 and 70%), while for 34% of workers the automation probability ranges between 30-50%. In the ESJS sample only 12% of adult employees are found to be facing a very low (less than 30%) chance of automation.

<Insert Figure 1 here>

Overall, the inferred automatability distribution based on the ESJS data is more similar to that implied by Arntz et al. (2016) and Nedelkoska and Quintini (2018) as opposed to Frey and Osborne (2013, 2017), although it is more heavily skewed to the left.[19] This confirms the value of relying on rich individual-level data capturing the within-occupational variance of skill requirements/tasks for the purposes of estimating the latent automatability function (1).

5.2. Determinants of jobs at risk of automation

The rich ESJS contextual information on workers' sociodemographic and job characteristics permits further exploration of the factors associated with a greater risk of automation. In particular, Table 3 displays the estimated OLS coefficients of the predicted probability of automation, $\widehat{y_{os}}$, as well as those of the following logistic regression[20]:

$$P({y_{hi}}^{*} = 1) = \beta_{0i} + \beta_1 X_i + \beta_2 J_i + \beta_1 O_i + \beta_1 I_i + \beta_1 C_i \qquad [2]$$

where $y_h$is defined as a dummy variable taking the value one if an individual i is employed in a job with a very high risk of automation and zero otherwise, X is a vector of individual sociodemographic characteristics (gender, age, education level, prior employment status), J is a vector of job-specific factors (private sector, training provision, contract type, employer tenure, multisite workplace, firm size, promotion prospects) and $\boldsymbol{O}, \boldsymbol{I}$ *and* $\boldsymbol{C}$ are occupation, industry- and country-specific indicator variables, respectively. The estimation procedure is performed in steps, first including the set of

([18]) As in Nedelkoska and Quintini (2018), there is marked variance in the estimated automation risk across EU countries (a standard deviation in the mean risk of 0.16), ranging from a high of 68%, 65% and 63% for Bulgarian, Polish and Slovakian workers, respectively, to a low of 37% and 36% for Irish and German employees. With an estimated 18% median risk of automation, Finland appears to be an outlier. The paper does not overstress the country-specific estimates, given the small sample-sizes per country and since the ESJS did not adopt a random probabilistic design. Nevertheless, the results confirm previous literature indicating a higher risk of automation among Central and Eastern European countries, as well as the Baltics and some Southern EU states (notably Greece), and a low risk in Scandinavian and some Northern countries.

([19]) The estimated percentages of adult EU workers at risk of automation are relatively sensitive to the specification of equation (1). For instance, using the detailed list of skill needs and tasks variables, without reducing them to a more limited control set, raises the estimated percentage of workers at very high and very low risk of automation to about 20% and 14%, respectively, compressing the shares of those in intermediate risk classes. However, an upper threshold of about 20-21% of very high risk of automation persists even when several specifications of equation (1) (such as dropping the level of foundation skills variables) are deployed.

([20]) For robustness purposes a multinomial logit model has also been estimated for a categorical dependent variable that contains four different degrees of automation risk, namely very high risk (>70% automation probability), high risk (between 50-70%), low risk (30-50%) and very low risk (<30%). The analysis confirms the overall robustness of the effects detected by estimation of equation (4). Results are available from the author upon request.

variables in **X** and subsequently **J** and **O,I**, which enables careful scrutiny of the impact of individual and job level determinants, whilst avoiding the 'bad control' problem due to the simultaneous inclusion of occupational and industry variables (Angrist and Pischke, 2009).

<Insert Table 3 here>

It is evident from the table that, all other things equal, jobs characterised by a high risk of automation tend to be predominantly occupied by male employees.[21] This is an outcome of the fact that men are more likely to sort into occupations and sectors with a higher automation risk, but also perform jobs with more 'automatable' skills. Specifically, in the ESJS sample men are more likely to be performing jobs that require a higher level of technical and numerical skills, which are positively linked to automatability, in contrast to communication, team-working and planning/organisation skills, which are more likely to characterise the jobs of female workers and have lower automation risk.

Moreover, it is found that individuals who have a higher educational attainment level face statistically significant lower odds of being in an automatable job. It is therefore notable that, in contrast to job polarisation theory, automatability risk does not disproportionately impact only medium-qualified workers, but is instead greater for employees that, in general, have lower skill levels. Prior labour market status is also found to be a significant determinant of substitutability by machines, since the risk of being in a job facing high risk is markedly greater for employees who were unemployed before finding their current job.

The analysis also reveals a statistically significant U-shaped relationship between age and automatability, confirming Nedelkoska and Quintini (2018) and implying that middle- and older-aged workers tend to face lower automation risk than young workers. However, after taking into account age effects, individuals with longer spans of tenure with their current employer are characterised by higher chances of automation.

