DRUID society

Wage returns to skills in the context of automation: the complementarity of social and problem-solving skills to technology adoption

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Abstract

Using detailed product-, firm- and individual-level data and the novel ontology relating European occupations and skills, this paper explores the complementarity of automation with social and problem-solving skills, focusing on the wage effects. The results show a consistent additional wage premium to social skills in manufacturing firms which recently adopted automation tools. The estimates are robust to different specifications, with the coefficients for the bundle of automation and social skills being positive across most demographic groups. This effect is even more pronounced for the low-skilled workers, emphasizing both the importance of soft skills on low-wage jobs and how innovation at firms can have significant positive effects on some sub-groups of the low-skilled. As one novel result,

we observe that the role of skills is different depending on how persistent the automation investments are at the firm. We observe that first-time automators start valuing the social skills first, while persistently automating firms reward the problem-solving skills instead. These results underline the importance of skills for dealing with the significant increase in coordination costs and potential coordination failures associated with introducing automation for the first time at the firm.

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JEL: J24 - Human Capital; Skills; Occupational Choice; Labor Productivity; J31 - Wage Level and Structure; Wage Differentials; O33 - Technological Change: Choices and Consequences; Diffusion Processes

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1. Introduction

The implications of technical change for the labor market have been in the debate on an ongoing basis since at least the second half of the previous century, receiving even more attention recently because of the increasing rapidness of technological development. Automation was estimated to affect as much as one half of the jobs of Europeans, with the number of workers whose jobs are highly likely to be at risk of automation counting in tens of millions; even more jobs are expected to be affected significantly enough for the skill requirements to change dramatically (Nedelkoska and Quintini, 2018).

The relationship between technical change and the trends in labor market has been a basis for the skill- and routine-biased technical change arguments for a long time. Vast number of empirical studies have reported strong correlation which creation, adoption and diffusion of new technology has with the increased demand for high-educated labor and the disproportionally high wage premium of higher education and on the high-skill jobs, interpreting this as the evidence for the skill bias of technology (e.g., Goldin and Katz, 2009; Spitz-Oener, 2006). At the same time, the empirical evidence reports the polarization of labor, especially in terms of employment levels, suggesting that technological development at least partially complements the lower-skilled labor (Autor et al., 2006; Barth et al., 2020; Aghion et al, 2019).

While the skewness of the new technology impact on labor is more than evident, the cause of it is not as clear. In principle, innovative technology increases the productivity of the skilled workforce disproportionally more than that of unskilled, which, in turn, increases the demand for higher-skilled labor when technology intensiveness increases and results in wage shifts in favor of such labor (Acemoglu, 1998; Acemoglu and Autor, 2011).

The skewness of technical change towards the (high-)skilled seems more than important both on the individual level and in terms of policy implications. The concept of a “skilled” worker, meanwhile, is less than obvious, as is the concept of skills which are complementary to technology. Rather surprisingly, in the empirical literature the workers falling into the category of “low-skilled” by the occupational definition sometimes turn out to reap the benefits of technology advances no less than the “high-skilled” (Aghion et al., 2019; Autor and Dorn, 2013). The routine-biased technical change framework answers this dilemma by suggesting that on the lower-skilled jobs, too, exist non-routine tasks which might be complemented by technology. Thus, Aghion et al. (2019) theorize that soft skills on the low-skill jobs drive the technology wage premium, since they imply a high interdependence of the job performance of higher- and lower-skill employees. Meanwhile, a substantial amount of literature deals with the negative aspects of technology impact on low-ranking labor, i.e., the substitution effect (e.g., Nedelkoska and Quintini, 2018; Frey and Osborne, 2017; Arntz et al., 2016), while the ones emphasizing the beneficiaries and their characteristics tend to overlook the low-skill jobs or focus on a different set of firms which generate new solutions – as do Aghion and his colleagues in the 2019 paper.

In contrast to other European-based papers on technology impact on labor, this paper focuses on the precise skills needed for jobs, adjusting the framework of non-routine social and cognitive and routine cognitive and manual job tasks (Autor et al., 2003) to the European occupations with the help of the European Commission’s ESCO (European Skills, Competences, Qualifications and Occupations) ontology. It is one of the few European-based studies focusing on the job tasks, similar to those making use of similar US data such as DOT (e.g. Autor et al., 2003) or O*NET (Aghion et al., 2019). Perhaps due to rather recent publishing, ESCO has not been exploited much for research purposes so far, with the existing published papers only having analysed skills demand in Europe (Brunello and Wruuck, 2019; Cedefop, 2016), in contrast to a similar PIAAC dataset which has been used rather extensively (e.g. Arntz et al., 2016; Nedelkoska and Quintini, 2018). PIAAC, however, has its limitations due to sampling, while this study combines the skills matched directly to occupations with a country's employee-level data.

This paper contributes to the existing literature in several ways. First, it adds to the broader literature on technology adoption effects on workers, as well as the one on routine-biased technical change (Goldin and Katz, 2009, Krussel et al., 2000, Acemoglu and Autor, 2011, Frey and Osborne, 2017, Autor and Dorn, 2013). The most important contribution is in the introduction of social and problem-solving skills in the context of technology adoption, exploiting a detailed employer-employee dataset and making use of extensive data on foreign trade in automation equipment and skills.

Second, we present the results within labor groups, exploring the joint effects of skills and automation at a more disaggregated level and showing the importance of soft skills for the lower-skill and younger employees. This allows to add to the rather scarce literature on the low-skill workers and innovation, and how automation at firms affects some sub-groups of the low-skilled positively due to their skill structure (Autor et al., 2019, Nedelkoska and Quintini, 2018, Aghion et al. 2019).

Finally, we contribute to the literature on the heterogeneity of firms' behavior related to the creation, adoption and diffusion of new technology and the larger-scale differential patterns of technology adoption (Acemoglu and Restrepo, 2018; Domini e al., 2020; Cirillo et al., 2021) by studying the patterns of automation at firms, such as persistence in automation and early versus later stages in automation. In particular, we show that firms at early stages of automation investments and the persistent investors in automation activities tend to value different kinds of skills. Introduction of automation for the first time at the firm means a significant increase in coordination costs for the firm. There is an increase in costs due to combining automation with the previous elements of the bundle of other innovation inputs at the firm (incl. organizational change) and figuring out the related critically needed changes in these other inputs. We expect the coordination capabilities at the firm, incl. the availability of social/soft skills, to be especially important in the early stages of adopting automation compared to the later ones.

We use an occupation-dependent skills measure, arguing that an individual working on a particular job already has the skills needed for it (hence continuing the task-based narrative of Acemoglu and Autor, 2011, Autor et al., 2003). In contrast to the proxies for technology-complementary skills (such as higher education proxying problem-solving, communication skills or flexibility, for instance), this assumption appears less ambiguous and clarifies the causes of wage premium to both high-educated and high-wage and other skilled workers. While we do not argue that higher educated individuals factually are beneficiaries, it is the demands on the workplace that make these people valuable on the market, and these demands are not constrained by hard skills (e.g., Spitz-Oener, 2006). Importantly, we use highly disaggregated data on all levels – firms, individuals, and skills.

The skills that we cover in this study are social skills and problem-solving skills. The skills measures are occupation-based, i.e., the terms “skill” and “skill requirements” are used interchangeably, implying that the employees possess the skill set deemed essential on their jobs.

For balancing the data, we use coarsened exact matching and run wage regressions with matching weights from for the wages one year after the introduction of automation tools – except for the robustness checks on automation persistence patterns. The coefficients of interest are checked for all manufacturing sector employees and separately by age and education level, exploring the potential heterogeneity of technology-skill effect.

The results suggest there indeed is complementarity between automation and social skills, both at the aggregated level and for all education groups – especially for the lowest-skilled. The results for the bundle of automation and problem-solving skills vary depending on the persistence of automation. The largest wage premium to social skills in the context of automation is for the lowest-educated employees. Importantly, while in the short term automation seems to complement social skills, in the longer term it complements the problem-solving ones.

2. Related Literature

The notion that technological progress is skill- (routine-) biased has been a matter of discussion for a while now. The basis for this statement can be found in numerous empirical investigations that report substantially different employment and wage outcomes for different labor groups such as educational (Katz and Murphy, 1992; Krussel et al., 2000; Goldin and Katz, 2009; Acemoglu and Autor, 2011; Barth et al., 2020) or occupational (Autor et al., 2003; Spitz, 2004; Acemoglu and Autor, 2011; Barth et al., 2020).

