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AUTOMATION-SKILL COMPLEMENTARITY: THE CHANGING RETURNS TO SOFT SKILLS IN DIFFERENT STAGES OF TECHNOLOGY ADOPTION

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Tartu 2024

ISSN-L 1406-5967
ISSN 1736-8995
ISBN 978-9985-4-1415-6 (pdf)
The University of Tartu School of Economics and Business Administration
https://majandus.ut.ee/en/research/workingpapers

Automation-skill complementarity: the changing returns to soft skills in different stages of technology adoption

Anastasiia Pustovalova, Priit Vahter[1]

Abstract

This paper explores the complementarity of automation with social and problem-solving skills, focusing on the wage effects. The results based on detailed firm- and individual-level data from Estonia show that in manufacturing firms which recently adopted automation tools, there is additional wage premium for employees' social skills. 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. The role of skills is different depending on how persistent the automation investments are at the firm. First-time automating firms start valuing the social skills first, while persistently automating firms reward the problem-solving skills instead.

Keywords: automation, technological change, social skills, problem-solving skills, wage differentials

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

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We gratefully acknowledge the support by the Estonian Research Council's research project PRG791 'Innovation Complementarities and Productivity Growth' and the support from Iceland, Liechtenstein and Norway under the EEA grant project No. S-BMT-21-8(LT08-2-LMT-K-01-073) Global2Micro. We are grateful for the comments by Tairi Rõõm, Jaanika Meriküll, Ouafaa Hmaddi and Alexey Rusakov.

1. INTRODUCTION

The relationship between technical change and the trends in the labor market has been the basis for the skill- and routine-biased technical change arguments for a long time. A vast number of studies have reported evidence supporting the skill bias of technology. Creation, adoption and diffusion of new technology has strong correlation with the demand for high-educated labor; this translates into disproportionally high wage premium of higher education and on the high-skill jobs. On the other hand, there is a substitution effect in the case of the lower-skilled labor. (e.g., Goldin and Katz, 2009; Spitz-Oener, 2006, Nedelkoska and Quintini, 2018; Frey and Osborne, 2017; Arntz et al., 2016).

However, there is still limited knowledge about the functioning of the complementarity of technology specifically with the soft skills of employees: especially on how social and problem-solving skills shape the effects of automation on earnings in the case of low-skilled employees, or in the case of different patterns of automation adoption. Also, there is not much research on potential positive technology effects on the low-skilled occupation group (Aghion et al. 2019a, 2019b).

This paper investigates the relationship between automation and wages: it explores the complementarity of automation with social and problem-solving skills, outlining the positive effects of automation on earnings of a sub-set of the 'low-skilled'. Our study contributes to the existing literature in two ways. First, using employer-employee level data from Estonia, it adds to the literature on technology adoption effects on workers, as well as on routine-biased technical change (Goldin and Katz, 2009, Acemoglu and Autor, 2011, Frey and Osborne, 2017, Autor and Dorn, 2013) by exploring the complementarity of social and problem-solving skills with automation in different skill groups (low, medium and high-skilled) and showing the importance of soft skills in shaping earnings especially for the lower-skilled employees at automating firms. Traditionally, the low-skilled are seen as disadvantaged by automation. However, we find that the complementary effect of soft skills and automation is larger for the earnings of the low-skilled compared to the high-skilled employees. This analysis allows us to add to the prior rather scarce investigations on the low-skill workers and innovation, and how innovation 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. 2019a, 2019b). Key theoretical models that we rely on in outlining the role of soft skills are by Deming (2017) and Aghion et al. (2019a). Deming (2017) emphasizes the role of soft skills in lowering coordination costs at the firm; Aghion et al. (2019a) shows that innovating firms have stronger complementarities between (i) labor of the low-skilled employees that have soft skills and (ii) high-skilled labor groups at the firm.

Second, we contribute to the literature on the heterogeneity of firms' adjustment related to adoption and diffusion of new technology (Acemoglu and Restrepo, 2018; Domini e al., 2020; Cirillo et al., 2021) by studying how the role of social and problem-solving skills differ by the patterns of automation, 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 (see, e.g., Desyllas et al. 2020 for a recent discussion on coordination costs and innovation). 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 later stages.

While the skewness of the new technology impact on labor is more than evident in the literature, the cause of it is not as clear. In principle, the productivity of the skilled workforce is improved by innovative technology more than that of the unskilled, which, in turn, increases the demand for higher-skilled labor when technology intensiveness increases; this results in wage shifts in favor of the skilled labor (Acemoglu, 1998; Acemoglu and Autor, 2011). The concept of a “skilled” worker, meanwhile, is less than obvious, as is the concept of skills, which are complementary to technology. Surprisingly, in the empirical literature the workers falling into the category of “low-skilled” by the occupational definition in some cases turn out to reap the benefits of technology advances no less than the “high-skilled” (Aghion et al., 2019a; Autor and Dorn, 2013). The routine-biased technical change framework answers this by suggesting that on the lower-skilled jobs, too, exist non-routine tasks which might be complemented by technology. Thus, Aghion et al. (2019a, 2019b) 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 (Agion et al. 2019a).

In contrast to other papers that investigate the effect of technology on labor in Europe, this paper focuses on the precise skills needed for jobs. We apply the framework of non-routine social and cognitive and routine cognitive and manual job tasks (Autor et al., 2003) to 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., 2019a). We combine the ESCO skills data in this paper with panel data from Estonia at the firm level, as well as the product and the individual levels, to investigate how automation contributes to the wages of employees.

We combine estimation of Mincerian wage regressions with coarsened exact matching. For balancing the data, we use coarsened exact matching on a number of individual- and firm-level covariates. This allows to compare the wages of the similar treatment group of individuals working in firms which introduced automation with the matched control group. Further, wage regressions (estimated also by skill groups) with weights from coarsened exact matching are run for the wages one year after the introduction of automation. The matching approach combined with the firm fixed effects addresses some key concerns about the endogeneity of automation in Mincerian wage equations. In additional robustness tests, we endeavour further to address potential remaining endogeneity of automation concerning the effects of automation, for example, due to any remaining reverse causality and omitted variable biases. For that, we estimate an IV regression where we build the instrumental variable for the firm-level automation adoption using more aggregate sector-level information on automation from earlier periods. For building the instrumental variable, we use information of past sector-level automation adoption in Estonia. This is similar to the econometric approaches applied based on firm-level data, for example, recently in Czarnitzki et al. (2023) analysis of the effects of firm-level adoption of AI and also in Bonfiglioli et al. (2020) analysis of robotization effects at the firm level.

2. LITERATURE REVIEW

The notion that technological progress is skill- (routine-) biased has been a matter of discussion for quite 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 such as educational (college / higher education premium – e.g. Katz and Murphy, 1992; 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 (SBTC) hypothesis initially emerged as a way to explain the labor market shifts in the USA in the 1980-s, the disputes followed as more data became available. Thus, Card and DiNardo (2002) argued that SBTC failed to explain the labor market tendencies in the US during the 1990-s such as wage inequality changes, the closing of the gender pay gap, and the age-related differences in education wage premium. The following investigations of developed economies and the US in particular (e.g. Autor et al., 2008; Autor, 2014; Spitz-Oener 2006), however, suggest that the technology-driven skill premium to wage has not vanished with time but rather needs modification concerning the complementary effects of the new information technology to the abstract and otherwise non-routine tasks and substituting ones to the routine tasks. To some extent, the focus in the literature has shifted from the more general definition of skill bias to the (non-)routine skill bias of new technology.