A number of job-related characteristics are found to be significantly related to the probability of automation. Jobs facing very high automatability risk tend to be predominantly in the private sector and in larger, single site, workplaces. Although in terms of raw descriptive statistics the probability of automation is higher for workers on fixed-term of temporary agency contracts (15.5% of adult employees on such temporary contracts face a very high risk of automation, as opposed to 13.5% of those on indefinite contracts), the effects are not statistically significant once other factors are taken into account. In automation-prone jobs, employees are also more likely to face limited promotion prospects and their job role and tasks have remained stagnant over time. They are also significantly less likely to have undergone any type of training for their job (on- or off-the-job, non-formal or informal) over the course of the previous year. This is striking, considering that upskilling and reskilling are argued to be key ingredients for mitigating the difficult transitions required for workers affected by technological skills obsolescence (Cedefop, 2018; McGuinness et al., 2018).

The ESJS collected unique information on the degree of skill mismatches affecting EU workers. In particular, employees were asked to assess the correspondence between their own skills and those

([21]) This finding is in contrast to that of Nedelkoska and Quintini (2018), who find that females face a higher risk of automation and attribute this to the fact that their jobs have more automatable tasks than male peers (even if females tend to sort into occupations with lower automation risk).

required by their jobs, both in terms of the total stock of skills and also for a set of eleven specific skills. Although such variables are likely to be endogenously related to the predicted risk of automation, given that both measures are confounded by the respondents' subjective assessment of skills needs in their job, inclusion of such uniquely detailed skill mismatch variables in the specification of equation (2) reveals some interesting findings. In particular, individuals who are employed in jobs at risk of displacement by machines are more likely to be affected by skill gaps in their digital skills, as well as in a variety of generic skills (communication, team working, customer-service, problem solving and planning). By contrast, they are less likely to experience gaps in their basic skills (literacy and numeracy) and in their level of required technical expertise (including knowledge of foreign languages).

Finally, the estimates further highlight a number of well-reported occupation and industry-specific impacts on the risk of automation (see Figures 2, 3). Individuals in crafts and elementary posts and those working as plant and machine operators face higher chances of being in highly automatable jobs, in contrast to those employed in high-skilled occupations (e.g. managers, professionals) and in services and market sales. Similarly, individuals employed in sectors providing social and personal services, education and health services and in the cultural industries face significantly lower automation chances, relative to those employed in the secondary and primary sector.

<Insert Figures 2, 3 here>

5.3. Labour market outcomes and the risk of automation

In addition to understanding factors associated with the risk of automation, this section focuses on testing how a job that is susceptible to being replaced by machines is associated with a variety of labour market outcomes. Table 4 demonstrates the estimated OLS relationship between the predicted (out of sample) probability of automation, $\widehat{y_{os}}$, as well as the likelihood of being in a job that has a very high risk of automation, y_h, with individuals' (log) gross hourly earnings, their job satisfaction, and their anticipated job insecurity and skills obsolescence.[22]

As is clear from the table, a higher degree of automatabity tends to be significantly associated with jobs in which workers have lower mean job satisfaction and a higher (perceived) likelihood of job insecurity. They are also more likely to believe that several of their skills will become outdated in the near future. It is also evident, based on estimation of a standard Mincer earnings function, which accounts for individuals' gender, a quadratic age term and years of employer tenure (to proxy for both general and specific human capital), that there is a strong negative relationship between the risk of automation and earnings. Employees in (highly) automatable jobs, for instance, receive about

([22]) In the ESJS adult workers were asked the following related questions;
- for earnings they were asked to declare '*On average, how much is your gross monthly earnings from your job (before deductions or credits of tax and national insurance)?*' and, in case of non-response, to state their income band. See McGuinness and Pouliakas (2017) for further details on the construction of the continuous hourly wage variable.
- for job security and skills obsolescence they were asked to state on a Likert scale from from 0 to 10, where 0 means very unlikely and 10 very likely '*How likely or unlikely do you think it is that each of the following may happen? (i) I will lose my job in the next year (ii) Several of my skills will become outdated in the next five years.*
- finally, a standard job satisfaction question was asked '*On a scale from 0 to 10, where 0 means very dissatisfied, 5 means neither satisfied nor dissatisfied and 10 means very satisfied, how satisfied are you with your job?*'

3.5% lower hourly earnings, ceteris paribus, relative to comparable workers facing lower degrees of automation risk.[23]

<Insert Table 4 here>

6. Conclusions

Much has been said and written recently on the threat posed by machines and robots to humans. Continuous advancements in artificial intelligence and advanced robotics, but also in a wide array of new technologies (e.g. nanotechnologies, 3D printing, bioengineering etc.) with potential to radically transform industries and occupations, have heightened concerns of employees, including this time high-skilled workers, becoming side-lined to machines. Despite such scaremongering, historical evidence as well as current estimates of the risk of automation, such as those presented in this paper, dispute claims of a future post-work society. It is important to always bear in mind that in dynamic economies that have set in place high quality, responsive and inclusive education and vocational training systems, as well as adequate social security safety nets that support career transitions, displaced or idle resources tend to be utilised in other value-creating industries and occupations over time. Moreover, in a standard Neo-Keynesian framework the translation of cost-saving technologies into cheaper goods and, hence, greater product demand, is also dependent on a high degree of demand elasticity as well as on a robust median wage level in an economy that can support greater consumption expenditure.