Since the skill-biased technical change hypothesis initially emerged to explain the labor market shifts in the USA in the 1980-s[2], the disputes followed as more data became available. Thus, Card and DiNardo (2002) argued that SBTC failed to explain the trends in the US during the 1990-s such as wage inequality rise, the closing of the gender pay gap, and the age-related differences in education wage premium. However, the following investigations of developed economies (e.g. Autor et al., 2008; Autor, 2014; the studies discussed below) suggest that the technology-driven skill premium to wage has not vanished but rather needs modification concerning the complementary effects of the new information technology to abstract and otherwise non-routine tasks and substituting ones to routine tasks. To some extent, the focus in the literature shifted from the more general definition of skill bias to the (non-)routine skill bias of new technology.

The SBTC argument is that the new technologies tend to complement skilled labor and substitute for the unskilled labor, with the rapid increase in the supply of skilled labor enforcing the development of such technologies even more (Acemoglu, 2002). The implementation of new technology supposedly augments the productivity of the skilled disproportionally more than that of the unskilled; in extreme cases, in some cases technology can substitute for the

[2] E.g., Levy and Murnane (2002), Katz and Murphy (1992), Goldin and Katz (1996) or Krussel et al. (2000).

unskilled labor completely. The RBTC literature follows similar logic, though skills in this case are linked to tasks instead of entire jobs.

Skill premium due to the recent technology developments seems prominent enough to be regarded as a stylized fact in most of the recent literature. However, if technical change is indeed skill-biased, the definition of the term “skilled” becomes crucial.

One branch of literature emphasizes the wage premium to higher education in general and in the context of the rapid technological development in particular (Acemoglu and Autor, 2011; Goldin and Katz, 2009; Krussel et al., 2000). While the evidence on the premium is univocal at this point, it is not as obvious what it is that higher education does to an individual – or rather what it is that an individual develops during the studies – that boosts their position on the labor market. In principle, higher education has something to do with broader, long-lasting knowledge, skills and competences that cannot be obtained during firm-level job training, separate narrow-focused courses and other short-term forms of education, even though these can be complementary.

Nonetheless, there is no reason to assume that the technology-complementary, wage-augmenting skills are bound to the ones obtained in college. As shown in Aghion et al. (2019), individuals on low-skill jobs – i.e., on the jobs requiring only minimal formal education and training – receive wage premium to working in innovative firms as well. In fact, in their findings the average premium for the low-skilled is even more pronounced than the premium for the intermediate- and high-skilled workers in R&D-intensive firms. This finding is supported by other papers which find the technology effects to be U-shaped across occupations, with the medium-skilled occupation group experiencing the most damage (Autor and Dorn, 2013; Acemoglu and Autor, 2011). These studies, though, mention the low-skilled only briefly. To this day, one can hardly find much literature that focuses on the low-skilled and the positive technology effects on it. Aghion et al. (2019) are one of the few that do focus on it after finding a surprising wage premium on some (though not all) low-skill occupations. Their focus, however, is on the firms that are engaged in R&D – i.e., the creation of new products and processes. Technological change, though, is also largely represented by the adoption and diffusion of new technologies.

Quoting Acemoglu and Autor (2011), occupation specifics explain wage differentials increasingly better than do education specifics. One other occupation-based approach would be the white- / blue-collar or managerial/technical job division. Barth et al. (2020) and a handful of other papers report much higher wage benefits of technology production and adoption for managers than for the employees on technical jobs, even though higher education is often required on both, suggesting that there remains a significant uncaptured skill component to the technology impact.

As mentioned before, there is also a task-based approach as in Autor et al. (2003), with routine tasks contrasted to the non-routine ones – those more ambiguous in execution and not understood well enough to be described as a set of commands. In line with the SBTC explanation through the impact on productivity, in Autor et al. (2003) technology acts complementary to the individuals who perform non-routine tasks as it allows them to outsource the time-consuming routine problems and work more efficiently in general. The technology-complementary tasks are classified broadly as non-routine analytical and nonroutine interactive (with nonroutine manual tasks assumed not to be affected by automation), while the tasks easily substitutable by technology are routine cognitive and routine manual. Thus, Autor et al. (2003) framework allows for the low-skill occupation groups (lower-level education groups) to enter the set of those for whom technology acts as a complement, given that their jobs require a substantial amount of non-routine analytical and/or interactive tasks. While the analytical non-routine tasks – with problem-solving, creativity and persuasion being the most evident examples – usually (though not always) intersect with the tasks that higher-educated, high-ranking employees tend to perform, the concept of non-routine communicative tasks implies more flexibility in terms of occupation and education. For this type of tasks, adaptability, social and language skills are what matters. Other authors also often include in this category negotiation and persuasion skills, coordination of others and the coordination of one's own work activities with others.

Given that medium-skill jobs largely include routine cognitive tasks, and a large portion of low-skill jobs include routine manual ones, the Acemoglu and Autor (2011), Aghion et al. (2019) and others' findings fit smoothly into the Autor et al. (2003) framework. Moreover, service occupations, though demanding little formal education, are the ones that often require complex communicative skills, and these are indeed the ones experiencing a rise in employment (Autor and Dorn, 2013) and wages (Aghion et al., 2019). Some more evidence on the aggregated level includes, for example, the papers by Alexandra Spitz (2004; see also Spitz-Oener, 2006) who explored the dramatic change in the workplace requirements in all occupations over two decades and showed that these have in turn affected educational requirements and skills upgrading in Germany. She also showed that for various groups of workers (occupation, age, education groups and their interactions) computer technology had a strong substitution effect in the case of routine manual and cognitive tasks and complementing one for the non-routine analytical and social ones. Akerman et al. (2015) also add to the empirics on routine versus non-routine tasks, making the case for the complementary and substituting effects of broadband internet adoption in firms. The literature using detailed employer-employee data, however, is still insufficient.

Our paper adds to the literature on the effect of technology adoption on labor by analysing the joint effect of automation and social and problem-solving skills of employees on their wages. We outline Deming (2017) and Aghion et al. (2019) as some of the most relevant theoretical frameworks to our study, explaining the potential pathways of complementarity of soft skills with technological change at the firm.

Deming (2017) shows that high-wage jobs increasingly demand social skills. Technological change is a likely explanation of this complementarity, as social interactions have been in the past difficult to automate. Deming (2017) outlines in his model, in particular, the role of social skills in lowering coordination costs at firms. Coordination costs are especially important in the case of introducing an innovation such as automation. Moreover, a central aspect in his model is the fact that social skills can be complementary with other (cognitive) skills. Thus, another bonus of social skills can be further enhancement of the complementarity of automation with other types of 'high' skills.

His model includes teams of production where team members use their task-based comparative advantage by "trading" tasks. In this model, social skills lower the costs of coordination and 'trading tasks' at the team and firm. Thereby the individual social skills are letting the employees more easily specialise on the tasks where they have comparative advantage in and at the same time work together with others in an efficient way. The model by Deming (2017) applies in the context of social skills and labour market the structure that is similar to Ricardian type of trade models, with employees instead of 'countries' and social skills as the inverse of iceberg trading costs, similar to trade models by Dornbusch, et al. (1977) and Eaton and Kortum (2002).

Next, Aghion et al. (2019) in their theoretical model as well as in empirical analysis show that the wage premium of working at R&D intensive firms is especially large in the case of these "low-skilled" employees that have high soft skills (a large part of which is social skills). An implication of their model is that low-skilled employees with significant soft skills (that are hard to replace by the firm) have more bargaining power and thus higher wages at more innovative firms compared to the less innovative ones. This higher bargaining power and higher wages of this group of employees reflects in their model the complementarity between workers in high-skilled occupations and these employees in "low-skilled occupations" that have a high proportion of soft skills in their skills bundle, e.g., developed by training and work experience at the firm. Also, the complementarity between social skills of some employee groups and traditional "high skills" of others is higher the more innovation-intensive the firm is. Although neither of these two papers focuses specifically on automation, similar logic on complementarities can be expected to hold for automation investments and soft skills as well.

Finally, we distinguish in our study between early stage versus later stage in adoption of automation at the firm and how the role of skills differs in these cases. These differences in how skills matter in the early versus later stages of automation at the firm can reflect the coordination costs and coordination failures at the firm due to the introduction of automation.

The various costly and complementary adjustments that enable automation and its effective operation can be difficult for firms to discover and to introduce (Brynjolffson and McElheran 2016, Brynjolffson and Mitchell 2017). The related coordination costs and potential for coordination failure are likely to be especially important and potentially disruptive in the early stages of automation, when firms have little prior experience with automation and need to update their bundle of innovation activities (including firm's organisational practices) to ensure that the positive effects of automation are materialised. One relevant type of coordination failure in adoption of automation is due to the managerial attention allocation problem (Ocasio, 1997, Joseph and Wilson, 2018, Ocasio and Joseph, 2018). Introduction of automation at the firm and combining it with a number of other complementary adjustments can mean an increased difficulty for management to allocate their main resource, management time, to the key components in the decision making process.