The skill-biased technical change argument is that the new technologies that emerge tend to complement the skilled labor and substitute for the unskilled, 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; taken to the extreme, in some cases technology is able to substitute for the unskilled labor completely. The routine-biased technical change literature follows a similar logic, though the 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 economic 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 information technology rise in particular (Acemoglu and Autor, 2011; Goldin and Katz, 2009). While the evidence on the premium is univocal, 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. An important aspect of higher education is that it gives general long-lasting knowledge and skills that cannot be obtained during firm-level on-job training, 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. (2019a), individuals performing low-skill jobs – i.e., the jobs requiring only minimal formal education and training – receive wage premium to working in innovative firms. 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 cannot find much literature that focuses on the low-skill occupation group and the positive technology effects on it. Aghion et al. (2019a) are one of the few that do focus on this labor group after finding a rather surprising wage premium on some low-skill occupations. Their focus in Aghion et al. (2019a), however, is on the firms that are engaged in research and development – i.e., the creation of new products and processes. Technological change, though, is also largely represented by the adoption and diffusion of new technologies.

The task-based approach as in Autor, Levy and Murnane (2003) contrasts the routine tasks to the non-routine tasks, i.e. to those more ambiguous in execution and not understood well enough to be described as a set of commands. In line with the skill-biased technical change explanation through the impact on productivity, in Autor, Levy and Murnane (2003) the technology acts complementarily 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 the non-routine analytical and the non-routine interactive (with the non-routine manual tasks assumed to be not affected by automation), whereas the tasks easily substitutable by the technology are the routine cognitive and the routine manual. Thus, the Autor, Levy and Murnane (2003) framework allows for the low-skill occupation groups (the 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 the non-routine analytical and/or the interactive tasks. While the analytical non-routine tasks – with problem-solving, creativity and persuasion being perhaps the most evident examples – usually (though not always) intersect with the tasks that the higher-educated and high-ranking employees tend to perform. The concept of the non-routine communicative tasks implies more flexibility in terms of the occupation and the education. For this type of tasks, adaptability, social and language skills are crucial. Other authors also often include in this category the negotiation and persuasion skills, the coordination of others and the coordination of one's own work activities with others.

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 the employees on their wages. We outline Deming (2017) and Aghion et al. (2019a) as some of the most relevant theoretical frameworks to our study, explaining the potential pathways of complementarity of social skills with technological change at the firm.

Deming (2017) shows that high-wage jobs increasingly demand social skills from employees. Technological change is a likely explanation of this complementarity and 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 the coordination costs at firms. Coordination costs are especially important in the case of introducing an innovation such as automation at firms. Moreover, a central aspect in his model is the fact that social skills can be complementary with other (cognitive) skills. Thus, an added bonus of social skills can be enhancement of the complementarity of automation with other types of 'high' skills.

Deming's (2017) model includes teams of production, where team members "trade tasks" to make use of their comparative advantage in terms of tasks. In this model, social skills lower the costs of coordination and 'trading tasks' at the team and firm. Thereby the individual social skills allow the employees to more easily specialise in the tasks for which they have comparative advantage. The model by Deming (2017) applies the structure that is similar to Ricardian type of trade models (Dornbusch, et al. 1977, Eaton and Kortum 2002), however, Deming applies this model in the context of social skills and labor market. Where in Ricardian model one has 'countries', in Deming's model we have 'employees'; where in Ricardian model we have the inverse of iceberg trading costs, in Deming's model we have 'social skills'.

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

Finally, we distinguish in our study between the early stage versus the 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 the 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 the 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. The firms need to update their bundle of innovation activities (including their organisational practices) to ensure that the positive effects of automation are materialised. A key reason for coordination failure in adoption of automation is the inadequacy in managerial attention allocation (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 the management. In particular, this concerns the allocation of time—the management's main resource—to the key components in the decision-making process.

To sum up, 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 does increase the complexity of the system and it ultimately also increases the probability of failures in coordination of the system. For example, Desyllas et al. (2020) provide 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, incl. collaboration within the firm to facilitate efficient transition to the new technology.

3. EMPIRICAL STRATEGY AND DATA

3.1. Data

We use panel data from Estonia at the firm 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.

For the employee-employer correspondence in 2011, the 2011 Census data is merged with the data of the Tax and Customs Board of Estonia. The Tax and Customs Board of Estonia also provides income data, with the 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 dummy variables for other types of skills. To address the possibility of omitted variable bias and to ensure correspondence to the skills' classification in the literature on routine-biased technical change, 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 by the education level. The data on education (ISCED-97 and ISCED-11 levels) is transformed into a single indicator of low, medium or high education level. The education up to and including lower secondary is coded as "low", upper secondary and post-secondary non-tertiary education corresponds to "medium", 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 product- and firm-level data of foreign trade (the imports) from the Tax and Customs Board of Estonia, we construct an additional dummy variable for a firm being an importer, and a dummy for imports of automation equipment (similarly to Domini et al. 2020), also a dummy for the firm having had prior automation (imports), and the number of previous automation cases. The firms are from the manufacturing industry. This provides a closer look into the effects of tangible automation, which is considered an established solution in this sector.

A small number of observations with missing or incorrect (as documented by Statistics Estonia) data on employment, firm age and income were removed. Additionally, occupation group Skilled agricultural, forestry and fishery workers (number 6 in the 1-digit ISCO-08 coding) was dropped from the analysis since in this group there were zero observations on individuals being simultaneously in automating firms and having interactive skills as an essential component of a job. Since the data does not allow to distinguish between the types of employment, we drop the low wage earners as a way of filtering out the non-full-time workers. The low wage earners are defined either as those whose wages are below the minimum wage, or those whose wages are below or equal to the minimum wage in a given observation year. Finally, the data was restricted to the workers 25 to 54 years of age (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 134 293.

3.2. Wage equation

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

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

Here subscripts i, j, t denote individual, firm and time (year) respectively. $Automation_{jt-1}$ is a dummy term for automation adoption (see next Section 3.3 on details of measurement of automation)[2]. $Social_{it}$ and $ProblemSolving_{it}$ are dummies for soft skills required on a job (social skills and problem-solving skills). 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 (Tallinn), 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's 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 to account for firm-specific fixed characteristics that might otherwise bias the estimates, the firm fixed effects (u_j) are added to the model.

The wage observations are taken for the year subsequent to 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 lagged effect, we explore the specification in which automation in the previous 5 years is used. This measure accounts for firms that acquired automation tools within the last 5 years. It is meant to reflect the longer-term effects and the persistent automation effects. Other ways to study the effects of automation are reported in subsection 4.1. This includes persistent automation practices (automation every year within the last 5-year window), first-time and otherwise irregular automation.

[2] It is well known that the effects of automation can take time to materialize (e.g., Brynjolfsson et al. 2018, among others). This is one reason for the use of lagged automation indicator. Another reason for choosing automation from period *t-1* rather than period *t* was due to the fact that the automation data is yearly, so automation could take place at the beginning or at the end of the year. Using *t-1* lags means that the 'estimated effects' are measured *post-factum* (i.e., after the automation investment). Whereas the period *t* indicator could reflect the post-, during- and before-automation effect, and thus could be more likely to reflect the non-random selection into automation. Here we do not want to capture the selection effect, thus we focus on a lagged automation indicator instead of the contemporaneous one.

3.3. Automation

The automation-related indicator is based on the product-level foreign trade data provided by Statistics Estonia and the use of the traditional taxonomy of automation tools 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 importing is not the only way how automation equipment can be obtained, in Estonia the magnitude of domestically produced automation equipment is small enough to overcome this limitation. See Tiwari (2023) for a more detailed discussion. Kalvet (2004) study reported importing as the main source for automation hardware in Estonia. According to more recent data, Estonia does not export sizeable amounts of such equipment (Tiwari 2023). This suggests limited domestic production.