The deployment of more capital investment expenditure by firms, following the introduction of a new technology, is also not an automatic or irreversible process (DeCanio, 2016). While innovation cycles and their commercial application in industry, most notably via rapid prototyping, have become shorter, the diffusion of new technologies within firms in a manner that is labour-disruptive can be long and uncertain. In addition to taking into account the relative cost of human versus capital factor inputs, relative to their marginal productivities, to decide on the degree of substitutability of capital for labour, many organisations realise that in a global economic environment their human capital constitutes a source of competitive advantage. Fast replacement of their workforce by machines may often come at a significant cost of lost organisation creativity, innovation and employee drive.

Moving from technical feasibility to actual market diffusion of capital investment also requires accounting for employers' incentives and commitment to their human resources. Assuming that jobs at high risk of automation must not only possess a specific skills/task mix that renders them susceptible to automation, but must also be characterised by employers disinclined to invest in their staff's human capital, it is hence possible to reassess the total stock of highly automatable jobs in the EU. Using the available ESJS data enables one to purge from the original estimate of very high risk jobs (14%) the share of employees employed in organisations consciously committed to their personnel's skills development. Doing so reduces the figure to 8.3% (accounting for firms that fully reimburse the cost of training) or to 7.6% (taking also into account employers who partly reimburse training expenditure).

([23]) Estimation of an extended wage equation with a wider control set that takes into account prior labour market status, a range of job characteristics (type of contract, sector, training provision etc.) as well as occupation and industry lowers the negative wage penalty to about 2%,though it remains statistically significant.

While pinpointing the exact figure regarding the share of EU jobs at risk of displacement by machines can be imperfect science, the available evidence does however highlight the need for policies that can shield specific population groups most vulnerable to technological unemployment or skills obsolescence. The ESJS data identify that it is typically lower-educated males, suffering from skill gaps in digital and transversal skills, and those employed for larger-sized firms in the private sector, who are faced with greater automation risk. Overall, sectors and occupations requiring medium- or lower-level skills are more prone to automation, while professional and interpersonal services provision (such as health care or education) are relatively insulated.

A key challenge for policymakers is thus to ensure that individuals who will soon see their jobs transitioning from a 'semi-analogue to a digital world' can do so with as little disruption as possible (Goolsbee, 2018). This process will require that they acquire relevant skills, are offered an adequate welfare safety net and exhibit a high degree of adaptability that will allow them to remain employable in future job markets. Modernising education systems and lifelong learning so that training programmes focus more heavily on key competences and soft skills, including the four C's – communication, collaboration, creativity and critical thinking – is admittedly a critical parameter of the equation.

Ensuring that we converge to a future we want will also require that EU stakeholders build high quality skills anticipation systems so as to prepare for emerging jobs and in-demand skills. Harnessing the power of digitalisation for making better policy decisions, such as by extraction of real time data on emerging jobs and in-demand skills, is another key input to the process. However, it is crucial that policymakers put in place safeguards so that there is adequate trust, transparency and governance in the interpretation and use of AI-generated intelligence in policy decisions.

With many advanced economies fundamentally struggling with low productivity, the advancement of digitalisation and AI holds significant promise for expanding efficiencies in a wide range of occupations and for new economic activities or markets emerging. But the move towards a new desirable 'future of work', such as a post-work or full employment society, instead of polarised labour markets, cannot rely only on more or better (re)skilling policies. A whole arsenal of innovation, competition and employment policies will have to be implemented together with forward-looking skills strategies to ensure equitable access for the majority of people to the profits and opportunities of digitalisation and automation.