In summary, we expect the coordination capabilities at the firm, including the availability of social skills, to be especially important compared to other skills and capabilities in the early stages of adopting automation. Adding new components such as automation for the first time to the bundle of potentially complementary innovation activities increases the complexity of the system and ultimately also the probability of failures in coordination of the system (see e.g. Desyllas et al. 2020 for a recent discussion on coordination failures). Soft skills such as communication skills, teaching skills and adaptation skills, can be vital here, as employees need to understand, adapt to and accept the new technology. Communication skills enable better coordination of these changes at the firm, incl. collaboration with colleagues and the management to facilitate efficient transition to the new technology.

3. Empirical strategy and data

3.1. Data

This paper adds to the literature on the effect of technology adoption on labor by analyzing the joint effect of automation and routine and non-routine skills of the employees on their wages. We use detailed data at the firm, as well as product and individual level and add to the limited studies on automation embodied in imported goods. Additionally, we explore a novel ESCO (European Skills, Competences, Qualifications and Occupations) ontology, which has, as of now, been used very little in academic literature in general. Finally, we explore the heterogeneity of the automation-skills effects across labor groups and automation persistence patterns.

The data is taken from several sources. The 4-digit occupation data on Estonian citizens is taken from the 2011 Population and Housing Census, two waves of Structure of Earnings Survey (2014 and 2018) and the Employment Register (2019). These datasets also provide other important information on employees, including education level, age, gender, place of residence. Some unchanging data (immigrant status, mother tongue) is extrapolated from the Census to further years. All the occupational data except the 2019 one is yearly; the data from the Employment Register is quarterly, and for the yearly measure the first available data on occupation is taken.

For the employee-employer correspondence in 2011, the 2011 Census data is merged with the data of the Tax and Customs Board of Estonia. Tax and Customs Board of Estonia also provides income data, with the resulting outcome variable constructed as the gross wages, summed yearly and transformed into logarithmic scale.

In addition to the non-routine interpersonal and problem-solving skills, we construct dummies for other types of skills. To address the possibility of omitted variable bias and ensure correspondence to the skills classification in routine-biased technical change literature, we select proxies for manual skills (using equipment, tools or technology with precision) and routine cognitive skills (following instructions and procedures; see subsection 3.4 for more information) and introduce interactions between automation and all four types of skills.

Apart from that, we control for the formal measure of skill represented in education level. The data on education (ISCED-97 and ISCED-11 levels) is transformed into a single broad indicator of low, medium or high education level. Education level up to and including lower secondary is considered low, upper secondary and post-secondary non-tertiary education corresponds to medium level, and tertiary education corresponds to high education level.

The information on firms, apart from the automation-related data, was taken from the Commercial Register. The Commercial Register data allows to extract information on firm age, size, type of ownership and industry. Based on the foreign trade data, we construct an additional dummy for a firm being an importer, a dummy for the firm having had prior automation and the number of previous automation cases. The firms are restricted to the manufacturing industry, giving a closer look into the effects of specifically tangible automation, which is considered an established solution in this sector.

Small number of observations having missing or incorrect data on employment, firm age and income was removed. Additionally, occupation group 6 in ISCO-08 was dropped from analysis since in this group there were zero observations with individuals being simultaneously in automating firms and having interactive skills as an essential component of a job; Armed forces occupations were excluded as well. Since the data does not allow to distinguish between the types of employment, I drop very low wage earners as a way of filtering out non-full-time workers. The low wage earners are defined either as those whose wages are below minimum wage, or those whose wages are below or equal to minimum wage level in a given observation year. Finally, the data was restricted to the workers aged 25 to 54 years old (prime-age workers) to reduce the possibility of skills mismatch and to further ensure that the individuals in the dataset are employed full-time. The number of observations in the main dataset is 134293.

3.2.Wage equation

We base the analysis on the estimation of log-linear Mincerian wage equations. The primary equation is specified the following way:

$$log\ log\left(w_{ij\,t}\right) = \alpha + u_j + \beta_1 Automation_{jt-1} + \beta_2 Social_{it} + \beta_3 ProblemSolving_{it} + \beta_4 Manual_{it} + \beta_5 RoutineCognitive_{it} + \beta_6 Automation_{jt-1} * Social_{it} + \beta_7 Automation_{jt-1} * ProblemSolving_{it} + \beta_8 Automation_{jt-1} * Manual_{it} + \beta_9 Automation_{jt-1} * RoutineCognitive_{it} + \beta_6 X_{it} + \beta_7 Z_{jt} + \lambda_t + \varepsilon_{it} \qquad (1)$$

Where subscripts i, j, t denote individual, firm and time (year) respectively. a_{jt} is a dummy term for automation adoption, $Social_{it}$ and $ProblemSolving_{it}$ are dummies for soft skills required on a job (social skills and problem-solving skills, correspondingly), and the coefficients of the interaction terms are of primary interest, allowing the drawing of conclusions about complementarity. X_{it} denotes individual-level controls, which include gender, education level, age and age squared, immigrant status and mother tongue, location in the capital city, 1-digit occupational groups of the International Standard Classification of Occupations (ISCO-08). Z_{jt} is a vector of firm-level controls; these include firm size and firm size squared, type of firm ownership (foreign or not), a dummy for the firm being an importer – to distinguish the effects of importing from the effects of importing automation equipment, since the automation indicator is fully based on firm imports; and a dummy for previous automation experience – whether the employer has adopted automation equipment prior to the current observation. The model also includes dummies for years of observation; finally, to address the possible endogeneity of automation and account for firm-specific fixed characteristics that might otherwise bias the estimates, firm fixed effects (u_j) are added to the model.

The wage observations are taken for the year after the one in which automation occurs. This is driven partly by the data restrictions (the firm-level observations are yearly, not allowing to account for the number of months after the automation occurred), but, more importantly, also by the nature of adjustment of workers and their performance to the changes in the firm operation – the reason that automation is expected to affect workers' wages in the first place is that it takes time either to adjust to new equipment and make it complementary to one's work or for the labor tasks to be gradually substituted by the machines. In addition to the 1-year gap between automation occurrence and wage results, I report the coefficients for other gaps up to t-5 and explore the results for the specification in which instead of automation at t-1 automation in the previous 5 years is used. The latter counts all firms that acquired automaton tools within t-1 and t-5 as automators and is meant to reflect automation effects which are less short-term and might not be captured after only one year since the introduction of automation. Yet other ways to approach the issue of automation persistence are reported in subsection 4.1 and include persistent automation practices (automation every year within the last 5-year window), first-time and otherwise irregular automation.

3.3. Automation

The automation-related indicator is based on the product-level foreign trade data provided by Statistics Estonia and the taxonomies in Acemoglu and Restrepo (2018) and Domini et al. (2020). A limitation of this strategy is that the firms that purchase automation equipment only domestically are in such setting wrongfully assigned into the control group – which would be a source of downward bias in the estimated effects. However, while one may argue that importing is not the only way that automation equipment can be obtained, in Estonia the magnitude of respective domestically produced products is small enough to overcome this limitation. Apart from the relatively old Kalvet (2004) study that reported importing as the main source of tangible automation in Estonia, in the more recent data still Estonia does not export sizeable amounts of such equipment abroad, which is an indirect indication of the lack of domestic production.

As in Acemoglu and Restrepo (2018) and Domini et al. (2020), in our data automation-related imported equipment consists of several product groups, aggregated to a firm-year level for the automation indicator. They are based on 6-digit Harmonised System codes of automation products proposed by the above authors (see Appendix B for details). The trade data for all Estonian firms is available at a product level since 1995; the occupation data availability, however, forces us to constrain the dataset so that the first observed year is 2011. The imports of automation equipment prior to 2011 are also accounted for in the estimation, in the form of binary indicators for prior automation having occurred and are used to control for the importing history (or lack thereof) and to ensure the filling of the gaps between observation years. Importantly, the cases when inward or outward processing procedure was used in imports were regarded as not being the cases of automation even if the purchased goods were automation equipment.