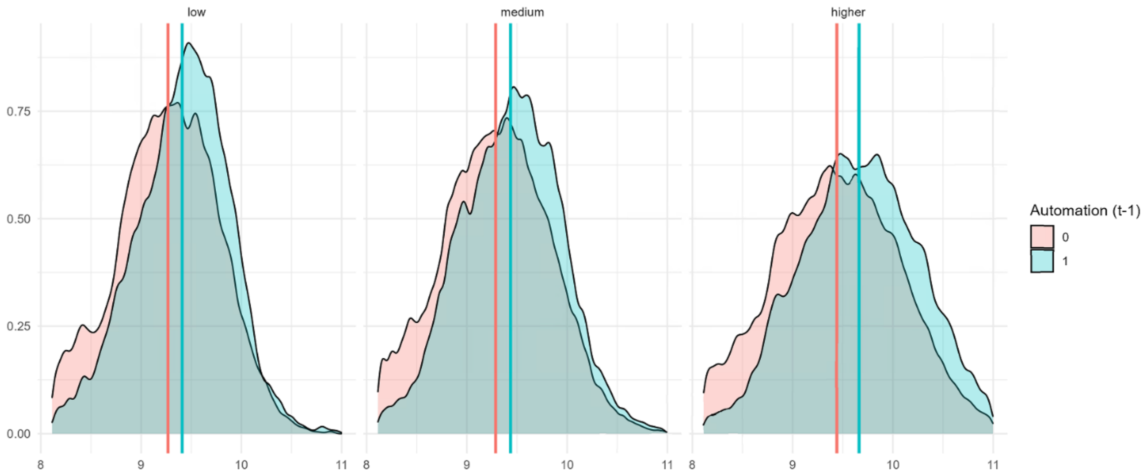
As in Acemoglu and Restrepo (2018) and Domini et al. (2020), in our data automation-related imported equipment consists of several product groups, aggregated to a firm-year level for the automation indicator. They are based on 6-digit Harmonised System codes of automation products proposed by the above 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 taken into account in the estimation. For that, we include binary indicator for prior automation experience. 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.

In general, automation in manufacturing firms might be considered an established solution. In our data, 28.7% of the observed manufacturing firms have adopted automation equipment at least once during the last 5 years. This translates 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). There are observations of automation investments only once ortwice within the last 5 years. However, there are also firms with persistent automation investments, e.g. 5 or 4 times within the last 5 years. The most frequently bought automation tools are Tools for industrial work, Machine tools and Regulating instruments.

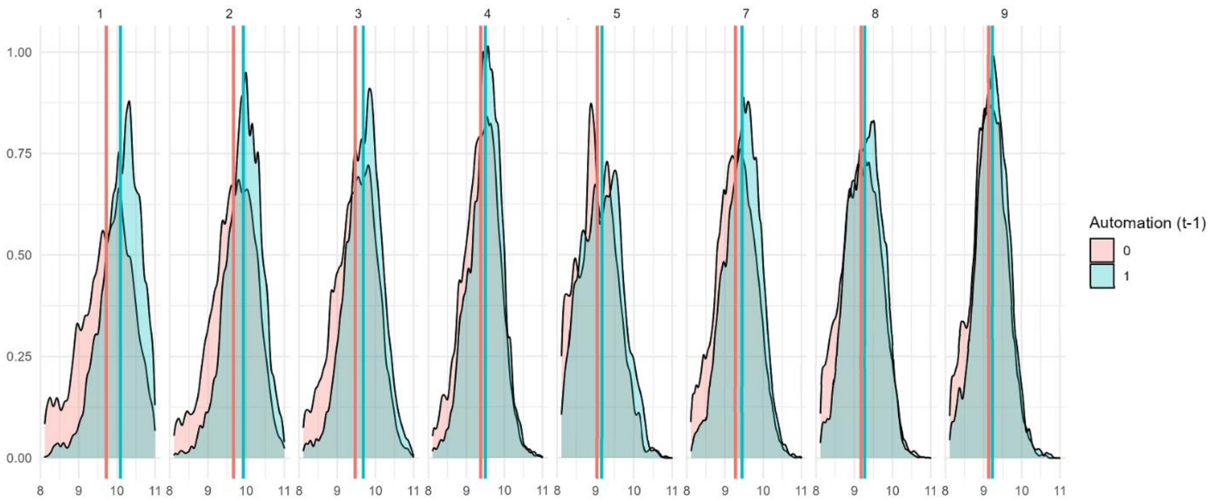
The average observed yearly wages in automating firms were significantly higher than in non-automating ones (Appendix C). At the same time, the wage premium is distributed unevenly, being larger in the case of higher-educated individuals and especially managers (*Figure 1*). The lower-educated, at the same time, are much more similar in terms of their wages, regardless of the kind of firm they are employed at. Automating firms tend to have younger employees. 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 groups



Panel B. Occupation groups



Notes. Vertical lines show mean values for groups. 134293 individual observations, prime-age (25-54 y.o.) workers. Education level is "high" for tertiary education, "medium" for general secondary, vocational and post-secondary non-tertiary education, and "low" otherwise. Digits 1, 2…9 are 1-digit 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). Group 6 (Skilled agricultural, forestry and fishery workers) was excluded from the analysis.

3.4. Skills

To classify employees by their skills requirements, this paper employs the framework of routine-biased technical change literature (Autor, Levy and Murnane, 2003; Spitz-Oener, 2006; Autor, Katz and Kearney, 2006) and the ESCO (European Skills, Competences, Qualifications and Occupations) ontology of European Commission.

ESCO is a classification constructed for European-based occupational titles, partly based on O*NET and the Canadian skill and knowledge glossary. The version of ESCO that is used in this paper is from August 2020. ESCO is primarily constructed by collecting feedback from experts. However, it is also regularly 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 extensive, with the number of occupation titles reaching 2942 and the number of skills and competences corresponding to them being over 10 thousand. We exploit the third hierarchy level of skills and the 4-digit ISCO-08 level of occupations. .

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 we performed principal component analysis based on the skill groups (see Appendix A). After principal component analysis, several subskills were removed. The detailed final list of social subskills and their definitions and examples can be viewed in Appendix B. The elements of social skills are “working in teams”, “giving feedback”, “coordinating activities with others”, “assisting and supporting co-workers”, “liaising and networking”, “developing professional relationships and networks”, “teaching and training” and “negotiating contracts and agreements”. The list is a rather typical one. A similar one can be found, for example, in Spitz-Oener (2006) or Nedelkoska and Quintini (2018). The list of social skills includes both the skills which are traditionally more represented on the high-skill jobs (negotiating, teaching, developing professional relationships) and the skills that are required on all kinds of jobs (coordinating activities with others, working in teams).

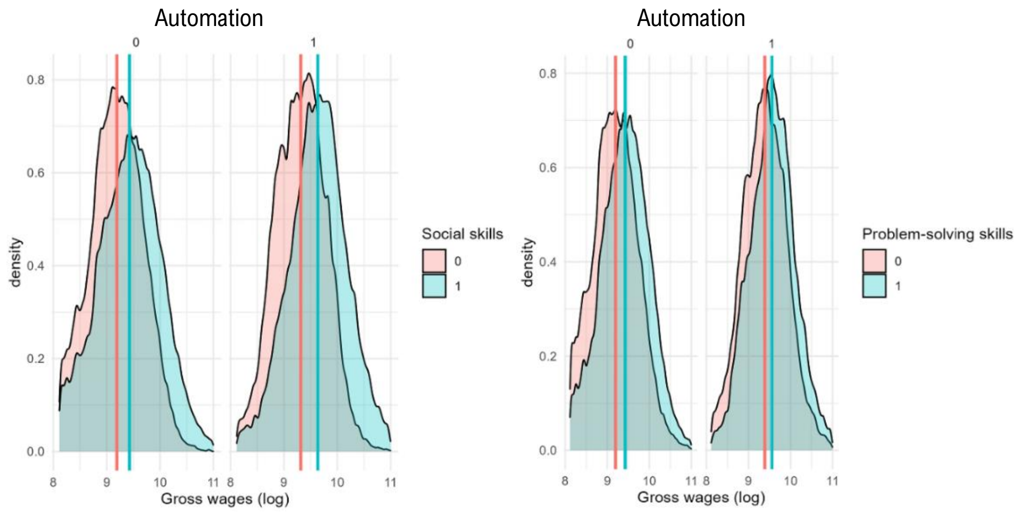
For the indicator of problem-solving skills, we use the ESCO pillar 1.9 “solving problems”, which is defined as “*developing and implementing solutions to practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts*”. It is hence a measure of non-routine cognitive tasks, which is similar to the one in Autor, Katz and Kearney (2006). The pillar consists of subskills “solving problems”, “developing solutions” and “implementing new procedures or processes”, and the examples of even narrower problem-solving skills (“identifying improvement actions”, “preventing technical problems with scenic elements”, “implementing airport emergency plans” etc).