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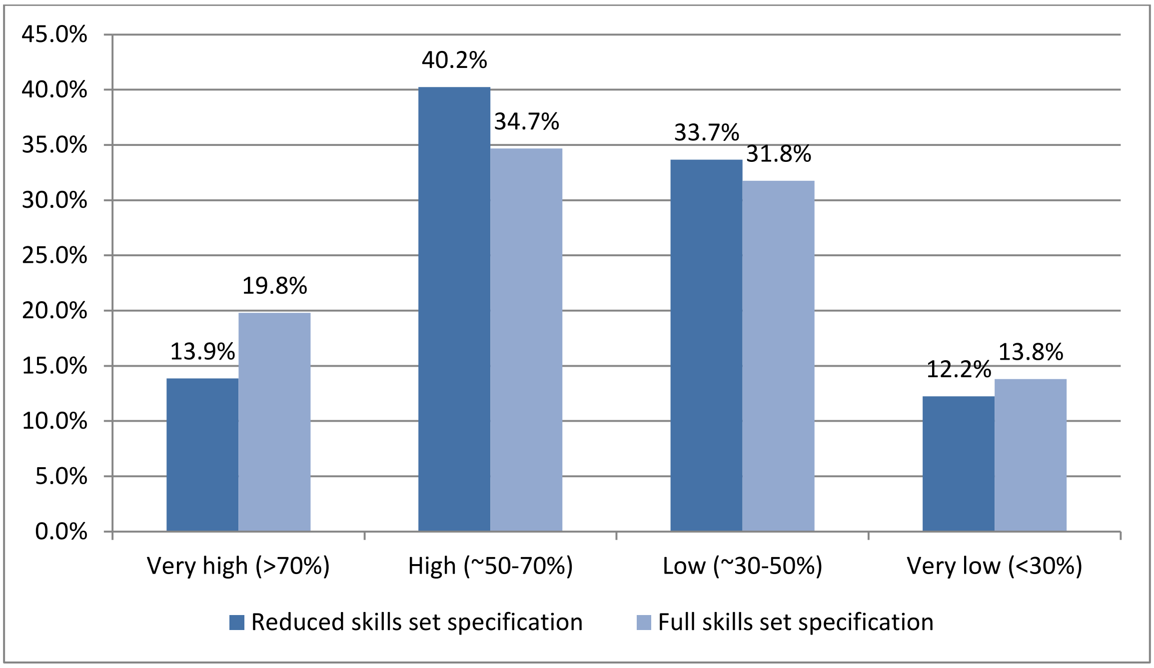
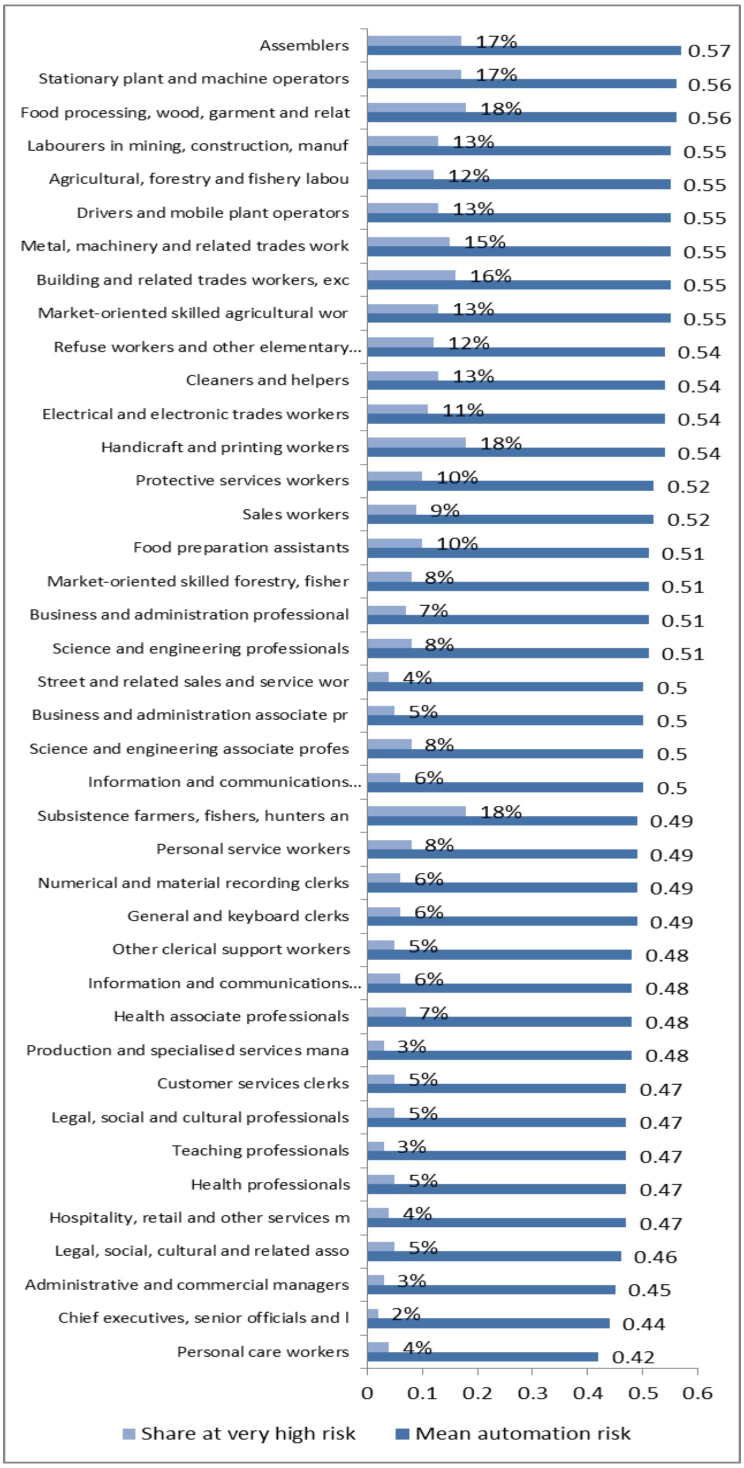
Figure 1 **Share of EU28 adult workers at risk of automation by degree of risk**