Table 1. Automation frequency (%) in manufacturing sector by persistence in automating

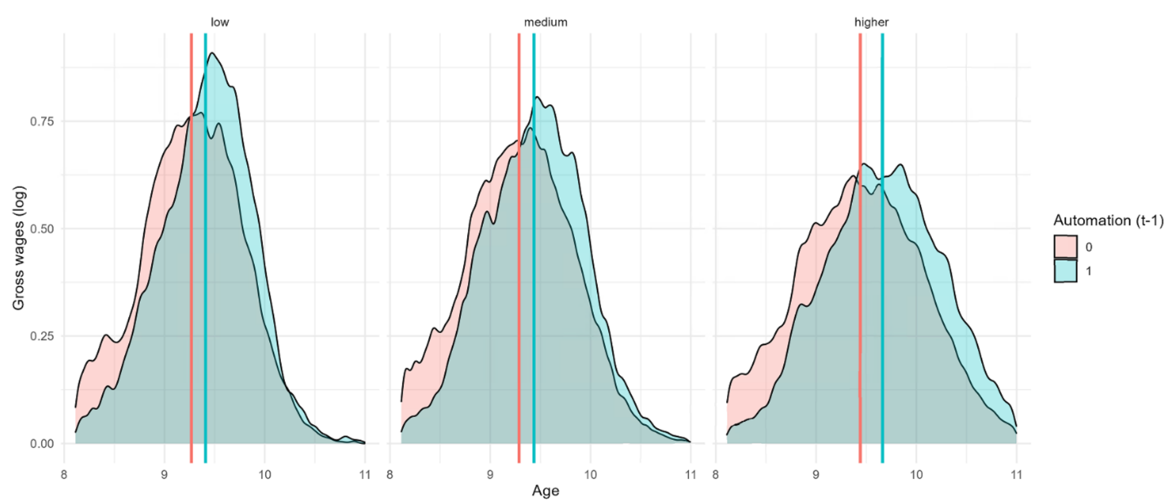
Number of times automation happened in the last 5 years	0	1	2	3	4	5
Individual observations						
All	48.2	13	8.1	6	8.5	16.2
Those that automated in t-1	-	12.5	11.9	10.2	19.4	46
Firm observations						
All	81.3	7.1	3.4	2.3	1.9	3.9
Those that automated in t-1	-	19.1	14.6	13.5	15.1	37.7

In general, automation in manufacturing firms might be considered an established on-shelf solution, expected to be integrated into the workflow without large disruptions. In our data, 28.7% of the observed manufacturing firms have adopted automation equipment at least once during the last 5 years (*Table 1*), translating into 51.8% of employees in the dataset working in such firms. The automating firms tend to be much larger, are more often the foreign-owned companies and are more likely to have previous experience with automation adoption (see also Appendix C). Both within firms and within individuals recent automation tends to gravitate either towards inconsistent (only once or, less frequently, twice within the last 5 years) or very consistent (5 or, less frequently, 4 times within the same period). Approximately a half of the observations where automation only happened once in the recent 5-year window are the ones which adopted automation equipment for the first time ever. The most frequently bought automation tools are Tools for industrial work, Machine tools and Regulating instruments.

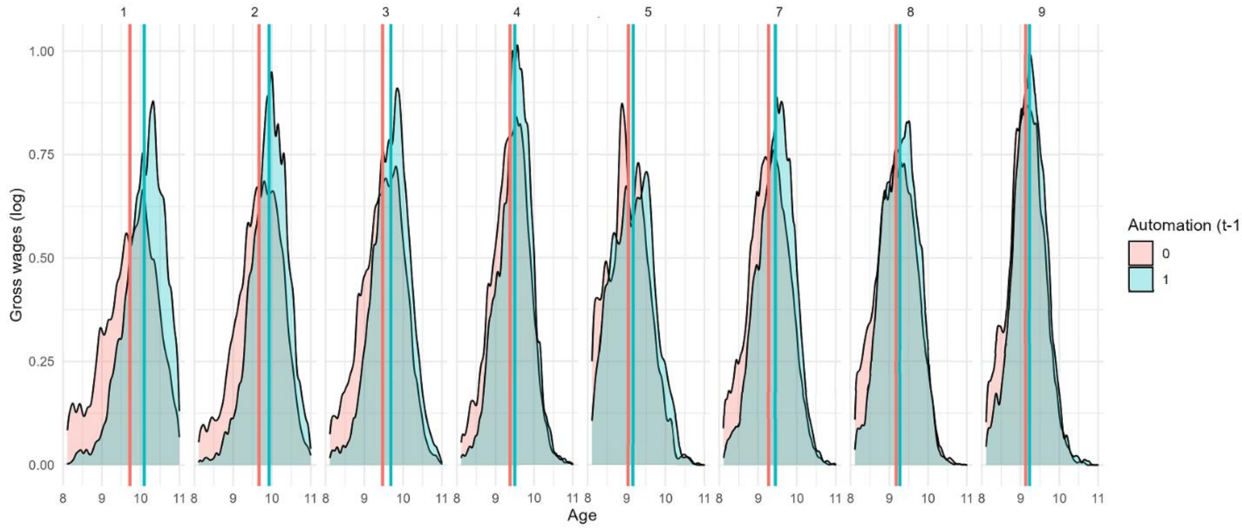
The characteristics of workers differ within the industry – for example, the average observed yearly wages in automating firms were significantly higher than in non-automating ones (Appendix C); at the same time, the wage premium is distributed unevenly, being shifted greatly in favor of high-skilled individuals and especially managers (*Figure 1*). The medium- and low-skilled, at the same time, are much more alike in terms of their wages, regardless of the kind of firm they are employed at. Automating firms tend to have younger employees who slightly more often have higher education and are a bit less frequently male (although the fraction of men in automating manufacturing firms is still 56.6%). Finally, there are fewer manual workers in the automating firms, such as craft and related trades workers and plant and machine operators and assemblers. There is no sizable difference in the fractions of the most low-skill elementary jobs (ISCO-08 group 9), though.

Figure 1. Log yearly wage density, by automation

Panel A. Education



Panel B. Occupation



Notes. Vertical lines show mean values for groups. ISCO-08 major groups: 1 – Managers, 2 – Professionals, 3 – Technicians and associate professionals, 4 – Clerical support workers, 5 – Services and sales workers, 7 – Craft and related trades workers, 8 – Plant and machine operators and assemblers, 9 – Elementary occupations.

3.4. Skills

This paper takes the framework of RBTC literature (Autor et al., 2003; Spitz-Oener, 2006; Autor et al., 2006) and the ontology in European Commission's ESCO (European Skills, Competences, Qualifications and Occupations) to classify employees by their skills requirements.

ESCO is a classification constructed for European-based occupational titles, partly based on O*NET and the Canadian skill and knowledge glossary; its version that is used in this paper was released in August 2020, while the first official version was published in 2017. ESCO is primarily constructed by collecting feedback from experts, however, it is also regularly being updated based on the latest trends in European job vacancies. ESCO combines several interconnected hierarchies, among which Skills and competences and Occupations are of interest in this paper. The level of detail in ESCO is rather extensive, with the number of occupation titles reaching 2942 and the number of skills and competences corresponding to them being over 10 thousand. I exploit the third hierarchy level of skills, however, and the 4-digit ISCO-08 level of occupations classification that correspond to the selected skills.

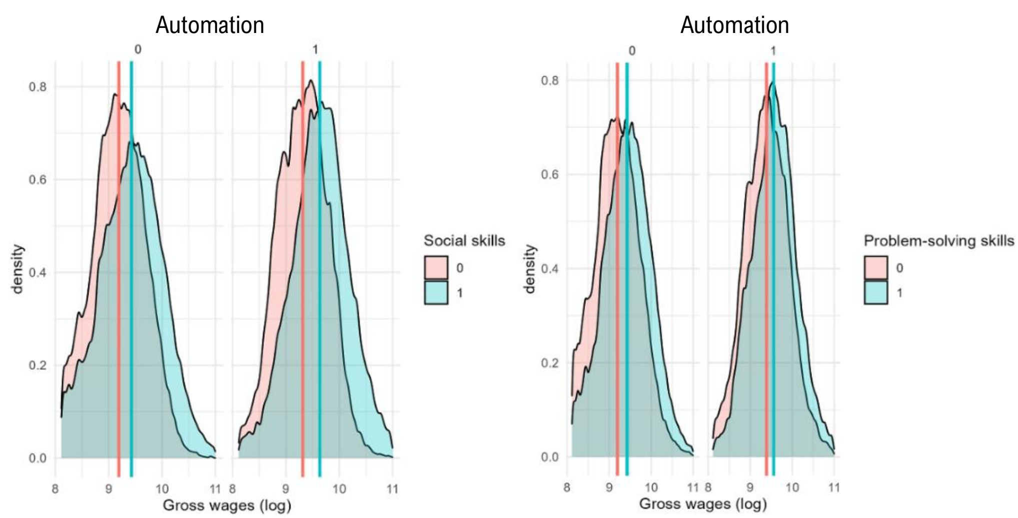
Complex communication (social skills) indicator combines several ESCO (sub-)pillars related to interactions with co-workers, clients and business partners that require collaboration and coordination with others. We selected the skills at a third hierarchy level based on their descriptions from the ESCO skill group that includes social skills – S1 Communication, collaboration and creativity and performed principal component analysis (Appendix A); after principal component analysis, several subskills were removed. The detailed final list of all subskills and their definitions and examples can be viewed in Appendix B. The list is a rather typical one (a similar one can be found, for example, in Spitz-Oener (2006) or Nedelkoska and

Quintini (2018)), and includes both the skills traditionally more represented on the high-skill jobs (negotiating, teaching, developing professional relationships) and the ones required on all kinds of jobs (coordinating activities with others, working in teams – akin to the measure in Aghion et al. (2019) which they use to test the hypothesis for the low-skilled).