Finally, we construct indicators for routine cognitive and manual skills. For routine cognitive skills, we use “following instructions and procedures” as a proxy (a definition similar to the one in Autor, Levy and Murnane 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 routine manual skills can be found in Spitz-Oener (2006) and Autor, Levy and Murnane (2003). Excluding the non-routine manual skills, on the other hand, should not bias the results, since these skills, according to Autor, Levy and Murnane (2003), are not expected to interact with automation in a meaningful way.

The specifics of ESCO data allow 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 skills 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’ manifest among 43% of employees overall, reaching 62% in the higher-educated. This skill is one of the most frequent social skills in all occupation groups except for the low-skill ones (the last 3 1-digit categories of ISCO-08), where “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 development of professional relationships.

Figure 2. Log yearly wage density, by skills and automation at t-1



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

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. Similar to the non-routine social skills, problem-solving skills are much less pronounced on low-skill jobs and among the 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. 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*). However, only social skills seem to be positively associated with the introduction of automation in the raw data. Both routine skills show minuscule, if any, mean wage differentials (Appendix C).

3.5. Coarsened exact matching

Although we account for the firm differences by adding firm fixed effects in the model, we also add coarsened exact matching (CEM), since the data is slightly unbalanced in terms of individual-level characteristics and highly unbalanced in firm-level ones (see *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. This creates the need to control for possible drivers of selection into automating firms and the pre-automation wages. In addition, the implementation of the matching procedure, as well as the introduction of the firm fixed effects, allows to address the possible endogeneity of automation.

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 the treated (the individuals who work in automating firms) and the controls (the comparison group) in terms of the key covariates is performed directly, with no need for 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 as the unmatched sample in terms of the covariates, or they were even more poorly balanced 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 a number of covariates, forming subsamples that consist of the treated and the controls with the same characteristics. The treatment effect is then calculated either by i) averaging the treatment effect values in the subclasses or ii) by running a regression with weights (adjusting for the imbalance in the number of the treated and the 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; the weights for matched controls are 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 the treated in subclass i, N_i^c is the number of the controls in subclass i, and N_d^c and N_d^t, respectively, the number of the controls and the number of the 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 based on them was done exactly. These are gender, education level, 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 the treated and the controls. 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 the treated is excluded from analysis. Another possible issue is that, while the individuals are balanced on the selected confounders, some imbalance may still remain in the case of other important confounders.

3.6. Robustness test: IV regressions

Coarsened exact matching combined with regression analysis that includes firm fixed effects alleviates some of the key concerns about the endogeneity of automation in our Mincerian wage equations. This approach, firstly, controls for unobserved fixed firm characteristics that might affect both automation and employees' wages at firms. Secondly, CEM enables to balance the observed 'pre-treatment' characteristics between the treatment and control group. In particular, it allows to take into account a number of observed employee level variables in constructing the control group.

However, even after taking these issues into account, there can be still concerns about potential remaining endogeneity of automation. This can be due to potential remaining reverse causality or omitted (unobserved) variable bias. For example, firms may be better able to engage in automation investments if they have had an improvement in performance and an increase in available resources, as these help to cover the sunk costs of automation (Czarnitzki et al. 2023). Or, alternatively, the adoption of automation may also reflect prior high levels of labor costs at the firm and low prior profitability, resulting in the need to lower these costs by automating. Also, omitted variables such as other firm-level and firm's eco-system level factors of productivity and innovation might cause biased estimates of automation effects. For these reasons, we remain careful in our paper with any strong causal claims.

To further account for endogeneity of automation in our Mincerian wage equations, we estimate in a key robustness test also IV regressions, where we build instruments for the firm-level automation based on the sector-level indicators of automation from earlier periods. For building these instrumental variables, we use information of past sector-level automation adoption in Estonia, adjusted by the number of employees. This is similar to the econometric approaches applied based on firm-level data in Czarnitzki et al. (2023) that investigates the effects of firm-level adoption of AI. This is also related to the instrumentation approach in the analysis of robotization effects in Bonfiglioli et al. (2020).

The key identification assumption in our application of the IV approach is that these past sector-level variables of automation adoption in Estonia are correlated with firm-level automation but not with the error term in the estimated Mincerian wage equation. We construct the following version of the 3-digit NACE sector level variables for building the IV: we use automation investments per employee (in logs) at 3-digit sector level in Estonia, from year *t-10*. Long lags help to ensure that the variable is less likely to affect current wages via channels other than diffusion of automation at the firm level. This instrument captures the idea that higher past within-industry diffusion of automation technologies fosters adoption of the same technologies by a firm in this industry.

It is important to recall that the adoption of automation in our Mincerian wage equations is a dummy variable. Estimating a probit model of automation and simply plugging in non-linear fitted values from a probit model to the second stage Mincerian equation would not be a correct approach in this case. This would lead to the well-known ‘forbidden regression’ problem (Angrist and Pischke 2009, Wooldridge 2010).

Instead, we use here the approach popularised by Angrist and Pischke (2009) and Wooldridge (2010) that helps introduce binary treatment into the 2SLS framework. This approach involves, first, estimating a binary response model (probit) by maximum likelihood as the first stage of analysis, with automation at firm level as the dependent variable and automation at sector level (in the past in Estonia, adjusted to the number of employees) among the explanatory variables. Next, instead of plugging in these predicted values from the probit model to the second stage, we use the estimated fitted probability of automation as an instrument for the observed firm-level automation dummy in our Mincerian wage equation. Based on Wooldridge (2010) and Angrist and Pischke (2009), the fitted probability derived from such first-stage maximum likelihood estimation is a suitable instrument in our second-stage model. With this approach, we avoid the biases due to incorrectly using non-linear first stage in 2SLS. As a bonus, we get more precise estimates than if we used linear probability model instead of probit in the first stage (Huntington-Klein 2022).

4. RESULTS

4.1. Automation, skills and wages

The main specification of interest in the following *Table 1* is the after-matching firm fixed effects model where the (log) wages depend on automation in the previous year,the skills, their interaction terms and other controls. We use this to test the hypothesis of whether the recent adoption of automation tools at a workplace interacts with social and problem-solving skill requirements in a way that produces the 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. These coefficients are presented in odd columns in *Table 1*. We observe in our key specification in column 1 of *Table 1* that introduction of automation at the firm (in *t-1*) is associated with about 2.6 per cent higher wages of its employees in the next year.[3]

Social skills are significantly associated with higher wages, with estimated coefficients that are both statistically and economically significant. Social skills of the individual are associated with about 0.95 to 1.14 per cent higher wages of the employee, depending on the specification of the model (see 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.

The column 2 of *Table 1* shows the key specification with the lagged automation dummy and its interaction terms with social and problem-solving skills indicators. Here 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 in the next period, as shown by the statistically and economically significant positive interaction terms. Having social skills increases the estimated effect of automation on wages by

[3] Robustness tests showing interaction terms of other skills with automation are shown in Appendices A and D.