Notes: The figure displays the estimated out-of-sample automation risk calculated for the whole ESJS sample of adult employees using two different specifications of equation (1), as shown in Table 2.
Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

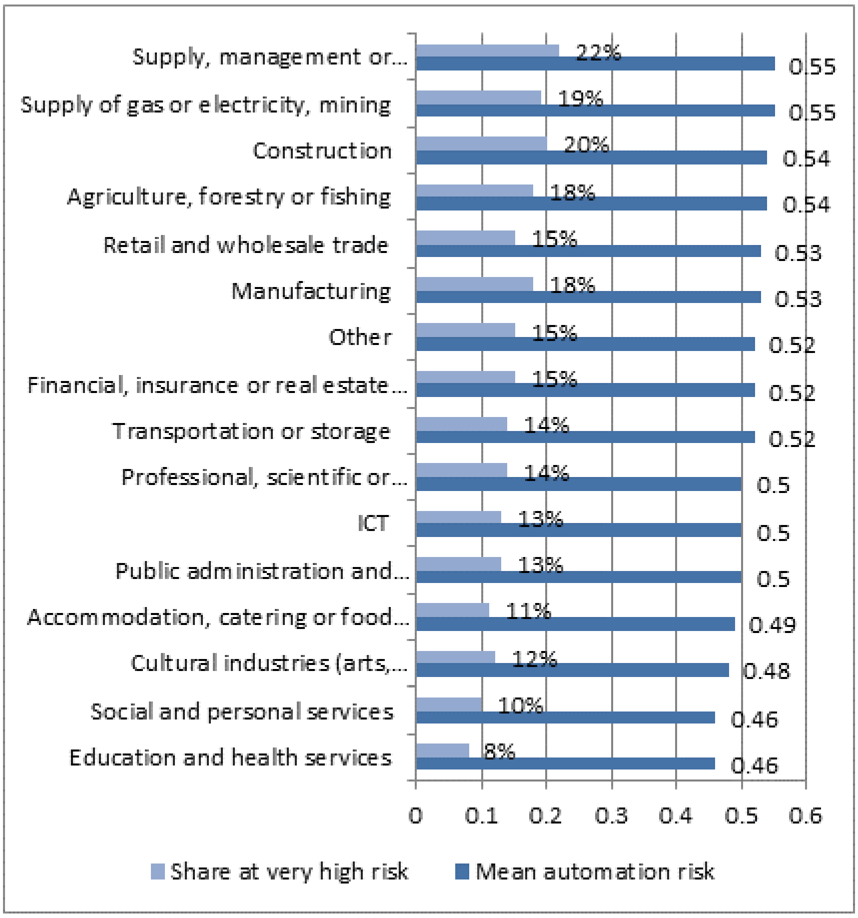
Figure 2 **Mean probability of automation by 2-digit occupation**



Notes: Out-of-sample predicted probability of automation based on estimation of equation (1); share of workers at very high automation risk defined as those with probability of automation over 70%.

Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

Figure 3 **Mean probability of automation by industry**



Notes: Out-of-sample predicted probability of automation based on estimation of equation (1); share of workers at very high automation risk defined as those with probability of automation over 70%.

Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

Table 2 **Estimation of latent relationship between 'true' automatability and skill requirements/tasks of jobs, logistic regression estimates, EU28**

	(1) *full skills set*	(2) *reduced skills set*
High frequency of routine tasks	1.39***	1.37***
	(0.107)	(0.103)
High frequency of autonomous tasks	0.78***	0.77***
	(0.064)	(0.061)
Importance of technical skills	1.06***	1.08***
	(0.017)	(0.016)
Importance of generic skills (summary variable)		0.71***
		(0.042)
Importance of customer service skills (summary variable)		0.90*
		(0.048)
Importance of communication skills	1.03	
	(0.022)	
Importance of team-working skills	0.88***	
	(0.018)	
Importance of problem solving skills	1.04	
	(0.023)	
Importance of learning skills	1.08***	
	(0.021)	
Importance of planning and organisation skills	0.88***	
	(0.016)	
Importance of foreign language skills	0.98	
	(0.013)	
Importance of customer handling skills	0.97**	
	(0.013)	
Advanced literacy skills (level)	0.56***	0.56***
	(0.052)	(0.051)
Advanced numeracy skills (level)	2.31***	2.28***
	(0.244)	(0.238)
No ICT skills needed (level)	0.59***	0.56***
	(0.060)	(0.054)
Country dummies (28)	√	√
Constant	2.53	0.74
	(1.696)	(0.436)
Observations	3,385	3,441