For the indicator of problem-solving skills, we use the ESCO pillar 1.9 "solving problems", which is defined as "developing and implementing solutions to practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts". It is hence a measure of non-routine cognitive tasks, which is similar to the one in Autor et al. (2006), though it does not represent the full range of non-routine cognitive skills definition that can be found in the literature, only focusing on the more practically oriented thinking skills.

Finally, we construct substitutes for routine cognitive and manual skills. For routine cognitive, we select "following instructions and procedures" – a definition akin to the selection in Autor et al. (2003). For manual skills, the ESCO classification does not allow to distinguish between routine and non-routine manual skills which is often (though not always) used in the literature. The closest skill pillar in ESCO is "using equipment, tools or technology with precision", which falls better into the category of routine skills, even though it is somewhat correlated with one of the problem-solving skills – "developing solutions" (Appendix A). A similar measure of specifically routine manual skills can be found in Spitz-Oener (2006) and Autor et al. (2003); excluding the non-routine manual skills, on the other hand, should not bias the results, since these skills, according to Autor et al. (2003), are not expected to interact with automation in a meaningful way.

Figure 2. Log yearly wage density, by skills



Notes. Vertical lines show mean values for groups. 134293 individual observations, only prime-age (25-54 y.o.) workers.

The specifics of ESCO data allows us to construct binary indicators of whether a skill or a group of skills is (are) essential for performing a given job (lowest-level occupational titles in the European classification of occupations). The resulting indicator, for example, for social skills is a dummy which takes a value of 1 if any of the skills selected after principal component analysis is essential on a job and zero if none is required. Thus, unfortunately, it is not possible to account for the intensity of the skills usage on a job nor distinguish between the workers with higher or lower levels of a particular skill. The analysis is constrained to the binary factors. The assumption here is that, if an employee works on a job that requires a certain skill, then this employee possesses such skill to a sufficient degree.

Overall, there are 57.2% of employees with a social skills requirement, 58.9% - with a problem-solving one, 40% – with routine cognitive tasks and 36.9% with (routine) manual tasks (Appendix C). In general, the fractions of all skills except routine cognitive and manual increase with an increase in education level. Social skills are most essential on the high-wage jobs – over 90% of managers, professionals and technicians and associate professionals have this skill requirement. Among the social skills, the most frequent one across occupations is Coordinating activities with others– 43% of employees overall, reaching 62% in higher-educated. This skill is the most or one of the most popular social skills in all occupation groups except for the low-skill ones (the last 3 1-digit categories of ISCO-08), where a similar but less individualistic in terms of performed work "working in teams" is the leading social skill. Other social skills that are considerably more skewed towards the high-skilled are the negotiation skills and the developing of professional relationships.

Within the problem-solving skills group, "developing solutions" is distributed uniformly within education groups, while the "implementation of new procedures and processes" resembles the pattern of social skills. Like the non-routine social skills, problem-solving skills are much less pronounced on low-skill jobs and within low-educated. Finally, routine cognitive tasks, or "following instructions and procedures", is almost uniform across education levels and is more frequent on managerial, clerical and elementary jobs, while manual skills are most crucial on craft and related trades jobs and for plant and machine operators and assemblers – the groups that are also less represented in automating firms.

Both non-routine skill groups are associated with higher mean wages (*Figure 2*), though only social skills seem to be positively associated with the introduction of automation in the raw data. Both routine skills show miniscule, if any, mean wage differentials (Appendix C).

3.5. Matching

Although we account for the firm differences by adding firm fixed effects in the model, we also add coarsened exact matching as a robustness test, since the data is slightly unbalanced in terms of individual-level characteristics and highly unbalanced in firm-level ones (Appendix C). Moreover, the selection of workers into automating firms cannot be assumed to be random, and some individual characteristics, including but not limited to gender and education, may influence the pre-automation wage, which sets the need to control for possible drivers of selection into automating firms and the pre-automation wages. In addition, the implementation of matching procedure, as well as the introduction of firm fixed effects, allows to address the possible endogeneity of automation.

Coarsened exact matching (CEM) is one of the ways to contrast the comparable individuals. The main advantage of such method, as opposed to other matching techniques such as those relying on modelling propensity scores, is that the balancing of treated (the individuals who work in automating firms in our case) and controls (the comparison group) in terms of the key covariates is undergone directly, with no need in further investigation of the resulting balance and sensitivity of the results to the propensity score model specification (Blackwell et al., 2009). Moreover, in our study design a single propensity score value cannot be extensive enough to capture both the reasons for selection into treatment (that is, *firm*-level covariates influencing the decision to automate) and the factors that influence the pre-treatment wages (which, in turn, are mainly observed on the level of *individual* workers). In the numerous specifications of propensity score models and subsequent matching algorithms, including the combination of matching on propensity scores and exact matching on selected variables, the resulting matched datasets were at best as balanced, or even more poorly balanced in the covariates than the unmatched sample. Thus, the balancing choice is in favor of CEM.

The main objective of CEM is to match individuals (semi-) exactly on several covariates, forming subsamples that consist of treated and controls with the same characteristics. The treatment effect is then calculated either by averaging the treatment effect values in the subclasses or by running a regression with weights adjusting for the imbalance in the number of treated and controls in the subclasses which were formed after matching and in the overall dataset. We use the latter approach, using the weights of 1 for all of the matched treated individuals and the weights for matched controls calculated as:

$$w_i = \frac{N_i^t}{N_i^c} * \frac{N_d^c}{N_d^t} \qquad (2)$$

Where w_i is the weight of a control observation in subclass i, N_i^t is the number of treated in subclass i, N_i^c is the number of controls in subclass i, and N_d^c and N_d^t, respectively, the number of controls and treated in the overall matched dataset. All unmatched members (including the unmatched treated) are assigned zero weights and thus excluded from the after-matching analysis.

The coarsening part of CEM refers to the splits in the continuous data, in our case these are the variables of age (the bins being 25-34, 35-44 and 45-55 years old) and firm size (up to 50, 50-249 and 250+ employees). The other covariates are factor variables, and the matching on them was done exactly. These are gender, education level (low, medium and high), occupation group (1-digit ISCO-08 codes), observation years, automation experience before current observation (dummy) and type of firm ownership (foreign or not).

Although the list is by no means exhaustive, it captures the main differences in treated and controls on the individual and firm sides. Besides, CEM suffers from the issue of dimensionality, and adding too many covariates may do more harm than good. The major problem with CEM is that it is prone to discard treated observations; however, in our specification only a small fraction of treated is thrown away from analysis. Another possible issue is that, while the individuals are balanced on the hand-picked confounders, some, possibly significant, imbalance may still remain in other important confounders.

4. Results

4.1. Main specification

The main specification of interest in the following *Table 2* is the after-matching firm fixed effects model where the (log) wages depend on automation in the previous year and skills, testing the hypothesis of whether the recent adoption of automation tools on a workplace interacts with social and problem-solving skill requirements in a way that produces wage premium. First, however, it is worth exploring how automation and skills affect wages separately, prior to the introduction of their interaction terms in the model.

Table 2. Log wage results for aggregated data

	Automation at t-1		Any automation within the previous 5 years		Automation within the previous 5 years, by year
	(1)	(2)	(3)	(4)	(5)
Automation (t-1)	0.0258*** (0.0061)	0.0233*** (0.008)			0.0175*** (0.0063)
Automation (t-2)					0.0155*** (0.0062)
Automation (t-3)					-0.0163*** (0.0065)
Automation (t-4)					0.0479*** (0.0064)
Automation (t-5)					-0.0027 (0.006)
Automation (previous 5 t)			0.0411*** (0.0067)	0.0127 (0.0084)	
Social	0.0111*** (0.0037)	0.0024 (0.0046)	0.0097** (0.0037)	0.0039 (0.0055)	0.0095** (0.0037)
Problem-solving	0.0115*** (0.0037)	0.0073 (0.0046)	-0.003 (0.0036)	-0.0267*** (0.0054)	-0.0031 (0.0036)
Automation x Social		0.0183*** (0.006)		0.0085 (0.0063)	
Automation x Problem-solving		0.0121* (0.0066)		0.0385*** (0.0065)	
Adj. R^2	0.4628	0.4631	0.4564	0.4565	0.4566
N	120261	120261	129030	129030	129030

Notes. * - p < 0.1, ** - p < 0.05, *** - p < 0.01.