1.8 per cent. Having problem-solving skills increases the estimated effect of automation on wages by 1.2 per cent.[4]

Table 1. Log wage results, by persistence in automation

	Automation at t-1		First-time automation at t-1		First-time automation within the previous 5 years		Automation all 5/5 times within 5 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation	0.0258***	0.0233***	-0.0042	0.005	0.0057	-0.0119	-0.0029	0.0122
	(0.0061)	(0.008)	(0.012)	(0.0172)	(0.0053)	(0.0076)	(0.0124)	(0.0139)
Social skills	0.0111***	0.0024	0.0095**	0.0089**	0.0138***	0.0101**	0.0055	0.0025
	(0.0037)	(0.0046)	(0.0041)	(0.0042)	(0.0037)	(0.0041)	(0.0059)	(0.0082)
Problem solving	0.0115***	0.0073	-0.0064	0.0053	0.0039	0.002	0	-0.0009
	(0.0037)	(0.0046)	(0.004)	(0.0041)	(0.0036)	(0.0041)	(0.0059)	(0.0085)
Automation x Social		0.0183***		0.0061		0.013**		0.0041
		(0.006)		(0.0139)		(0.0064)		(0.0095)
Automation x Problem solving		0.0121*		0.0149		0.0065		0.0427***
		(0.0066)		(0.0147)		(0.0068)		(0.0107)
Adj. R^2	0.4628	0.4631	0.4481	0.448	0.4573	0.4574	0.486	0.4854
N observations	120261		101826		129009		55908	
N matched treated	45080		5874		31671		20207	

Notes. Significance levels: * - $p < 0.1$, ** - $p < 0.05$, *** - $p < 0.01$. Robust standard errors in parentheses. Results after coarsened exact matching. Controls not reported in the table include gender, age, age squared, education level, 1-digit (ISCO-08) occupation groups, routine cognitive and manual skills (and their interactions with the automation dummy in the even columns), location in the capital city, immigrant status, mother tongue, firm size, firm size squared, firm ownership dummy, importer dummy and a dummy for automation experience prior to the relevant observation(s). Columns 5 and 6 exclude the firms which automated 5/5 times within the previous 5 years.

Next, we explore the distinction between persistent and non-persistent automation and the role automation and skills play when automation is introduced for the first time. These results are presented in columns 3-8 and 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. Our results in columns 5 and 6 suggest that social skills are important and have a positive effect for the employees in the newly automating firms, that are adjusting to the adoption of the new technologies. However, there is adjustment time involved. Such firms do not recognize the value of such skills right away (see columns 3 and 5) but with some time lag. As the firms become more experienced and persistent in automating (columns 7 and 8), the significant wage premiums of social skills are fully substituted by even higher significant wage premiums of problem-solving skills.

[4] We report further models with i) interaction terms of automation with other skills and ii) robustness tests of the models with interaction terms of automation with social and problem-solving skills in Appendix D. For example, see Table D4.

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 and ultimately also increases the potential coordination failures in the system of complementary inputs. Our finding in *Table 1* suggests that coordination costs and the potential for coordination failures associated with the adoption of new technology are likely to be especially important and potentially disruptive in the early stages of automation. In the early stages of adoption, firms have little prior experience with such disruptive changes: they are less likely to have good skills of coordinating complex changes in their innovation process.

Previous evidence from Estonia has shown also that persistently automating firms have much higher productivity compared to firms that automate only occasionally or are in early stages of their automation investments. The occasional/early-stage automating firms have in some sectors even lower productivity than the firms that do not automate (Tiwari 2023). This finding, again, suggests the importance of adjustment costs in early stages of automation.

4.2. Heterogeneity by demographic groups

Frequent result in the literature on technological change, is the increase in inequality due to the creation, adoption and diffusion of the new technology. The increased inequality is partly explainable by the differences in skill endowments and requirements. The most established standard difference is between low- and high-skilled, or, more recently, between high-, medium- and low-skilled employees. Examples in the literature range from the canonical Acemoglu and Autor (2011) to the more recent Aghion et al. (2019a). Moreover, some recent papers argue that the 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 2*) and age (*Table 3*) groups.

The division into education groups shows a striking difference in wage returns. While the positive joint effect of automation and social skills appears to be universal, the magnitude of this interaction coefficient differs significantly. The highest wage premium is observed in the lowest-skill group (with education below upper secondary), which is consistent with the implications in Aghion et al. (2019a, 2019b)—i.e., soft skills drive the wage premium for the low-skilled in innovative firms. At the same time, consistent with the standard views of the literature on skill- and routine-biased technical change, without non-routine skill requirements the effect of automation is negative for the low-skilled (and quite significantly so).[5] At the same time, employees with higher education experience no returns from automation without the skills. The only significant relationship between automation and the wages of this group comes from the combination with social skills.

The overall wage effect of automation is positive for the high-skilled, which is similar to what the descriptive statistics implied (*Figure 1*). Unlike the implications of the raw data, the overall automation returns in our econometric analysis are *negative for the low-skilled*. The difference comes from controlling for the broad occupation groups in the regression: when this variable is dropped from the equation for the low-skilled, the individuals working in automating firms have higher wages overall compared to the ones in non-automating firms

[5] A prior study by Dauth et al. (2021) from Germany finds in the case of both the lower skilled and medium skilled employees sizable negative effects of automation on earnings. However, they do not investigate how social skills may help to counter this effect. For low skilled employees without social skills, our analysis in Table 3 points to the similar negative effect of automation on earnings as in Dauth et al. (2021).

Finally, the subsamples of the older employees reveal results somewhat 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 wage premium again. The coefficients for the younger workers partly resemble the ones for 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 for this group. Finally, the overall effect of automation on wages becomes more pronounced with the increases in education whereas it decrdecreases with increases in the age. See models (1), (3) and (5) in *Table 2* and *Table 3*. Social and problem-solving skills are especially relevant and useful for the lower-skilled and the younger employees, regardless of automation

Table 2. Log wage results for recent automation, by education level

	Education – low		Education - medium		Education - 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 skills	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		0.0846***		0.0158**		0.038***
Social		(0.0181)		(0.0073)		(0.0139)
Automation (t-1) x		0.0271		-0.0111		-0.0213
Problem solving		(0.0193)		(0.0082)		(0.0135)
Adj. R^2	0.2891	0.2882	0.3992	0.3992	0.4713	0.4714
N observations	15423		72584		32254	
N matched treated	5805		26476		12799	

Notes. Significance levels: * - p < 0.1, ** - p < 0.05, *** - p < 0.01. Education level is “high” for tertiary education, “medium” for general secondary, vocational and post-secondary non-tertiary education, and “low” otherwise. Robust standard errors in parentheses. Results after coarsened exact matching. Controls not reported in the table are the same as in Table 1.

Table 3. Log wage results for recent automation, by age group

	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 skills	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		42956		43541	
N matched treated	13427		15990		15663	

Notes. Significance levels: * - $p < 0.1$, ** - $p < 0.05$, *** - $p < 0.01$. Robust standard errors in parentheses. Results after coarsened exact matching. Controls not reported in the table are the same as in Table 1.

4.3. Robustness tests: IV estimation

To further account for potential endogeneity of automation, we also estimate instrumental variable regressions as a part of our robustness tests. We report here IV models for the key specification that investigates the effects of automation at *t-1* and the interaction of automation with dummies for social and problem-solving skills.

The IV model is using Estonia's past (from year *t-10*) 3-digit sector-level automation investments per employee in the IV-model's first stage for predicting propensity to automate at the firm level. The past sector-level automation turns out to be a significant predictor for future firm-level adoption of automation. However, we note that in the case of more detailed analysis of the type of automation investments (first time automating firms vs the persistent ones), this IV approach did not produce suitable strong instruments.