Notes: Odds ratios of regression coefficients following logistic estimation of equation (1); Robust se in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

Table 3 **Determinants of risk of automation, OLS and logistic estimates, EU28**

Specifications	(1) *X*	(2) *X & J*	(3) *X & J & O&I*	(4) *X & J & skill mismatches*	(5) *Odds of very high risk (X & J)*
Male	0.03***	0.03***	0.02***	0.03***	1.39***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.042)
Age band: 30-39	-0.01***	-0.01***	-0.01***	-0.01***	0.86***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.041)
Age band: 40-54	-0.01***	-0.01***	-0.01***	-0.01***	0.84***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.041)
Age band: 55-65	-0.01***	-0.01***	-0.01***	-0.01***	0.81***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.051)
(omitted: Age band: 24-29)					
Education: Medium	-0.01***	-0.00**	-0.00	-0.00**	1.04
	(0.002)	(0.002)	(0.002)	(0.002)	(0.049)
Education: High	-0.02***	-0.02***	-0.01***	-0.02***	0.92
	(0.002)	(0.002)	(0.002)	(0.002)	(0.045)
(omitted: Low education)					
Previous LM status: Unemployed	0.01***	0.01***	0.01***	0.01***	1.14***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.048)
Private sector		0.02***	0.00***	0.02***	1.24***
		(0.001)	(0.001)	(0.001)	(0.040)
No training in last 12 months		0.01***	0.01***	0.01***	1.28***
		(0.001)	(0.001)	(0.001)	(0.041)
Part time		0.00	0.01***	0.00	0.99
		(0.002)	(0.002)	(0.002)	(0.045)
Permanent contract		0.00	0.00	0.00	0.99
		(0.002)	(0.002)	(0.002)	(0.039)
Years in job		0.00***	0.00***	0.00***	1.00**
		(0.000)	(0.000)	(0.000)	(0.02)
Organisation with multiple sites		-0.00**	-0.00***	-0.00	0.97
		(0.001)	(0.001)	(0.001)	(0.030)
Small size firm (1-50 employees)		-0.01***	-0.01***	-0.01***	0.87***
		(0.001)	(0.001)	(0.001)	(0.027)
Not promoted since start of job but changed tasks		0.01***	0.01***	0.01***	1.20***
		(0.001)	(0.001)	(0.001)	(0.047)
No changes in job role since start of job		0.01***	0.01***	0.01***	1.21***
		(0.001)	(0.002)	(0.001)	(0.048)
(omitted: Promoted)					
Occupation dummies (ISCO 1-digit)			√		
Industry dummies (NACE 16 categories)			√		
Country dummies (28)	√	√	√	√	√
Gap: ICT skills				0.02***	
				(0.002)	
Gap: literacy skills				-0.01***	
				(0.002)	
Gap: numeracy skills				-0.01***	

				(0.002)	
Gap: technical skills				-0.03***	
				(0.002)	
Gap: communication skills				0.02***	
				(0.002)	
Gap: team working skills				0.01***	
				(0.002)	
Gap: foreign language skills				-0.00***	
				(0.001)	
Gap: customer serving skills				0.01***	
				(0.002)	
Gap: problem-solving skills				0.01***	
				(0.002)	
Gap: learning skills				0.00	
				(0.002)	
Gap: planning skills				0.01***	
				(0.002)	
Constant	0.49***	0.46***	0.46***	0.45***	0.06***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.009)
Observations	47,913	47,575	47,575	47,575	48,258
R-squared	0.49	0.50	0.52	0.52	

Notes: Columns (1-4): OLS regression coefficients of equation (2) with $\widehat{y_{os}}$ as dependent variable; Column (5) logistic regression coefficient of equation 2 with y_h as dependent variable. Robust se in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