These coefficients are presented in *Table 2*, while the more detailed exploration of how the wage contributions of soft skills change depending on the inclusion or exclusion of other skills can be viewed in Appendix A. We observe in our key specification in column 1 of *Table 2* that introduction of automation at the firm (in *t-1*) is associated with about 2.6 per cent higher wages of its employees in next year. Note that this estimate is based on the within-firm effect of automation, as we use firm fixed effects in the model.

Social skills are significantly associated with higher wages, with estimated coefficients in columns 1, 3 or 5 of *Table 2* that are both statistically and economically significant. Social skills are associated with about 0.95 to 1.1 per cent higher wages of the employee, depending on the specification of the model (columns 1, 3 and 5). However, the results concerning the role of problem solving are ambiguous, with estimates that vary between insignificant and positive and significant depending on the specification (e.g., compare 1 and 5 in *Table 2*).

In column 2 of *Table 2* we confirm the key proposition of complementarity between automation and social and problem-solving skills. We observe that these two categories of skills increase the estimated 'effect' of automation in *t-1* on wages, as shown by the statistically and economically significant positive interaction terms. Having social skills increases the estimated effect of automation on wages by 1.8%. Having problem-solving skills increases the estimated effect of automation on wages by 1.2%. The positive role of automation and social skills in determining wages is further confirmed in a robustness check in column 5 of *Table 2*, where we introduce 5 automation lags together with skills proxies in the model.

We further observe some heterogeneity in columns 3 and 4 that needs to be explained. These specifications use a dummy for automation in a longer-term time-window of 5 years, as a key proxy for automation adoption by the firm. These specifications still suggest that the longer-term automation indicators are either individually or together with a combination of problem-solving skills positively and significantly associated with wages at the firm. The lack of role of social skills in interaction with automation might look surprising, but this heterogeneity is explained by next steps of analysis in our *Table 3* where we distinguish two key types of automating firms.

4.2. The role of persistence in automation

There, we explore the distinction between persistent and non-persistent automation and what role automation and skills play when automation is introduced for the first time. These results (*Table 3*) reflect the difference in the extent of persistence of automation – in the frequency with which firms automate – and the novelty of automation equipment for the workplace. The mixed result in columns 3 and 4 of *Table 2* concerning the role of social vs problem-solving skills can be explained if we distinguish between persistent automating firms that automate for all of previous 5 years (columns 5 and 6 in Table 3) and first-time automating firms (see esp. columns 3 and 4 in Table 3).

Our results suggest that social skills are important and have a positive effect for the employees in newly automating firms, which are still adjusting to the adoption of the new technologies. However, there is adjustment time involved. Such firms recognize the value of such skills not right away (columns 1 and 2) but with some time lag (columns 3 and 4). As firms become more experienced and persistent in automating (columns 5 and 6), the significant wage premiums of social skills are substituted by even higher significant wage premiums of problem-solving skills.

Adding new components such as automation for the first time to the system of complementary innovation activities at the firm increases the complexity of the overall innovation process at the firm and the potential for failures in coordination in this system combining various complementary inputs. Our finding in *Table 3* suggests that coordination costs and potential coordination failures associated with new technology adoption at firm are likely to be especially important and potentially disruptive in the early stages of automation, when firms have little prior experience in dealing with such disruptive changes and are less likely to have good skills of coordinating complex changes in their innovation process.

Table 3. Log wage results, by persistence in automation

	First-time automation at t-1		First-time automation within the previous 5 years		Automation all 5/5 times within the previous 5 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Automation	-0.0042	0.005	0.0057	-0.0119	-0.0029	-0.0224
	(0.012)	(0.0172)	(0.0053)	(0.0076)	(0.0124)	(0.0149)
Social	0.0095**	0.0089**	0.0138***	0.0101**	0.0055	0.0101
	(0.0041)	(0.0042)	(0.0037)	(0.0041)	(0.0059)	(0.0082)
Problem-solving	-0.0064	0.0053	0.0039	0.002	0	0.0244***
	(0.004)	(0.0041)	(0.0036)	(0.0041)	(0.0059)	(0.0081)
Automation x Social		0.0061		0.013**		-0.0031
		(0.0139)		(0.0064)		(0.0093)
Automation x Problem-solving		0.0149		0.0065		0.0267**
		(0.0147)		(0.0068)		(0.0104)
Adj. R^2	0.4481	0.448	0.4573	0.4574	0.486	0.4788
N	101826	101826	129009	129009	55908	57102

Notes. * - p < 0.1, ** - p < 0.05, *** - p < 0.01.

4.3. Heterogeneity by demographic groups

If there is a point that repeats in the literature on technological change and its labor market effects universally, it is the argument about the inequality that is produced by creation, adoption and diffusion of new technology. While the difference in skill endowments and requirements are seen as part of the explanation, there is still a disparity observed for the labor groups. The most established polarization is between low- and high-skilled, or, more recently, between high-, medium- and low-skilled workers. Examples in literature range from the more canonical Acemoglu and Autor (2011) to the more recent Aghion et al. (2019). Moreover, some recent papers argue that age and aging trends influence the probability of automation – as do Acemoglu and Restrepo (2017); the studies of the individual-level automation effects by age, however, remain scarce. This subsection zooms in on the joint wage effects of automation and skills by education (*Table 4*) and age (*Table 5*) groups.

The division into education groups shows a striking difference in wage returns. While the positive joint effect of automation and social skills seems universal, its magnitude varies significantly. The highest wage premium is observed in the lowest-skill group, consistent with the implications in Aghion et al. (2019) – i.e., soft skills are what drives the wage premium for the low-skilled in innovative firms. At the same time, consistent with the canon of RBTC, without non-routine skill requirements the effect of automation is negative for the low-skilled (and significantly so). At the same time, employees with higher education are the only ones who experience no returns to automation without the skills; here, the only significant relationship between automation and wages comes from the combination with social skills.

Table 4. Log wage results, by education level

	Low		Medium		High	
	(1)	(2)	(3)	(4)	(5)	(6)
Automation (t-1)	-0.0402**	-0.0632***	0.0191**	0.0212**	0.0331***	0.0247
	(0.0174)	(0.0227)	(0.0075)	(0.0097)	(0.0128)	(0.0177)
Social	0.0407***	0	-0.002	-0.0092*	0.0271***	0.0094
	(0.0107)	(0.0137)	(0.0045)	(0.0056)	(0.0088)	(0.011)
Problem-solving	0.0409***	0.0301**	0.0299***	0.035***	-0.0206***	-0.0107
	(0.0108)	(0.0136)	(0.0046)	(0.0058)	(0.0075)	(0.0095)
Automation (t-1) x Social		0.0846***		0.0158**		0.038***
		(0.0181)		(0.0073)		(0.0139)
Automation (t-1) x Problem-solving		0.0271		-0.0111		-0.0213
		(0.0193)		(0.0082)		(0.0135)
Adj. R^2	0.2891	0.2882	0.3992	0.3992	0.4713	0.4714
N	15423	15423	72584	72584	32254	32254

Notes. * - p < 0.1, ** - p < 0.05, *** - p < 0.01.

The overall wage effect of automation is positive for medium- and high-skilled, which is similar to what the raw data implied (*Figure 1*). Unlike in the raw data, the summed automation returns are *negative for the low-skilled*. The difference comes from controlling for broad occupation groups in the regression – when this factor variable is dropped from the equation for the low-skilled, the individuals working in automating firms have higher wages overall than the ones in non-automating firms due to the Automation x Problem-solving coefficient becoming positive and significant.

Finally, for the older employees reveal results are similar to those of the higher educated: automation on its own does not correlate with significant differences in wages, while in combination with social skills there is a premium. The coefficients for the younger workers partly resemble the ones for low- and medium-skilled – i.e., those who have not completed tertiary education. An important difference, however, is that the interaction of automation and social skills does not seem to affect wages in this cohort. At the same time, for the younger employees social and problem-solving skills are associated with higher wages regardless of automation – something that cannot be said about the older workers. Moreover, automation without any of the skill requirements also produces positive wage returns in this group. Finally, *the overall effect of automation on wages is increasing in education and decreasing in age* (columns 1, 3 and 5 in both *Table 4* and *5*). Social and problem-solving skills are especially relevant and useful for lower-skilled and younger employees.