The IV estimation results are presented in *Table 4*. Automation on its own has no statistically significant association with wages of individuals. As before (in *Table 1*), social and problem-solving skills are associated with higher wages. The column 2 of *Table 4* outlines the key IV specification with the lagged automation dummy and its interaction terms with social and problem-solving skills. The results here, as in our non-IV approach in *Table 1*, confirm the expected complementarity between automation and social or problem-solving skills. In the IV specification, we observe that these categories of skills increase the estimated effect of automation on wages in the next period. This positive interaction effect is both statistically and economically significant. Having social skills and also automation at the workplace is in this specification associated with 9.1 percent higher wages (calculated as exp(0.0869)-1). Having problem-solving skills and automation at the workplace is associated with 5.9 percent higher wages. Notably, there is no positive effect of automation on wages unless the individual is working in an occupation that requires social or problem-solving skills. This confirms our similar previous findings based on non-IV specification in *Table 1*. We note that the IV estimates of the interaction effects of skills and automation are somewhat higher than the corresponding ones from the non-IV specification.[6]

Table 4. Robustness test: IV regression analysis, 2nd stage of 2SLS model, dependent variable is log of yearly wages

	(1)	(2)
Automation (t-1)	-0.0294	-0.0683
	(0.0531)	(0.055)
Social skills	0.0163***	-0.0186***
	(0.0036)	(0.0064)
Problem-solving skills	0.0094***	-0.0114*
	(0.0035)	(0.0068)
Automation(t-1) x Social		0.0869***
		(0.0135)
Automation (t-1) x Problem-solving		0.057***
		(0.015)
Adj. R^2	0.4591	0.4602
N observations	133952	
N matched treated	47067	
Corr. IV	0.0649	
Corr. after first stage	0.4488	

Notes. Significance levels: * - $p < 0.1$, ** - $p < 0.05$, *** - $p < 0.01$. Robust standard errors in parentheses. Coefficients from the 2nd stage of 2SLS model, with log of wages as dependent variable. IV variable: automation investments per employee at sector level in Estonia (at t-10). Other firm and individual level controls are included in each model: other controls are similar to the Mincerian wage equation in Table 1. All models include firm fixed effects. The 1st stage of the IV model is reported in Appendix E.

5. CONCLUSIONS

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, in different stages of automation different skills might be valued differently. This paper explores the presence of automation-skill complementarity in the manufacturing sector. It investigates the wage returns for social and problem-solving skill requirements in the context of automation at the firm.

We find that, at least in the short term, social skills (note: skills especially related to coordinating activities with others) are consistently positively associated with wages in automating firms whereas 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 at the workplace.

Moreover, the positive outcomes of social skills might be short-term and appear to matter more in the early stages of automation at the firm. For instance, our results suggest that social skills are important and positive for the workers in the newly automating firms, which still adjust to

[6] Czarnitzki et al. (2023), similarly, report in their study of effects of AI on productivity of firms' coefficients that are higher in absolute values in their IV models compared to the non-IV ones.

the new technologies. As the firms become more experienced and persistent in automating, the wage premiums of social skills are substituted by even higher rates of problem-solving skills' wage premium.

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 innovation process and ultimately also the potential for failures in coordination of various complementary inputs. See, for example, 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 of key importance of social skills in early automating firms suggests that coordination costs and the 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 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 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 and younger people. For the lowest-skill group, automation overall has a negative effect on wages (as also found by Dauth et al. 2021), but its combination with social skills, on the contrary, creates a large and significant wage premium. This confirms the prediction from Aghion et al. (2019a) model that there are substantial benefits of innovation at firms especially for low skilled employees that also have soft skills, but here this is found in the context of automation. Importantly, the discussion on the effects of technological development on labor generally still treats the employees on the lower end of skill and wage distributions as likely net losers from technological development. The data suggests, however, that soft skills related to coordinating activities with others, negotiating and developing professional relationships create an advantage for all employees, especially for the less skilled ones and in the short term, whereas problem-solving skills are beneficial in the setting where automation is persistent.

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APPENDICES

Appendix A. Principal component analysis and correlations

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

	Eigenvalue	% of variance	Cumulative % of variance
Comp 1	2.786	27.8596	27.8596
Comp 2	1.5655	15.6549	43.5145
Comp 3	1.2523	12.5234	56.0379
Comp 4	1.1591	11.5912	67.629
Comp 5	0.8625	8.6253	76.2543
Comp 6	0.696	6.9596	83.2139
Comp 7	0.6072	6.0719	89.2858
Comp 8	0.4432	4.4325	93.7183
Comp 9	0.3738	3.7383	97.4565
Comp 10	0.2543	2.5435	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. The list of these variables can be seen in Table B1.

After having discarded the principal components 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 discarded skill pillars are "mediating and resolving disputes" (S112) and "giving instructions" (S182).

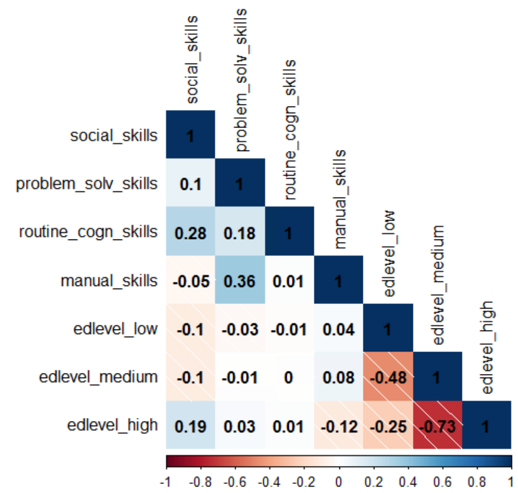
Table A2. Contributions of variables to components (%)

	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

The remaining "working in teams", "giving feedback", "assisting and supporting co-workers", "coordinating activities with others", "developing professional relationships and networks", "negotiating contracts", "liaising and networking" (S120) and "teaching and training" are further used in the main analysis. The umbrella measure of social skills is constructed, being a dummy that takes the value of 1 if dummies for any of the above skills take the value of 1. The correlation between the four skill groups is rather low, with the only difference in model results coming from the separation of problem-solving and manual skills in manufacturing firms into separate categories (Table A3).

Figure A1. Correlations between skills

Panel A. *Groups of skills*



Panel B. *Individual subgroups of skills and education*

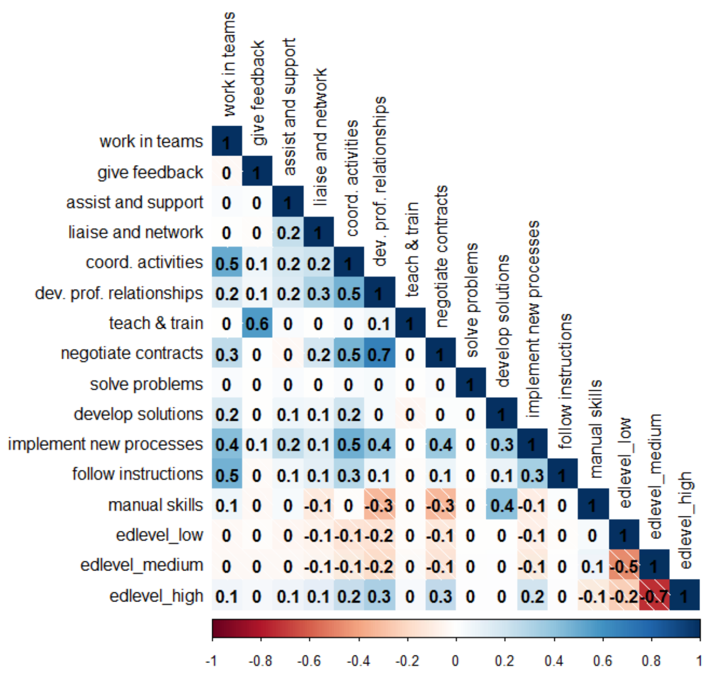


Table A3. Contributions of skills to wages

	Only SS	Only PS	SS & PS	SS & PS & RCS	SS & PS & MS	PS & RCS & MS	SS & PS & RCS & MS
Social skills (SS)	0.0141***		0.0143***	0.0139***	0.0162***		0.0159***
	(0.0035)		(0.0035)	(0.0036)	(0.0035)		(0.0036)
Problem solving (PS)		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 (RCS)				-0.0011		0.0045	0.001
				(0.0031)		(0.003)	(0.0031)
Manual skills (MS)					-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. Controls not reported: gender, age, age squared, 1-digit occupation groups, education level, mother tongue (binary), immigrant status, location in the capital city, firm size, firm size squared, firm ownership (binary, foreign), importer dummy, automation in previous 5 years (dummy); year dummies, firm fixed effects. No matching.

Appendix B. Descriptions of skills and automation subgroups

Table B1. Skills by ESCO pillars

Panel A. *Social skills*

ESCO pillar	Skill description	Examples
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.	- cooperate with colleagues - work in teams - collaborate with designers - work in shifts
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.	- comment drafts - give constructive feedback - provide performance feedback
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.	- support colleagues - support managers - assist scientific research
Liaising and networking	Developing alliances, contacts or partnerships, and exchanging information with others.	- share good practices across subsidiaries - use internet chat - work with healthcare users' social network
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.	- consult with business clients - cooperate to resolve information issues - brainstorm ideas
Developing professional relationships or networks	Developing alliances, contacts or partnerships with colleagues, clients and stakeholders.	- maintain relationship with suppliers - attend events - represent the company
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	- teaching safety procedures - coaching and mentoring - training on

ESCO pillar	Skill description	Examples
	life, future learning or for a particular job or set of jobs.	operational procedures
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.	- conclude business agreements - negotiate price - develop licensing agreements

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

ESCO pillar	Skill description	Examples
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.	- solve problems in healthcare - treat flood damage - prevent technical problems with scenic elements
Developing solutions	Developing solutions to practical, operational or conceptual problems which arise in the execution of work in a wide range of contexts.	- identify needs and technological responses - think analytically - develop solutions to information issues
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.	- implement short term objectives - apply export strategies - adapt to changes in technological development plans
Following instructions and procedures (routine cognitive)	Following instructions given verbally or in writing and following standard or agreed procedures.	- implement instructions - follow reporting procedures - follow written instructions
Using equipment, tools or technology with precision (manual)	Use workpieces, tools, precision instrumentation or equipment independently to carry out manual activities, with or without minimal training.	- use measurement instruments - use hand tools - use electrical wire tools

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)

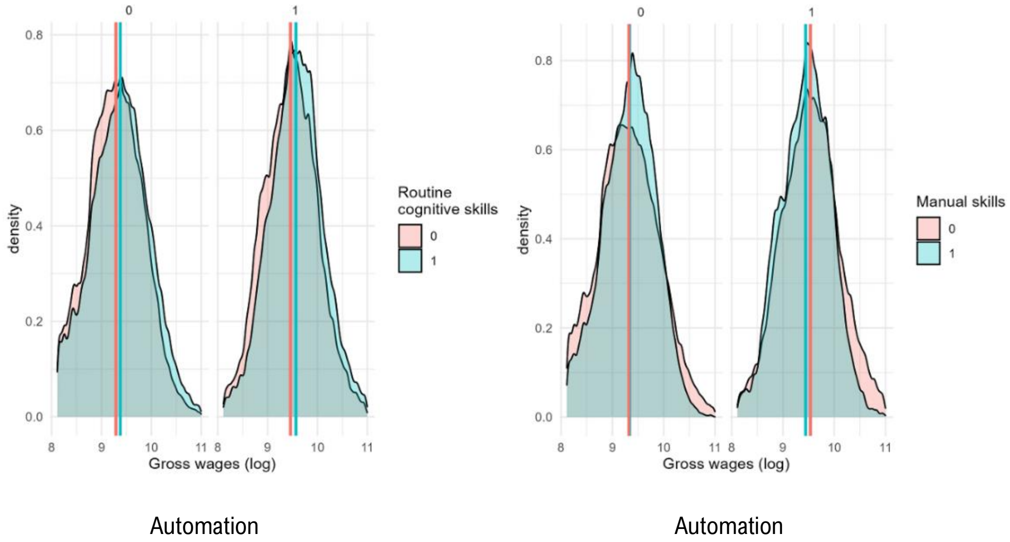


Table C1. Means and mean standardized differences

	Mean, controls (automation at t-1)	Mean, treated (automation at t-1)	Mean standardized difference
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) (dummy)	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. Mean standardized difference (MSD) is a measure for comparing the treated and controls via differences in means, adjusted for the standard deviation in automating firms: $\frac{\mu_{automating}-\mu_{non-automating}}{\sigma_{automating}}$.

Table C2. Skill frequencies

	All	Education – low	Education - medium	Education - higher	Managers	Professionals	Technicians and associate	Clerical support workers	Services and sales workers	Craft and related trades workers	Plant and machine operators and	Elementary occupations	Female	Male
Work in teams	38.3	34.1	36.9	43.3	88.7	42.2	45.6	50.8	31.6	35.2	24.9	18.8	26.7	46.6
Give feedback	0.4	0.1	0.2	0.9	0	2.7	1.5	0.1	0.6	0	0	0	0.6	02
Assist and support co-workers	2.7	0.9	2.3	4.6	0	6.2	16.7	4.6	0.6	0	0	0.3	3.7	2
Liaise and network	3.9	1	3	7.4	14.9	3.4	6.9	18.9	40.9	0	0	0	6.4	2.2
Coordinate activities with others	42.9	25.1	38.1	62.2	99.2	84.6	81.2	83.1	61.2	30.8	9.6	16.9	34.8	48.8
Develop prof. relationships	19.2	4.3	12.9	40.1	9.4	71.3	40.2	7.2	65.6	0.7	0.3	0	19.8	18.8
Teach and train	0.2	0	0.1	0.4	0	2.1	0.1	0	0.4	0	0	0	0.2	0.1
Negotiate contracts and agreements	24.2	11.2	18.9	42.1	92.9	61.2	58.2	7.5	51.4	12.3	0	0	23.7	24.5
Solve problems	0.1	0	0.1	0.1	0	0.1	0.3	0	0.6	0	0	0	0.1	0
Develop solutions	71.6	71	71.6	71.8	92	78	68.1	72.3	63	67.5	75.3	56.4	59	80.6
Implementing new procedures and processes	26.7	17	22.3	41	90.4	60.9	48	69.1	24.7	0	18.3	8.8	23.1	29.3
Social skills	57.2	44.6	52.9	72.7	99.3	90.8	93	87.2	96.6	52.6	25.7	21.6	47.7	64
Problem-solving skills	58.9	55	58.7	61.4	93.9	67.1	54.6	69.8	25.1	61.8	59.1	9	43.7	69.9
Routine cognitive skills	40	38.2	39.9	40.9	75.5	26.6	42.9	58	33.4	35.4	31.5	43.7	34.4	44
Manual skills	36.9	41.5	40.1	27.9	0	29.5	16.1	7.4	0	55.1	54.2	10.6	26.3	44.6

Appendix D. Robustness

Table D1. Persistence, other skills

	Automation at t-1		First-time automation at t-1		First-time automation within the previous 5 years		Automation all 5/5 times within 5 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine cognitive skills	-0.0034 (0.0032)	-0.0037 (0.0042)	-0.0025 (0.0036)	-0.0012 (0.0037)	0.0007 (0.0031)	-0.002 (0.0037)	0.001* (0.0051)	0.0104 (0.0081)
Manual skills	-0.0126*** (0.0038)	0.0035 (0.0048)	-0.013*** (0.0042)	-0.0107** (0.0043)	-0.0103*** (0.0038)	-0.015*** (0.0043)	-0.0275*** (0.0061)	0.0023 (0.0086)
Automation x Routine cognitive		-0.0004 (0.0062)		-0.0202 (0.0137)		0.0086 (0.0064)		-0.0444*** (0.0101)
Automation x Manual		-0.0362*** (0.0064)		-0.0332** (0.0139)		0.0163** (0.0067)		-0.0186* (0.0103)

Table D2. Education, other skills

	Education - low		Education - medium		Education - high	
	(1)	(2)	(3)	(4)	(5)	(6)
Routine cognitive skills	-0.0084 (0.0099)	0.0158 (0.0132)	0.0077* (0.004)	0.0018 (0.0052)	-0.0163** (0.0065)	-0.0177** (0.0085)
Manual skills	-0.0151 (0.0109)	-0.0025 (0.014)	-0.0012 (0.0048)	0.0066 (0.006)	0.0086 (0.0081)	0.0195* (0.0105)
Automation x Routine cognitive		-0.0493*** (0.0187)		0.0122 (0.0077)		0.0015 (0.0122)
Automation x Manual		-0.0202 (0.0192)		-0.0163** (0.008)		-0.021 (0.0137)

Table D3. Age groups, other skills

	25-34 y.o.		35-44 y.o.		45-54 y.o.	
	(1)	(2)	(3)	(4)	(5)	(6)
Routine cognitive skills	0.0131** (0.0059)	0.0064 (0.008)	-0.0092 (0.0056)	-0.005 (0.0074)	0.0003 (0.0054)	0.0092 (0.007)
Manual skills	-0.0326*** (0.0071)	-0.0141 (0.0091)	-0.0088 (0.0069)	-0.0024 (0.0087)	-0.0035 (0.0065)	0.0044 (0.008)
Automation x Routine cognitive		0.0126 (0.0114)		-0.0105 (0.0108)		-0.0215** (0.0104)
Automation x Manual		-0.0372*** (0.0119)		-0.0129 (0.0114)		-0.0169 (0.0107)

Table D4. Further robustness tests

	(1)	(2)	(3)	(4)	No matching (5)
Automation (t-1)	0.0238***	0.0106	0.0278***	0.0423***	0.0105
	(0.008)	(0.0085)	(0.0097)	(0.0086)	(0.0077)
Social skills	0.0024	0.0024	-0.0018	0.1385***	0.0037
	(0.0046)	(0.0051)	(0.006)	(0.0045)	(0.0044)
Problem solving	0.0073	-0.0007	-0.0007	0.1259***	0.008*
	(0.0046)	(0.0051)	(0.0059)	(0.0047)	(0.0044)
Routine cognitive	-0.0038	0.0028	0.0252***	-0.0027	0.0016
	(0.0042)	(0.0045)	(0.0052)	(0.0045)	(0.004)
Manual skills	0.0034	0.0067	0.0027	-0.1324***	-0.0056
	(0.0048)	(0.0053)	(0.0062)	(0.0047)	(0.0046)
Automation (t-1) x Social	0.0183***	0.021***	0.022***	0.0162**	0.0275***
	(0.006)	(0.0065)	(0.0072)	(0.0065)	(0.0059)
Automation (t-1) x Problem solving	0.012*	0.0089	0.0007	-0.0065	0.0062
	(0.0066)	(0.0071)	(0.0079)	(0.0071)	(0.0063)
Automation (t-1) x Routine cognitive	-0.0003	-0.0049	-0.0185**	-0.0017	-0.0031
	(0.0062)	(0.0065)	(0.0073)	(0.0067)	(0.0059)
Automation (t-1) x Manual	-0.0361***	-0.029***	-0.0271***	-0.0287***	-0.025***
	(0.0064)	(0.0069)	(0.0076)	(0.0069)	(0.0061)
Adj. R^2	0.4631	0.4689	0.4754	0.3672	0.4594
N	120261	109005	85111	120261	134293
Firm FE, year FE	+	+	+	+	+
Occupation groups in CEM	+	-	+	+	-
Skills in CEM	-	+	+	-	-
Occupation groups in reg.	+	+	+	-	+

Table D4 above reports the results of different specifications with interactions allowed between automation and skill groups. Due to occupations and skills (skill requirements) being necessarily related, we show different specifications with and without controlling for occupation groups in matching and in the final regressions. Columns 1-4 are after-matching results, the controls not reported in the table are the same as in the main results (see notes under Table 1), unless stated otherwise.

A significant difference is created by excluding occupation groups from the regression: even though it does not influence the interactions with automation almost at all (the focus of our interest here in this paper), the skills themselves become assigned comparatively large positive (social, problem-solving) or negative (manual) wage returns, showing just how much of the skills' effect can be explained by broad occupational definitions. Interestingly, these coefficients (around 12-14% in terms of size) are in line with other papers reporting the wage differentials due to skills and skill requirements (e.g., Hanushek et al. (2015) show similar estimates for standalone problem-solving skills, while Deming (2017) reports similar values for standalone social skills). The coefficient of automation also becomes higher in this specification, though not nearly as much as is the case for skills.

The main coefficients of interest here in the robustness test in Table D4, however, are the ones for the interactions between automation and skills. There is a consistent pattern of positive correlation between the introduction of automation and social skills—in all specifications there is a wage premium which is over +1%. At the same time, in all specifications having routine manual skills requirements on a job decreases the wages to an even higher degree than having social skills requirements increases them. The results for cognitive skills that are not social ones are less obvious, with problem-solving only having a significant positive correlation with the introduction of automation in the main setup (Table 1 column 2), and even there the coefficient is smaller than that of social skills and automation. Routine cognitive skills, consistently with the literature, are negatively associated with wages when automation takes place in one of the models. However, in this model (3) a large part of the dataset is discarded, including the treated observations, so the results should be treated with more caution

Table D5. Robustness test in section 4.3: 1st stage of the IV model. IV: automation investments per employee at sector level in Estonia (at t-10)

	Probit	OLS
Industry IV (probit) / predicted from IV (OLS)	0.00003***	1.15245***
	(0.00000)	(0.02614)
Employment	0.00156***	-0.00006***
	(0.00002)	(0.00001)
Foreign ownership	0.67226***	-0.03688***
	(0.00781)	(0.00672)
AIC	146110.71547	
R-squared		0.20143
F-statistic		11263.70434

Notes. Dependent variable - the dummy for firm-level automation in t-1. The first row shows coefficients for different variables: ‘Probit’ column - sector-level automation investments per employee in t-10, ‘OLS’ column - predicted propensity to automate, obtained after the Probit stage. Significance levels: * - $p < 0.1$, ** - $p < 0.05$, *** - $p < 0.01$. Robust standard errors in parentheses.

KOKKUVÕTE

Automatiseerimise ja oskuste komplementaarsus: pehmete oskuste väärtus tehnoloogia rakendamisel

Käesolev artikkel uurib tootmise automatiseerimise ja ettevõtete töötajate sotsiaalsete ning probleemilahendusoskuste omavahelist komplementaarsust eht täiendavust, keskendudes seejuures uue tehnoloogia ja oskuste koosmõjudele töötajate palkadele. Eesti ettevõtete ja töötajate ühendatud andmestikul põhinenud uurimistöö tulemused näitavad selgelt, et töötleva tööstuse ettevõtetes, mis on hiljuti investeerinud tootmise automatiseerimisse, esineb täiendav palgapreemia töötajate sotsiaalsetele oskustele. Erinevus automatiseerimise mõjudes palkadele sõltuvalt sotsiaalsete oskuste olulisusest töökohal on seejuures eriti suur madalama kvalifikatsiooniga töötajate puhul. Antud tulemused rõhutavad pehmete oskuste tähtsust lisaks kõrgema kvalifikatsiooniga töökohtadele ka madalama kvalifikatsiooniga töökohtadel ning toovad esile, kuidas innovatsioon ettevõtetes võib ka teatud vähemkvalifitseeritud töötajate gruppidele olulist positiivset mõju avaldada. Oskuste roll varieerub sõltuvalt sellest, kui järjepidevad on ettevõtete automatiseerimisse tehtavad investeeringud. Esmakordselt tootmist automatiseerivad ettevõtted hakkavad automatiseerimise varastes etappides ettevõttes eriti väärtustama töötajate sotsiaalseid oskusi (mille alla kuuluvad mh koordineerimise, meeskonnatöö, õpetamise ja juhendamise oskused). Pikaajaliselt ja järjepidevalt automatiseerimisse investeerivad ettevõtted väärtustavad kõrgema palga näol eriti just probleemide lahendamise oskusi.