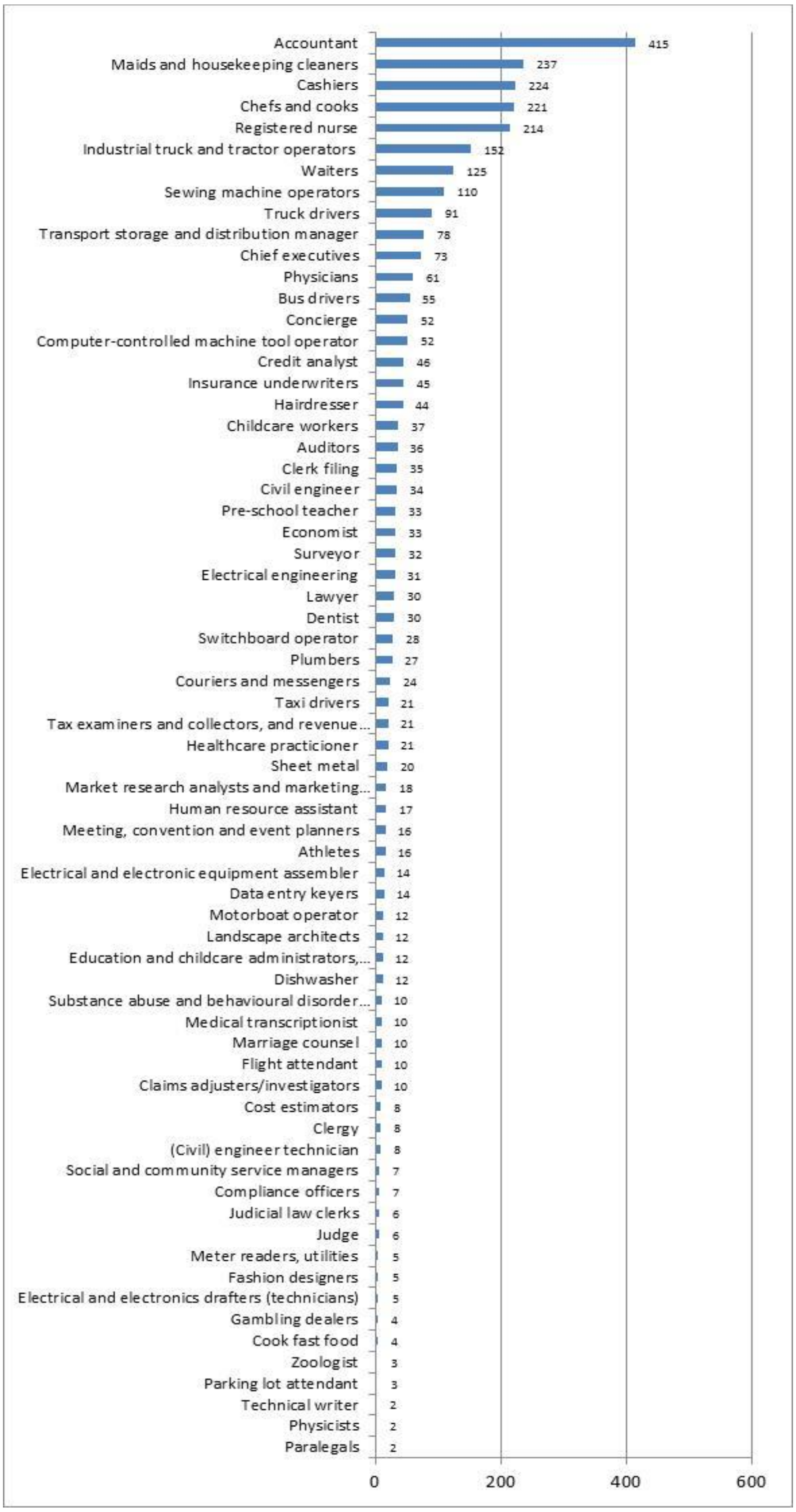
Table 4 **Labour market impact of automation risk, OLS estimates, EU28**

	(Log) hourly earnings	*Job satisfaction*	*Job insecurity*	*Skills obsolescence*
Probability of automation	-0.103*** (0.024)	-1.225*** (0.086)	0.627*** (0.117)	0.492*** (0.123)
Very high risk of automation (dummy)	-0.031*** (0.008)	-0.315*** (0.031)	0.099** (0.043)	0.088** (0.044)
R2	0.57	0.06	0.11	0.07
N	39,290	47,505	44,935	45,424

Notes: OLS regression coefficients with $\widehat{y_{os}}$ as independent variable in row (1) and y_h in row (2); Col 1 is based on estimation of a Mincer-type earnings function including age (and its quadratic), gender, education attainment level and years of employer tenure as additional control variables; Col. 2-4 include as control variables a standard set of individual and job characteristics as well as occupation and industry dummies as in column (3) of Table 3. Robust se in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