Table 5. Log wage results, by age

	25-34 y.o.		35-44 y.o.		45-54 y.o.	
	(1)	(2)	(3)	(4)	(5)	(6)
Automation (t-1)	0.0267**	0.0355**	0.0181*	0.0087	0.0017	0.0012
	(0.0124)	(0.0163)	(0.0109)	(0.0141)	(0.0098)	(0.0127)
Social	0.0304***	0.024***	0.0085	-0.0031	0.0148**	0.0005
	(0.007)	(0.0089)	(0.0068)	(0.0083)	(0.0062)	(0.0076)
Problem-solving	0.0226***	0.0251***	-0.004	-0.0064	0.0023	0.0041
	(0.0069)	(0.009)	(0.0065)	(0.0082)	(0.0062)	(0.0078)
Automation (t-1) x Social		0.0117		0.0247**		0.0311***
		(0.0114)		(0.0107)		(0.0101)
Automation (t-1) x Problem-solving		-0.004		0.0065		-0.0026
		(0.0124)		(0.0115)		(0.0109)
Adj. R^2	0.3787	0.3791	0.4619	0.462	0.4716	0.4719
N observations	33764	33764	42956	42956	43541	43541

Notes. * - p < 0.1, ** - p < 0.05, *** - p < 0.01.

5. Conclusion

The reports of the technology creation, adoption and diffusion being biased towards non-routine skills and against routine ones is present in numerous pieces of economic literature. However, the evidence on the importance of soft skills, as well as the complementarity of new technology for the lowest-skill labor, is still lacking. Moreover, on different automation stages different skills might be valued more. This paper explores the presence of automation-skill complementarity in the manufacturing sector. It investigates the wage returns to social and problem-solving skill requirements in the presence of recent automation at the firm. We account in our analysis also for the context of age, education and the persistence in the employers' automation patterns.

We find that, at least in the short term, social skills are consistently positively associated with wages in automating firms, while the wage premium of problem-solving skills is somewhat ambiguous. This ambiguity is driven by the difference in persistence of automation – i.e., the frequency with which firms automate, – and the novelty of automation equipment for the workplace.

Moreover, the positive outcomes of social skills might be short-term, appearing to matter more in the early stages of automation. Thus, in our results social skills are important and positive for the workers in the newly automating firms, which still adjust to the new technologies (although such firms do not recognize the value of such skills right). As firms become more experienced and persistent in automating, the wage premium of social skills is substituted by even higher rates of problem-solving skills' premium.

Adding new components such as automation being first-time to the system of complementary innovation activities increases the complexity of the innovation process at firm and ultimately also the potential for failure in coordination in this system (e.g., see Desyllas et al. (2020) for a recent discussion on coordination failures or Deming (2017), for the analysis of the role of soft skills in lowering coordination costs in work teams). Our finding on social skills in early automators suggests that coordination costs and potential for coordination failure are likely to be especially important and potentially disruptive in the early stages of automation. This is the stage when firms have little prior experience automation and need to update their bundle of innovation activities (including firm's organisational practices) to ensure that the positive effects of automation are materialised.

One of our key findings is also that the positive correlation between automation and social skills is universal across education groups; moreover, these skills have even higher value for the less educated. For the lowest-skill group, automation overall has a negative effect on wages, but its combination with soft skills, on the contrary, creates a large and significant wage premium. This confirms the prediction in Aghion et al. (2019) about substantial benefits of innovation at firms especially for the low-skilled employees that have soft skills, but in the context of automation. Importantly, the focus of the discussion surrounding the effects of technological development on labor generally treats the employees on the further end of skill and wage distributions as net losing parties. The data suggests, however, that soft skills related to coordinating activities with others, negotiating and developing professional relationships create an advantage for all workers, especially the less skilled ones, in the short term, while problem-solving skills are beneficial in the long run.

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Appendix A. Principal component analysis and correlations

Table A1. PCs 1-10: eigenvalues and proportions of variance

	Eigenvalue	Cumulative % of variance
Comp 1	2.786	27.8596
Comp 2	1.5655	43.5145
Comp 3	1.2523	56.0379
Comp 4	1.1591	67.629
Comp 5	0.8625	76.2543
Comp 6	0.696	83.2139
Comp 7	0.6072	89.2858
Comp 8	0.4432	93.7183
Comp 9	0.3738	97.4565
Comp 10	0.2543	100

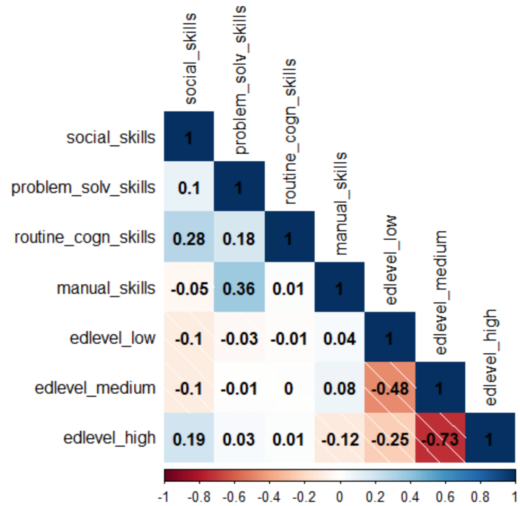
The individual skills selected for this exercise are all skills at a third hierarchy level from ESCO's "communication, collaboration and creativity", which correspond to communication and collaboration skills. After having discarded the PCs with eigenvalues < 1 (i.e., explaining less than one variable), 4 principal components were left, explaining together appr. 68% of the variation in the dataset (Table A1). Further, the skills with contributions of less than 20% were discarded. Thus, each component up to component 4 includes at least two variables, and the fourth component includes one variable with an over 65% contribution (Table A2). The remaining S181, S182, S186, S121, S123, S111, S120 and S130 are further used in the analysis as a single dummy.

Table A2. Contributions of variables to components (%)

	Comp 1	Comp 2	Comp 3	Comp 4
working in teams (S181)	8.1847	1.4075	*35.9469*	0.0544
giving instructions (S182)	9.6782	0.0002	7.4762	8.1927
giving feedback (S183)	0.4238	*49.0574*	0.3961	0.002
assisting and supporting co-workers (S186)	2.0587	0.0215	0.7193	*60.4874*
liaising and networking (S120)	7.803	0.1338	*23.7791*	10.5993
coordinating activities with others (S121)	*21.9927*	0.1916	7.6361	0.203
developing professional relationships and networks (S123)	*20.6118*	0	5.3159	3.2338
teaching and training (S130)	0.2871	*48.6949*	0.2329	0.0304
negotiating contracts (S111)	*21.0748*	0.3973	0.1828	12.5221
mediating and resolving disputes (S112)	7.8852	0.0958	18.3148	4.6747

Figure A1. Correlations between skills

Panel A. Groups of skills



Panel B. Individual subgroups of skills and education

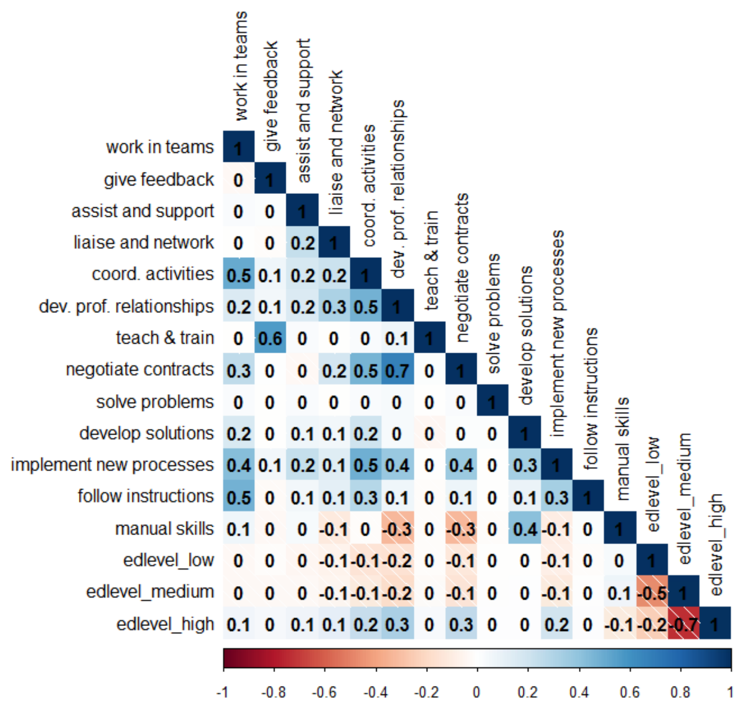


Table A3. Contributions of skills to wages

	Only SS	Only PS	SS & PS	SS & PS & RCS	SS & PS & MS	PS & RCS & MS	SS & PS & RCS & MS
Social skills	0.0141***		0.0143***	0.0139***	0.0162***		0.0159***
	(0.0035)		(0.0035)	(0.0036)	(0.0035)		(0.0036)
Problem-solving		0.0037	0.0043	0.004	0.0097***	0.0076**	0.0095***
		(0.0033)	(0.0033)	(0.0033)	(0.0035)	(0.0035)	(0.0035)
Routine cognitive				-0.0011		0.0045	0.001
				(0.0031)		(0.003)	(0.0031)
Manual					-0.0167***	-0.0147***	-0.0167***
					(0.0037)	(0.0037)	(0.0037)
Adj. R^2	0.4587	0.4586	0.4588	0.4587	0.4589	0.4588	0.4589

Notes. No matching, setup as in Eq.1 without interactions.

Appendix B. Descriptions of skills and automation subgroups

Table B1. Skills by ESCO pillars

Panel A. Social skills

ESCO pillar	**Skill description**
Working in teams	Working confidently within a group with each doing their part in the service of the whole. Understanding and respecting the roles and competencies of other team members.
Giving feedback	Providing founded feedback on the performance of subordinates, co-workers and students through both criticism and praise in a respectful, clear, and consistent manner. Highlighting achievements as well as mistakes and set up methods of formative assessment.
Assisting and supporting co-workers	Assisting and supporting colleagues, managers, volunteers and other co-workers in the performance of their tasks or in the operations of a business unit.
Liaising and networking	Developing alliances, contacts or partnerships, and exchanging information with others.
Coordinating activities with others	Communicating and liaising with colleagues, clients and other agencies on operational matters, problems and activities. Cooperating and liaising with outside agencies, clients and other organisational units to adapt the timing and nature of the activities.
Developing professional relationships or networks	Developing alliances, contacts or partnerships with colleagues, clients and stakeholders.
Teaching and training	Facilitating the acquisition of new knowledge and skills. Leading and guiding individuals and groups through a process in which they are taught the necessary skills and knowledge for life, future learning or for a particular job or set of jobs.
Negotiating and managing contracts and agreements	Negotiating and managing contracts and agreements with others concerning matters such as prices, terms of service, employment conditions, access to land and facilities.

Panel B. Problem-solving and the proxies for routine cognitive and manual skills

ESCO pillar	**Skill description**
Solving problems	Developing and implementing solutions to practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts.
Developing solutions	Developing solutions to practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts.
Implementing new procedures or processes	Implementing new business procedures or processes to resolve practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts.
Following instructions and procedures	Following instructions given verbally or in writing and following standard or agreed procedures.
Using equipment, tools or technology with precision	Use workpieces, tools, precision instrumentation or equipment independently to carry out manual activities, with or without minimal training.

Table B2. Automation equipment by Harmonised System codes

Tools	**HS codes**
Industrial robots	847950
Dedicated machinery (including robots)	847989
Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221,846231, 846241, 84629120, 84629920
Machine tools	845600-846699, 846820-846899, 851511-851519
Tools for industrial work	820200-821299
Welding machines	851521, 851531, 851580, 851590
Weaving and knitting machines	844600-844699, 844770-844799
Other textile dedicated machinery	844400-845399
Conveyors	842831-842839
Regulating instruments	903200-903299

Appendix C. Descriptive statistics

Figure C1. Log annual wages, by skills and automation (cont. Figure 2)

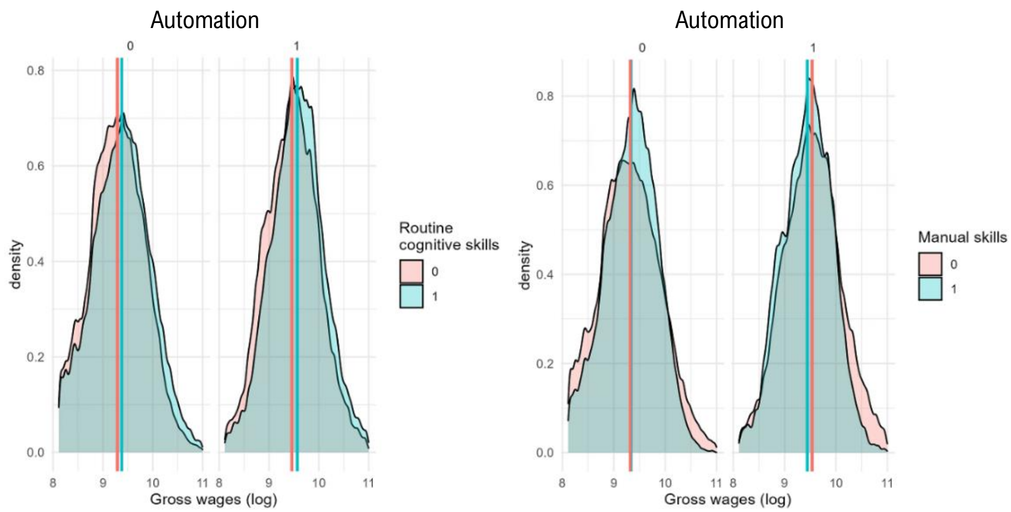


Table C1. Means and mean standardized differences

	Mean, controls (t-1)	Mean, treated (t-1)	MSD (t-1)
Male	0.59	0.566	-0.05
Age	40.733	40.082	-0.078
Education – low	0.141	0.137	-0.014
Education – medium	0.59	0.575	-0.031
Education – high	0.268	0.288	0.044
Managers	0.09	0.075	-0.056
Professionals	0.058	0.078	0.072
Technicians and associate professionals	0.119	0.126	0.022
Clerical support workers	0.044	0.064	0.079
Services and sales workers	0.02	0.008	-0.123
Craft and related trades workers	0.35	0.296	-0.119
Plant and machine operators and assemblers	0.235	0.282	0.106
Elementary occupations	0.084	0.071	-0.053
Social skills	0.573	0.569	-0.008
Problem-solving skills	0.562	0.641	0.164
Following instructions	0.418	0.366	-0.106
Manual skills	0.355	0.396	0.085
Gross annual wage	13088.274	15324.705	0.259
Gross annual wage (log)	9.326	9.498	0.326
Automation (previous 5 years)	0.255	1	-
Automation experience before t-1	0.236	0.698	1.006
Number of employees	122.189	345.869	0.589
Foreign ownership (dummy)	0.293	0.647	0.742

Notes. Observation are "treated" if individuals work in firms which automated 1 year prior and "controls" otherwise. Mean standardized difference is calculated as $\frac{\mu_{automating}-\mu_{non-automating}}{\sigma_{automating}}$.

Table C2. Skills frequencies

	All	Education – low	Education - medium	Education - higher	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Services and sales workers	Craft and related trades workers	Plant and machine operators and assemblers	Elementary occupations	Female	Male
Work in teams	0.383	0.341	0.369	0.433	0.887	0.422	0.456	0.508	0.316	0.352	0.249	0.188	0.267	0.466
Give feedback	0.004	0.001	0.002	0.009	0	0.027	0.015	0.001	0.006	0	0	0	0.006	0.002
Assist and support co-workers	0.027	0.009	0.023	0.046	0	0.062	0.167	0.046	0.006	0	0	0.003	0.037	0.02
Liaise and network	0.039	0.01	0.03	0.074	0.149	0.034	0.069	0.189	0.409	0	0	0	0.064	0.022
Coordinate activities with others	0.429	0.251	0.381	0.622	0.992	0.846	0.812	0.831	0.612	0.308	0.096	0.169	0.348	0.488
Develop prof. relationships	0.192	0.043	0.129	0.401	0.094	0.713	0.402	0.072	0.656	0.007	0.003	0	0.198	0.188
Teach and train	0.002	0	0.001	0.004	0	0.021	0.001	0	0.004	0	0	0	0.002	0.001
Negotiate contracts and agreements	0.242	0.112	0.189	0.421	0.929	0.612	0.582	0.075	0.514	0.123	0	0	0.237	0.245
Solve problems	0.001	0	0.001	0.001	0	0.001	0.003	0	0.006	0	0	0	0.001	0
Develop solutions	0.716	0.71	0.716	0.718	0.92	0.78	0.681	0.723	0.63	0.675	0.753	0.564	0.59	0.806
Implementing new procedures and processes	0.267	0.17	0.223	0.41	0.904	0.609	0.48	0.691	0.247	0	0.183	0.088	0.231	0.293
Social	0.572	0.446	0.529	0.727	0.993	0.908	0.93	0.872	0.966	0.526	0.257	0.216	0.477	0.64
Problem-solving	0.589	0.55	0.587	0.614	0.939	0.671	0.546	0.698	0.251	0.618	0.591	0.09	0.437	0.699
Routine cognitive	0.4	0.382	0.399	0.409	0.755	0.266	0.429	0.58	0.334	0.354	0.315	0.437	0.344	0.44
Manual	0.369	0.415	0.401	0.279	0	0.295	0.161	0.074	0	0.551	0.542	0.106	0.263	0.446