Annex

Figure A1 **Frequencies of matched ESJS job titles with FO occupations**



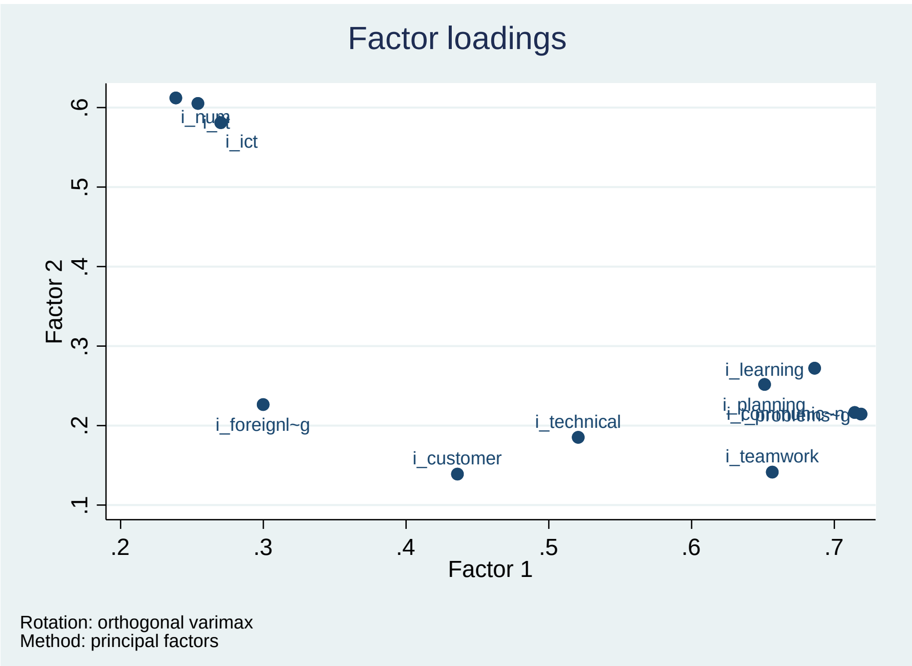
Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

Table A1 **Text mining analysis – examples of keywords to match ESJS job titles with FO occupations**

Occupation	***Keywords***	***'True' automation risk (FO)***
Accountants and auditors	*accountant, certified accountant, chartered accountant, financial control, financial controller, management accounting, accounting, accountancy; audit, auditor, auditing*	1
Athletes	*athlete, fitness, sports instructor, fitness trainer, healthcare trainer, personal trainer, football*	0
*Driver**	*bus, driver, busdriver, drive, motor vehicle driver, tram driver, tramway, truck driver, lorry, car driver, parking, can driver, delivery man, delivery van, delivery driver, delivery operator, delivery person, van delivery, deliverer*	1
Cashiers	*cashier, cash, cash register, checkout assistant, checkout attendant, ticket issuing*	1
Chief executives	*chief executive, ceo, chief financial officer, chair, company director, managing director, company manager, cfo, company owner, board member, regional manager, vice president, executive director*	0
Childcare workers	*childcare, child care, child minder, child minding, baby sitter, nanny, day care*	0
Dentist	*Dentist, dental, teeth, stomatology, stomatologist, dental prosthesis*	0
Flight attendant	*Flight attendant, air hostess, airhostess, cabin crew*	0
Judicial law clerks	*Judicial, judicial clerk, judge's assistant, court secretary, judge's clerk, law clerk, legal secretary, court post, court recorder*	1
Maids and housekeeping cleaners	*Maid, cleaner, chambermaid, maiden, cleaning, housekeeper, housekeeping*	0
Motorboat operator	*Boat, boat machinist, boatsman, assembling of boats, specialist boatbuilder, boat maintenance, boat builder, captain*	1
…		

Table A2 **Factor analysis – reduction of skill requirements variables**

Factor	*Variance*	*Difference*	*Proportion*	*Cumulative*
Factor 1	3.26247	2.37738	0.8641	0.8641
Factor 2	0.88509	0.60784	0.2344	1.0985
Factor 3	0.27726	0.12052	0.0734	1.1720
Factor 4	0.15674	.	0.0415	1.2135
N	46,322			
Rotated factor loadings	*Factor 1*	*Factor 2*	*Factor 3*	*Factor 4*
Importance of technical skills	0.5544	0.0973	-0.0828	**0.2048**
Importance of communication skills	**0.7336**	0.1021	0.1997	-0.1568
Importance of team-working skills	**0.6728**	0.0187	0.0485	-0.1374
Importance of foreign language skills	0.3214	0.2699	**0.2395**	0.1173
Importance of customer service skills	0.4532	0.0565	**0.3457**	-0.0536
Importance of problem-solving skills	**0.7462**	0.1133	0.0699	0.0946
Importance of learning skills	**0.7271**	0.1487	-0.0058	0.177
Importance of planning skills	**0.6782**	0.2189	0.071	0.062
Advanced literacy skills (level)	0.1794	**0.5667**	0.0665	-0.017
Advanced numeracy skills (level)	0.1155	**0.5219**	-0.0299	0.0444
No ICT skills (level)	-0.2541	**-0.3352**	-0.1897	-0.0913
Cronbach α	*Average inter-item correlation*	*alpha*		
Importance of generic skills	0.53	0.85		
Importance of selling-customer service skills	0.29	0.45		



Notes: Principal factors method; orthogonal varimax rotation; Rotated factor loadings (pattern matrix) and unique variances

Source: ESJS microdata http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey