Technequality

Understanding the relation between technological innovations and social inequality

Skills, automation, and earnings: Employment on technology driven labor markets

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Description of deliverable (100 words)

Deliverable 2.2 examines whether cognitive and non-cognitive skills are early indicators of status attainment during the school-to-work transition, and whether differences in attainment can be attributed to differences in technological developments. This subproject examines the relation between social attainment in the transition from school to work and automation risks, cognitive and non-cognitive skills acquired at school, parental social status, and educational credentials. To do this, we analyze register data from Finland, the Netherlands, and Sweden, as well as survey data from Germany on graduates' early work careers.

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1. Introduction

Throughout history, technological innovations have revolutionized production methods thereby increasing productivity and welfare. This is also likely to be the case with the most recent wave of innovations in the form of robotization, big data, machine learning, and artificial intelligence. However, as with previous technological revolutions, these latest innovations will likely imply that a number of task and jobs will be entrusted to machines instead of to humans. Furthermore, in contrast to earlier revolutions, in which machines replaced routine tasks like transporting parts, assembling machinery or administrating data, machines in the most recent wave of technological change have been said to be increasingly proficient at carrying out complex non-routine tasks such as driving cars, diagnosing diseases, or providing elderly care.

If correct, these conjectures regarding the impact of the current technological transformation would imply fundamental changes in the determinants of social inequality. Whereas labor market inequality often has been regarded as primarily a function of social class and educational credentials, cognitive and non-cognitive skills are now frequently hypothesized to impact inequalities above and beyond their relationship to class and education.

The main hypothesis is that the more technological innovations drive skill requirements, the more strongly employers in the affected sectors will select employees on the basis of cognitive and non-cognitive skills rather than on class or credentials. The most extreme scenario would imply that skill differentials would become the only determinants of inequality, with class background and education losing their predictive power. To be employable, humans need to be able to work with machines, to complement machines, or to compete with machines. Cognitive and non-cognitive skills would then be crucial for labor market success, in particular in those sectors of the economy most affected by technological change.

Empirical evidence for the actual significance of these purported developments is however largely lacking, and the question remains to what extent and how social inequalities in European countries are related to technological developments. The aim of Task 2.1 was therefore to examine the relationship between the risk of automation of different occupations, cognitive and non-cognitive skills, and status attainment in the transition from school to work taking into account differences in class background and educational attainment. We have done

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this by examining school-leavers' early work careers in Finland, Sweden, the Netherlands, and Germany. The datasets from the countries differ in character and informational content, and Deliverable 2.2 therefore consists of four parts; an introductory part outlining the issues and reporting on some basic comparative analyses, and three appendixes focusing on specific aspects of the relationships between skills, automation, class, credentials and earnings (Appendixes 1 to 3) in which full use of the specificities of the datasets has been made.

The next section, Section 2, outlines the debates around automation and automation risks as well as on the importance of cognitive and non-cognitive skills for social inequality. Section 3 in turn describes the data, the operationalizations and the methods used, and Section 4 the results obtained. Section 5 concludes by placing the results in relation to previous research. Appendix 1 then studies the relationship between automation risks and workers' employment and earnings. The analysis focuses on the entry process into the labor market as well as the salaries obtained, and asks if the automation risks may be moderated by workers' cognitive and non-cognitive skills. A similar question is asked in Appendix 2, although here the analysis centers on the risk of short- and long-term economic precariousness. Finally, Appendix 3 turns to the role of social class on modern labor markets examining the relationship between automation risk, class background and status attainment. One hypothesis here holds that workers' careers will converge on the class position of their parents, while a second states that career mobility will decrease once a worker attains the class position of the parents. This analyses examines the two hypotheses and their connection to automation risk.

2. Background

A number of social science theories attempt to explain social inequality, for instance human capital theory, positional good theories, social closure theory, and cultural capital theory. Although different, these theories share a strong emphasis on the acquisition and subsequent application of various specific skills. Yet current technological developments may change the very nature of inequality in European countries. Workers that cannot adapt their skills to work with machines in their respective jobs and occupations may experience intra-generational downward mobility, becoming unemployed, inactive, or by being forced to accept jobs below their education level (Levels et al., 2014). These processes are usually associated with employees in lower-skilled routine jobs and middle-income service sector jobs (Levels and

Fourage, 2016). However, the actual impact may be felt throughout the labor market, as machines are now said to have mastered complex non-repetitive tasks. Consequently, digitization and automation may also affect higher educated workers, and even (semi-) professionals whose educational credentials and successful occupational closure have long secured a safe spot in societies' middle (e.g. clerks, trained nurses) and upper middle classes (e.g. lawyers, medical doctors, accountants) (Susskind and Susskind, 2015). Professionals may in other words also find their work deskilled, or be at risk of downward mobility if they lack the required skills for working with machines.

2.1. Automation risks

The driving factor behind these purported changes is the transformation of production processes initiated by technological change. These changes may lead to the automation of specific tasks, or even of the whole range of tasks that characterizes a specific occupation. The likelihood that this will occur will obviously be related to both the types of technologies that are developed and the extent to which different tasks are carried out within different occupations.

An attempt to gauge the U.S. occupations most likely to be affected by these changes in the production processes, i.e. which occupations were most at risk of automation, was made by Frey and Osborne (2013, 2017). They started from an assessment by computer experts of the likelihood that a limited number of specific occupations would undergo large-scale automation, a subsequent analysis of the character of some of the tasks associated with the occupations deemed at risk of automation, and a final extrapolation of the automation risks to a larger set of occupations based on the importance of these tasks in these occupations. This procedure generated a likelihood that a certain occupation would be fully automated, in turn yielding an estimate of the number of jobs that would be affected in the USA.

This approach was criticized for inter alia ignoring variations in the importance of tasks within occupations (Arntz et al., 2016, 2017) as well as for overestimating the extent to which occupations may be impacted by automation (Coelli and Borland, 2019), both factors that would raise the estimate of jobs at risk of automation. Arntz et al. (2017) for instance estimated that around 10 % of all jobs in the USA would be at risk of automation, compared to the

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estimate of almost 50 % by Frey and Osborne (2013). Nevertheless, the approach used by Frey and Osborne (2013) has been hugely influential and has spawned a minor industry of "automation risk" studies, including both comparative studies (e.g. Nedelkoska and Quentini, 2018; Pouliakas, 2018) as well as country studies of e.g. Finland (Pajarinen and Rouvinen, 2014), Germany (Brzeski and Burk, 2015) and Sweden (Fölster, 2014).[1]

One conclusion from these exercises is that automation risk varies; between tasks, between jobs, between occupations, between industries, and between countries. Some tasks seem susceptible to automation in the relatively near future, whereas this in other cases is much less likely. This was of course the starting point for Frey and Osborne (2013), and something that subsequently has been documented repeatedly. Variation in task frequency and intensity will in turn have repercussions for the likelihood that different jobs, occupations and industries will be affected. What more, due to variation in all these dimensions, countries are likely to be impacted by automation differently. Arntz et al. (2016) for instance estimated that the share of workers in high risk jobs in Germany was almost twice the share in Finland (12 and 7 % respectively). Moreover, the cross-country differences appeared not primarily to be due to country differences in occupational or industrial structure, but rather to variations in task structure between jobs, occupations and industries in different countries (see Nedelkoska and Quentini, 2018, for similar results). The impact of automation is in other words likely to differ between workers in the same occupation in different countries.

Analyses of the relationship between automation risk and individual level outcomes appear so far to have been limited to cross-sectional analyses of e.g. wages and unemployment. These tend to show a clear negative relationship between for instance automation risk and wages, yet the findings also indicate that there are substantial country differences in these relationships. Nedelkoska and Quentini (2018) for instance reported that standard earnings equations augmented with an automation risk variable show the effect in Germany to be clearly above and in Sweden clearly below the OECD average, with the German estimate more than twice as large as the Swedish. Furthermore, for some countries no significant association was found.

[1] A different approach to modelling automation risk was applied by Manyika et al. (2017) who estimated the risk of automation directly based on the task characteristics of different jobs.

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Another striking feature of most of these studies is that they only pay limited attention to the actual automation risks experienced by workers. Many of them note that, irrespective of the estimated level of job automation risk, it need not be the case that the workers in these jobs actually will experience automation-induced unemployment or wage loss. Even workers in a high risk job with high risk skills need not be exposed to redundancy, and even if they are laid-off they may be able to find satisfactory employment elsewhere. Financial, legal and institutional factors may i.a. prevent employers from transforming jobs in the ways that might be technologically possible. Furthermore, jobs in other sectors may be available to the workers actually laid-off, and workers may retrain and thereby elude unemployment. To get a better grip on the actual risks of automation it is therefore necessary to move from the abstract level of tasks, jobs and occupations to the concrete level of workers and their careers.

2.2 Cognitive and non-cognitive skills

As noted, machines are increasingly believed to be able to autonomously perform tasks that were long thought to be exclusively reserved for humans, including reading, writing, recognizing patterns, strategizing, and complex decision-making. As a consequence, the content of many jobs will change. To be employable, workers will likely need to accommodate machines. This directs the spotlight at workers' cognitive and non-cognitive skills as these will enable them to supplement and adapt to machines in both the short- and the long-run and thereby buffer them from the risk of downward mobility due to automation.

Although frequently used, the precise definition of the terminological couple cognitive and non-cognitive skills is elusive. Cognitive skills, often also labelled intelligence, has been defined as "a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience" (Gottfredson, 1997). Although not the only definition, cognitive skills would then be indicative of an ability to learn and to reason, rather than of actual knowledge. The measurement of cognitive skills is often carried out using general standardized intelligence tests, or tests of specific sub-fields of intelligence such as verbal or spatial ability. One important characteristic of these measurements is that the correlation between the various sub-scores generally is high, which in turn also applies to their correlation with the overall

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score.

Non-cognitive skills are in contrast personality traits that are weakly correlated with cognitive skill.[2] Although clear in principle, this definition begs the question of which non-cognitive personality traits are to be regarded as salient. Extensive lists of supposedly crucial personality dimensions have been produced, and a large number of scales and other indicators developed to measure these different dimensions. The perhaps most commonly used non-cognitive personality classification is the so-called Big Five model, a theory identifying extraversion, conscientiousness, agreeableness, openness, and emotional stability/neuroticism as the central personality traits. As is the case with other non-cognitive dimensions, a number of different scales such as the short Big Five Inventory-10 and the longer Five Factor Personality Inventory have been designed to elicit information regarding these traits.

Cognitive skills have repeatedly been found to be associated with labor market success, in particular in the longer run. Analyses of cognitive skills prior to labor market entry have shown positive effects on outcome measures such as earnings in middle age, and the same goes for non-cognitive skills (see e.g. Brunello and Schlotter 2011, Farkas, 2003, and Ones et al., 2012, for reviews). However, the changes in the workplace associated with the recent wave of automation can be conjectured to increase the importance of information processing, as the acquisition of new skills may need to continue after graduation. Furthermore, these changes may not only involve learning novel skills, but also using pre-existing skills in a different manner. It has thus been speculated that the reorganization of the workplace as a result of automation may lead to a greater emphasis being placed on non-cognitive personality traits (Deming, 2017a). An increased use of teamwork may for instance lead to workers with high scores on agreeableness being rewarded, or an increased use of flexible, unsupervised, work may benefit employees with high conscientiousness scores.

Although there seems to be no doubt that pre-labor market cognitive and non-cognitive skills are related to subsequent employment, wages and earnings, relatively little is known about these conjectures regarding their relationship to automation. Deming (2017b, 7) reported that

[2] Non-cognitive skills are sometimes referred to as social skills, soft skills, characters skills or personality traits.

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pre-market cognitive skills were "strongly predictive of labor market success". However, recent analyses indicate that the returns to cognitive skills decreased after the turn of the millennium (Deming, 2017a; Edin et al., 2017). In contrast, there is evidence suggesting that the returns to non-cognitive skills increased during the 2000s. Deming (2017a) found that the returns to "social" skills increased between the 1990s and the 2000s, and that the growth in wages was greatest among workers with social skills in occupations that required these skills. Likewise, Edin et al. (2017, 23) also documented a secular rise in the returns to non-cognitive skills during a similar period, in particular in occupations characterized as "abstract, non-routine, social, non-automatable and offshorable tasks".

There are in other words indications that the impacts of cognitive and non-cognitive skills have changed in line with the suggestions that these generic skills, in particular non-cognitive skills, have become more salient in wage determination. However, there is still no evidence directly linking these skills to automation risks.

2.3 Social class

The analysis of the relationships between parental social status, education, and status attainment has been central to much sociological research into social mobility in industrialized societies (Ishida et al., 1995). These associations are often referred to as the origin-education-destination (OED) triangle. The relationship between class origin and education refers to educational inequality, while the association between education and attainment pertains to returns to education. Finally, the relationship between parental social status and status attainment relates to inter-generational mobility.

The cross-country patterns of these associations show both similarities and discrepancies; similarities in the overall associations between class and education as well as between class of origin and of destination, discrepancies in the strength of these associations (e.g. Ishida et al., 1995). These patterns may come about in different ways, basic mechanisms of social reproduction common across countries may for instance be affected differently by the structure of the educational system and of the labor market. An example of the former relates to the OE link, the relationship between class origin and educational attainment. Educational inequality can be said to depend on two distinct mechanisms: children

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from advantaged social backgrounds do better in school and also tend to continue with education longer (Erikson and Rudolphi, 2010). This distinction between the so-called primary and secondary effects is common across countries. However, educational reform may impact on the strength of these effects, changing them in different directions (Erikson and Rudolphi, 2010).

While the changes in the associations may come about in myriad ways, one strand of the literature has focused on the so-called meritocracy thesis: the idea that as societies develop social attainment will increasingly be based on merit and not on ascription. The association between origin and education as well as between origin and destination would here decrease, while the association between education and destination would increase (Devine and Li, 2013). One purported driver of such a trend was said to be industrial change, specifically the move from industrial to post-industrial production (Bell, 1973). A strong version of this thesis would hold that an increasing emphasis by employers on documented or proven skills would eliminate the relationship between class origin and class destination, net of measures of education and other skills.

Although the weaker version of the thesis has received relatively mixed support (Devine and Li, 2013; Bernardi and Ballarino, 2016), one issue in research to date is the frequent lack of measures of skills beyond education. This in particular applies to cognitive and non-cognitive skills. Goldthorpe (2007) suggested that class background could exert a causal effect on both cognitive and non-cognitive skills, implying that the elements of the OED triangle should be examined in conjunction with measures of skills. Moreover, there is still limitations in our understanding of how these associations are formed, for instance how the association between origin and destination evolves over the work career. Of the different mechanism that have been suggested for a causal effect of social background on social attainment, the possibility that class background affects aspirations has received relatively limited attention (see e.g. Bernardi and Ballarino, 2016). Further analyses of these mechanisms would thus seem necessary in order to understand if, and if so how, class may affect careers even on automated labor markets.

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2.4 Summary

This leads us to a summary of the available results as well as the lacunae in this evidence. Current approaches to automation risk analyses come in two strands, either linking automation to expert analyses by way of the tasks used in jobs assessed to be at risk or directly via assessments of task usage. Recent analyses using both approaches have underscored the substantial disparities in automation risk; between jobs, occupations, industries, and countries. Likewise, there appears to be large variations in the relationship between automation risk and outcomes such as wages along the same dimensions. With regard to cognitive and non-cognitive skills, previous research has documented positive associations between both skill dimensions and status attainment. However, there appears to be some variability in which non-cognitive skill is related to what outcome, with the Big Five-dimension conscientiousness found to impact attainment most consistently. Research also seems to indicate that social background continues to be of importance for status attainment in modern societies.

Earlier research has nonetheless left some research gaps worth exploring. This in particular includes the relationship between automation risk and the generic cognitive and non-cognitive skills, as little in know regarding how risks and skills relate to each other. The role of skills is furthermore of relevance of analyses of the meritocracy thesis, as these could be said to be incomplete if they lack measures of cognitive and non-cognitive skills. Research on automation risk has so far also been primarily cross-sectional, and a longitudinal perspective could cast additional light on the real risks faced by workers in specific occupations. Do for instance workers trained to work in an occupation at risk for automation actually end up with lower earnings or experience more unemployment? Finally, most research seems to have focus on prima age workers, raising the question whether the risks associated with specific occupations are stable or if they vary over workers' careers. Such a career perspective would finally also benefit our understanding of the relationship between class of origin and class of destination.

3. Data and method

The data for these analyses consists of databases from Finland, the Netherlands, Sweden and Germany. The analyses for Finland use register data provided by Statistics Finland for the whole Finnish population from 1987 onwards. Annual occupational information is available from 2004, so the analyses have been restricted to those graduating in 2003 or 2004. For persons

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with compulsory education as highest level of education, year of graduation is two years earlier because they have been 16 at the time of graduation and occupational information is measured only from age 18 onwards. Excluded from the analyses are those older than 30 years of age when they obtained highest educational degree (to eliminate individuals with extensive employment experience prior to graduating), persons who moved abroad or died during the observational period, those who lacked occupational information, as well as persons who did not have any information on parental class during their teenage years (i.e. both parents are unemployed, outside the labor force or missing for other reason). Together with some limitations related to variables mentioned below, these restrictions result in a sample of 1973-1986 birth cohorts that have graduated from their highest education in 2003-2004. The sample for the analyses of individual earnings 1 year after graduation has encompassed 17 593 women and 25 610 men, whereas the sample for the analyses of earnings 10 years after graduation has consisted of 31 810 women and 21 713 men. The sample with only graduates from vocational programs consists of 6 291 women and 14 481 men in the analyses 1 year after graduation, and 6 909 women and 15 894 men in the analyses 10 years after graduation

The analyses for Sweden have drawn on annual register data on earnings and occupations pertaining to graduates from schools and universities 1996 to 2007 born between 1966 and 1978. As the cognitive and non-cognitive data stems from placement tests in connection with military enlistment the sample is limited to males. The data encompass earnings and occupational information from graduation up until 2012. Individuals who obtained their highest educational qualification after age 30 have been excluded as they may have left school earlier but graduated later for different reasons. The sample for the analyses of earnings 1 year after graduation contains 32 795 observations, while the sample for the analyses of earnings 10 years after graduation includes 30 193 observations.

The Dutch data has been a combination of survey and administrative data. The starting point has been the Voortgezet Onderwijs Cohort Leerlingen (VOCL'99) survey collected from a random sample of pupils in the first year of secondary education in 1999 (Kuyper et al. 2003). The survey included 10 % of all graduates from primary education in 1999 with sampling was done on the school level. 246 out of 1144 school locations in the Netherlands were randomly selected, and out of these 126 agreed to participate. Within these 126 school locations there

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were 825 first grade classes with 19,391 pupils, representing about 11% of that school entry cohort (Van Berkel 1999). From the VOCL sample, persons with a diploma from MBO levels 3 and 4 between 2006 and 2012 have been selected. We have not included levels 1 and 2 as they are not considered a full degree within the Dutch education system. These data have been merged with register data from Statistics Netherlands with information on earnings, working hours and "activity" from graduation up until 2018. Listwise deletion on key variables has been performed, so that the final sample consists of 1 868 men after one year and 1 423 men after ten years and 1 995 women after one year and 1 615 after ten years.

The German data has been drawn from the German National Educational Panel Study (NEPS; Blossfeld & Roßbach, 2019), more precisely from the so-called Starting Cohort 4 (SC4) which includes 16 425 students from all types of German schools that attended grade 9 in 2010 (mainly of the birth cohorts 1995/1996). Students were sampled in a stratified two-stage sampling procedure, sampling first schools and then classes within schools (Aßmann et al., 2019).[3] Only students who successfully had graduated from vocational training have been included, in practice between 2013 and 2017 (mainly in 2015 and 2016). Listwise deletion of variables implies that our final sample has consisted of 800 men and 558 women.

The data from the four countries roughly pertain to the approximate time period 2000 to 2020, with a wider window in Finland, Sweden and the Netherlands and a narrower in Germany. As pointed out by Coelli and Borland (2019), the original automation risk assessments were made based on O*NET scores from 2010 and said to refer to the situation the upcoming one or two decades. Although our analyses start a bit earlier, the time period in which the automation risk scenario should be most pressing would roughly seem to correspond to the period examined here.

[3] We use data from Starting Cohort 4 (SC4) of the NEPS: *doi:10.5157/NEPS:SC4:10.0.0*. From 2008 to 2013, the data collection was funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, the NEPS has been conducted by the Leibniz Institute for Educational Trajectories (LIfBi) in cooperation with a nationwide network.

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3.2. Variables

3.2.1. Earnings

The dependent variable has been earnings from work, a variable that has been operationalized differently in the four countries depending on the available information. In Finland and Sweden this has been annual earnings from work taken from the register data. The measure includes all taxable (earned) income such as wages and salary, pension income and taxable social benefits. In the Netherlands and Germany, earnings from work have pertained to hourly wages. In the Dutch case, the hourly wage has been obtained from register data using information on the sum of wages from all employment contracts during a month divided by working hours. Negative wages as well as hourly wages lower than 3.86€ (the minimum wage for 19-year-olds in 2006) and higher than 4SD above the mean of the wage distribution ten years after attaining a MBO3/4 diploma (49.35€) have been excluded. In Germany, hourly wages have referred to the first reported wage from the first employment spell after graduation from VET (if several spells started at the same time: spell with highest working time). In all four cases, the dependent variable has been the natural logarithm of earnings.

3.2.2. Cognitive and non-cognitive skills

Two of the main independent variables have been cognitive and non-cognitive skills. The Finnish measure of cognitive skills has been information on individual grade point average (GPA) in theoretical and science subjects (languages, mathematics, natural and social sciences). There is unfortunately no measure of non-cognitive skills for Finland. The Swedish measures have been based on information from placement tests conducted in connection with military enlistment at age 18. The cognitive tests cover induction, verbal comprehension, spatial ability and technical comprehension, while the non-cognitive include personality traits such as intensity and emotional stability. The four cognitive dimensions have been combined into one general index. In contrast, the personality tests have provided the basis for the creation of three of the Big Five personality domains; viz. extraversion, conscientiousness, and emotional stability. The Dutch measure of cognitive skill has been the total score on an "entry test" of abilities in three domains; mathematics, language, and information processing (Kuyper et al. 2003). Values for students who only finished two of the three subdomains were imputed by Statistics Netherlands (Kuyper et al. 2003). The measure of non-cognitive skills has been the Five Factor Personality Inventory (FFPI) (Hendriks et al 1999), from which measures of the Big

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5 dimensions extraversion, conscientiousness, and emotional stability have been included in the analyses. The German measure of cognitive skills has been mathematics competencies measured in grade 9 (Durchhardt & Gerdes, 2013), WLE estimator. For non-cognitive skills, indicators extraversion, conscientiousness, and emotional stability from the Big Five personality traits measured with short instrument BFI-10 in grade 9 have been used (Rammstedt & John, 2007). The cognitive and non-cognitive measures of skills have all been z-standardized.

3.2.3. Automation risk

The other central independent variable has been the automation risk of an occupation, here measured using an indicator of occupational automation risk created by the Technequality project (see deliverable D1.1). Although somewhat unfortunate in the light of the varying automation effects reported Section 2.1, the EU-level measure coded for 2-digit ISCO08 values has been used to obtain the most valid occupation-specific information about the share of tasks replaced by automation and technology (% of tasks on which less time is spent).

In the case of Finland, the occupational information in the Finnish registers pertains to the last week of each year. Some information may thus be missing, particularly in the beginning of the career as employment can be less stable. The automation measure is matched with the occupational information of the first occupation (up to 5 years after graduation), and the same measure has been used for the analysis of the income 10 years after graduation. In order to obtain the best possible sample, the occupational information has been coded in if the person was earlier or has remained employed by the same company or public institution most of the year.

For the analyses for Sweden, a detailed educational classification (distinguishing 329 different degrees) has been linked to automation risks at the occupational level. The automation risk associated with a specific degree has been defined as the average automation risk of the occupations in which graduates typically find themselves. Since some educational tracks are general and do not lead to a specific set of skills, and therefore to typical occupations,

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educational tracks linked to occupations with a large variation in automation risks have been excluded from the analyses.[4]

A similar approach has been used for the Netherlands, where automation risk also applies to the occupation that a diploma normally leads to. It has been estimated using a conversion matrix supplied by Research Centre for Education and the Labour market (ROA) that match ISCO 2-digit codes to Dutch Education number (ONR) codes. Using data from the Dutch labor force surveys from 2006-2008, a weighted average of the automation risk of the most frequent 50 % of occupations within each education code was subsequently calculated. Finally, in Germany the occupational automation risks have likewise been applied to the occupation trained for.

3.2.4. Control variables

In addition to the variables discussed above, the analyses have also included four control variables; parental socio-economic status (SES), immigrant background, gender, and years of education. In the case of Finland, parental SES has been based on information regarding parental employment during the individuals' teenage years. The highest occupational class of the parents has provided the basis for an indicator of parental SES, here measured as EGP classes: 1) Higher service (EGP I), 2) Lower service (EGP II), 3) Skilled non-manual/manual (EGP IIIa+V+VI), 4) Self-employed/farmers (EGP IVabc), and 5) Semi-/unskilled (EGP IIIb+VII) (Erikson et al., 1979). The models also control for gender and immigrant background, which in the latter case indicates if the individuals' parents were born abroad (less than 1% of the sample). Finally, the analyses control for individual highest educational attainment, measured in years. As the Finnish register data registers educational qualifications rather than years of enrolment/attainment, the variable has been coded according to the student credits (and optimal time) required for a degree (compulsory 9 years, secondary 12, bachelor 15, master 17, doctorate 20). For analytical purposes, the variable has been centered to the mean.

[4] The criteria used is that we require the inter-quartile range in automation risks for each educational track to be less than 15 percent, meaning that if the value of the 75th percentile minus the value of the 25th percentile is more than 15 percent for specific educational tracks individuals with such a track are excluded (and also excluded if N in each track <21). Somewhat less than one third of the educational tracks have an inter-quartile range below 15, which means a reduction of tracks to 98 from 329. This means that many general tracks are excluded and in fact all exams below secondary school (up to 9 years of schooling), but also some general tracks at higher educational levels.

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The Swedish data on parental SES has been taken from the censuses, with SES coded in the same manner as in Finland.[5] Gender and immigrant background have come from the registers, with immigrant background defined as having been born abroad. As in Finland, the analyses also control for educational attainment, measured in years.

In the Netherlands, parental SES has been based on parental household income (in 2003 when the individuals were around age 16), grouped into quintiles. Furthermore, the education registers distinguish MBO Level 3 from Level 4 and this has been coded as a binary variable. Immigration background has been based on the country of birth of pupils and parents obtained from Dutch register data. A binary variable has been created distinguishing between pupils with two Dutch born parents (coded as 0) from pupils with at least one foreign born parent or who themselves were not born in the Netherlands (coded as 1). Another dummy variable provided in the administrative data has distinguished women (coded as 1) from men (coded as 0).

Finally, in Germany parental SES has also been based on parental occupation and coded using the same EGP classification as in Finland. Immigrant background has been based on information from student and parent questionnaires, and has distinguished between student and at least one parent born in Germany or missing information (coded 0) and student or both parents born outside Germany (coded 1). Gender has been based on information given by the school, coded as a dummy variable distinguishing women (coded 1) and men (coded 0).

3.3. Method

The aim of this, introductory, part of the deliverable is to provide a preliminary analysis of the relationship between different types of skills, automation risk and social inequality, analyses intended to supply a backdrop to more detailed analyses of specific aspects of this overarching question in the subsequent parts of the deliverable (Appendix 1 to 3). The data described above have therefore been analyzed using a series of basic OLS regressions of log earnings (annual earnings or hourly wages) on cognitive and non-cognitive skills, on automation risks,

[5] One difference is however that category 3 in Sweden also includes EGP IIIb, as it was not possible to separate EGP IIIa and IIIb.

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on skills and risks, on skills, risks, and parental SES, and on skills and risks including interaction terms between the two.

To explore the short- and long-term implications of automation risk on inequality, separate analyses of earnings one year following graduation as well as of ten years after graduation have been conducted. These analyses have been carried out separately for men and women, and in addition to the key independent variables skills, automation risks, and parental SES[6], all regressions also include the dummy variable immigrant background.

Due to data limitations in the Netherlands and in Germany, as well as difficulties in assigning automation risks for non-vocational degrees, the main analyses have focused on graduates from vocational programs. However, in order to provide some evidence on the impact of automation across all types of educational programs, the analyses for Finland and Sweden have also been included analyses of graduates from all educational programs. In addition to the variables mentioned above, these analyses also include controls for years of education.

4. Results

We start our discussion of the results by looking at the analyses of the transition from school to work among graduates with upper-secondary school vocational degrees. These analyses focus on the relationship between the different dimensions of skills, the automation risk associated with different occupations, parental SES and earnings in the period immediately after graduation. The results are presented in Table 1a-d showing the results for Finland, Sweden, the Netherlands and Germany respectively. The analyses for the Netherlands and Germany furthermore include an indicator for level of education, as this may vary among the graduates from vocational programs.

On the whole, these results do not support the idea that there are any universal relationships between these variables. Although the concepts of cognitive and non-cognitive skills are measured with a varying set of indicators in the four countries, the core ideas underlying the

[6] In the analyses for Finland, Sweden and Germany in which parental SES has been operationalized using occupation, the "second highest" class (EGP II) has been used as the reference category. Along the same lines, in the analyses for the Netherlands in which parental SES has been based on income, the second highest quintile has been used as the reference category.

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different operationalizations are the same. Nonetheless, despite this shared conceptual core, the results are very diverse.

The simple associations between earnings and cognitive and non-cognitive skills among graduates with vocational training one year after graduation are displayed in Model 1. The results indicate that cognitive skills are negatively related to earnings among Dutch women, unrelated to earnings among Swedish and Dutch men, and positively related to earnings among men and women in Finland and Germany. Non-cognitive skills are in turn unrelated to earnings in the Netherlands and among German women, while they show a positive relation to earnings among Swedish (conscientiousness) and German (emotional stability) men. As for the association between automation risk and earnings, these are shown in Model 2. Here automation risk is negatively related to earnings in Finland and the Netherlands, unrelated to earnings in Germany, and finally positively related to earnings among Swedish men. As is evident in Model 3, with the exception of the negative effect of cognitive skills among Dutch women, these results also generally hold when skills and risks are included in the same analysis. The same can furthermore also be said of the results when including parental SES in Model 4, although social class is related to early attainment in three of the four countries, there is nonetheless very little change in the effects associated with the skills and automation variables.

Continuing with the interaction models, Model 5, the interaction terms indicate that the importance of cognitive skills decreases with increasing automation risk among Finnish men, that cognitive skills are unrelated to automation risk in the Netherlands and in Germany, while among Finnish women and Swedish men the importance of cognitive skills increases with increasing automation risk. Likewise, with regard to non-cognitive skills these are positively related to automation risk in Sweden (cons.) while they in the Netherlands and Germany are unrelated to automation risk.

The analyses of Table 1 encompassed graduates from vocational upper-secondary programs only, and these analyses are in Table 2 extended to graduates from all levels of education for the two countries for which such data are available. The analyses therefore also include years of education as an additional control variable. In comparison to the results in Table 1, the results in Table 2 evince clear similarities. Cognitive skills can thus in Model 1 be seen to be

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positively related to earnings among Finnish women and Swedish men. Likewise, as evident from Model 2 (and 3) automation risks are negatively related to earnings in Finland, but positively in Sweden. None of these associations are again more than marginally affected by the addition of parental SES in Model 4. Finally, the interaction effects in Model 5 also point in the same direction. The overall pattern of results is clearly very similar, the difference primarily being that the effects show in Table 2 are better established. The main exception from these overall similarities relates to the results for cognitive skills among Finnish men, this effect is now negative in Models 1 through 4. However, the results for Finnish men in Model 5 of Table 2 are again very similar to the results in Table 1.

This is obviously a very mixed set of results, not even the simple associations between cognitive skills and earnings or automation risk and earnings show stable patterns across the countries. Taken as a whole, the results in Tables 1 and 2 would seem to suggest that the relationships between skills, risks and earnings in the school-to-work transition is very context dependent. As noted above, even the "simple" relationships between earnings and skills as well as between earnings and risk diverge across countries and sub-groups (gender and educational level) in ways that would seem to prevent broad conclusions. This in turn suggests that other factors shape the transition, and therefore these relationships.

While this lies beyond the current analyses, one possibility, beyond the differences in the available data, would seem to be the types of vocational training program offered in the four countries. Although not the only potential explanation, the distinctions between apprenticeship and school-based vocational training, both within and between countries, has often been found to be a strong predictor of labor market success among graduates. Other conceivable candidates could be differences in family formation patterns as well as opportunities for further education.

Such life-cycle dependencies could however be expected to become attenuated over time, for instance with increasing specific occupational and general labor force experience among the former school leavers. Tables 3 and 4 therefore present the results from the same set of analyses and sub-groups as Tables 1 and 2, but after 10 years on the labor market rather than

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immediately upon graduation. Due to data restrictions, the results for year 10 are only available for Finland, Sweden, and the Netherlands.

The results for the different dimensions of skills among vocational upper-secondary graduates at year 10 presented in Table 3 show relatively clear patterns. Cognitive skills are in Model 1 positively related to earnings in both Finland, Sweden, and among Dutch men, while the estimates for Dutch women are non-significant. As for non-cognitive skills, extraversion is positively related to earnings in both Sweden and the Netherlands, while there is a (less well-established) negative effect of emotional stability in Sweden. However, automation risk in Models 2 and 3 is unrelated to earnings in Finland, positively in Sweden, and negatively related to earnings in the Netherlands. As previously, none of these estimates change with the addition of parental SES in Model 4, even though social background tends to be related to attainment here as well. As for the interaction terms in Model 5, these again seem to suggest very varied relationships between skills, automation risks, and earnings in the three countries.

Turning finally to the long-term relationships among graduates from all levels in Finland and Sweden, Table 4, these again show very diverse picture. In Model 1, cognitive skills are positively related to earnings in both Finland and Sweden, and all non-cognitive skill display clear but varied effects on earnings in Sweden. Automation risk is unrelated to earnings in Finland in Model 2, and positively in Sweden. Models 3 and 4 once again display no discernable differences to the earlier ones, despite social class being a significant predictor of attainment even after 10 years on the labor market. The interaction effects in Model 5 indicate that among Finnish men, the importance of cognitive skills decreases with increasing automation risk while there is no relationship between cognitive skills and automation risk among Finnish women and Swedish men. Finally, the effect of emotional stability among Swedish men increases with increasing risk.

While the results in Tables 3 and 4 display strong similarities to the ones in Tables 1 and 2 there are a few notable differences. In contrast to the results for year 1 after graduation, these results show cognitive skills to be generally positively related to earnings. Moreover, the results for year 10 also, with the exception for emotional stability, tend to show positive associations between non-cognitive skills and earnings. This suggests that some of the results reported in

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Tables 1 and 2 may be specific to the early phases of the school-to-work transition, and that other factors may become more important in the longer run. The differences in the effects of automation risk do however remain. Interesting, in the light of the initial hypothesis regarding social class, is also that the class variables remain important predictors of attainment 10 years after graduation even after taking both skills and risks into account.

5. Conclusions

Technological change has historically impacted on social inequality in dramatic fashion, and it is to be expected that the current wave of innovations will further transform attainment processes. The starting point for Deliverable 2.2 has been conjectures relating inequality to employment risks linked to automation as well as to cognitive and non-cognitive skills above and beyond their significance for obtaining different educational credentials. The purpose of this introductory part of the deliverable has been to set the stage for further analyses of specific dimensions of these conjectures examined in Appendixes 1 to 3 through basic analyses of inequality in the form of earnings and measures of cognitive and non-cognitive skills as well as of automation risk holding parental SES (and the level of education constant).

Before reviewing the results, some limitations of these comparative analyses should be noted. The analyses have i.a. relied on common, EU-level, automation risks. Although this was the best measure available, this is nonetheless problematic since previous analyses have found large differences in automation risks across countries, and also certain differences in the association between risk and outcomes such as wages. To the extent that differences in working hours also are related to automation risks, it should also be remembered that the analyses for two countries relied on annual earnings while they for the other two made use of hourly wages. However, some advantages in relation to earlier analyses can also be highlighted. The central question has here been the impact that technological change in the form of automation may have for workers, in contrast to the largely exclusive focus of automation on jobs or occupations in prior studies. Another contrast relates to the longitudinal analyses conducted here and the cross-sectional perspective of previous research. The former here refers both to the fact that automation risks in most cases refer to the occupations for which graduates have been trained before entering the labor market as well as to the fact that the analyses have been carried out separately for the first year and the tenth year after

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graduation. Furthermore, these results also explore the relationships between automation risk and different dimensions of generic skills, something overlooked in earlier work.

As for the results, taken together they offer little support for the idea of a pervasive and largely similar transformation of social inequality in the wake of recent technological change. In contrast to what could be expected given some of the literature, the concept of automation risk would seem ambiguous and highly context dependent. Rather than risk evincing a stable relation to inequality in all countries, the impact of automation risk varies substantially. These results underscore the variability reported in earlier research, which, as observed above, had documented notable differences in both automation risks and associations between risk and wages across countries.

Cross-country stability is instead evinced by cognitive and non-cognitive skills, which in the longer run show similar, and largely expected, results. Although the results one year after graduation are quite diverse, ten years after graduation we find positive associations between wages and both cognitive and (most cases of) non-cognitive skills. These results for workers who have become established on the labor market in other words align well with previous results relating to prime-age workers. It is worth reiterating that the stability in the pattern of these results across the countries stands in stark contrast to the variability in the results for automation.

In this context it should also be mentioned that the results for skills and automation are largely unaffected by the inclusion of measures of social class, and that these class measures generally retain explanatory power despite the simultaneous controls for generic skills. The death of class may once again to have been announced somewhat prematurely.

The importance of context for the relationship between wages and automation risk applies primarily to the between-country comparisons. We have in many cases obtained fundamentally different results when we compared graduates from e.g. vocational programs one year after graduation in Finland, Sweden, the Netherlands and Germany as well as graduates ten years after graduation from all programs in Finland and Sweden. While this may be due to differences in variable definitions caused by differences in the data used (e.g. current

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occupation vs. training occupation, or wages vs. earnings), it may nonetheless be useful to consider potential substantive reasons for these discrepancies as considerable variability has been reported elsewhere as well.

Although an analysis of these contextual dependencies are beyond this introduction, one hypothetical explanation could be institutional differences within and between the countries. One such difference relates to the structure of educational programs, specifically to the structure of vocational training programs. A recurrent finding in the literature is that the extent to which a program involves apprenticeship or school-based training will affect the short- as well as the long-term prospects of graduates. Something similar relates to further and adult training, were differences in the extent to which such training is available may affect workers' vulnerability in the face of structural change.

In addition, previous research has emphasized that automation risk may vary due to differences in work organization, viz. the specific tasks carried out by workers in an occupation. There may be substantial discrepancies in the actual tasks that are part of ostensibly similar occupations, and work may also be reorganized differently as a result of technological development. However, the empirical values of these conjectures will have to be examined elsewhere.

The remainder of Deliverable 2.2 examines some of these issues in greater detail. Appendix 1 explores the relationship between automation risks related educational degrees, focusing in particular on the labor market entry process. Labor market entry is examined using sequence analysis, documenting distinct patterns of entry. These labor force participation patterns are however unrelated to automation. In contrast, wage growth during the entry phase is affected by the automation risks associated with one's degree. These basic results are modified by the graduates' personality traits, but not by their cognitive abilities.

Appendix 2 investigates these issues from a slightly different angle, concentrating on the risk of long-term labor market precariousness. This again turns out to be largely unrelated to the automation risks linked to one's degree, instead precariousness is closely related to years of

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education. Once the strong correlation between automation risk and length of education is taken into account it is the latter that dominates.

Appendix 3, finally, deals with the inter-generational transmission of social status. Two distinct hypotheses regarding the linkages between class attainment of parents and offspring are examined: relative risk aversion and counter-mobility. Both are found to be supported by the data, even after taking the offsprings' cognitive abilities into account, indicating that social class continues to be of relevance for status attainment on modern labor markets.

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Tables

Table 1a. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. Finland

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (GPA)	0.062*** (0.009)		0.062*** (0.009)	0.063*** (0.009)	-0.096* (0.046)
Automation risk		-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)
Cognitive skills * Automation risk					0.004*** (0.001)
Parental SES 1				-0.140* (0.059)	
Parental SES 2				-0.020 (0.028)	
Parental SES 3				-0.004 (0.028)	
Parental SES 5				0.002 (0.026)	
Men					
Cognitive skills (GPA)	0.078*** (0.011)		0.075*** (0.011)	0.078*** (0.011)	0.481** (0.073)
Automation risk		-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.010*** (0.002)
Cognitive skills * Automation risk					-0.010*** (0.002)
Parental SES 1				0.034 (0.062)	
Parental SES 2				0.033 (0.032)	
Parental SES 3				0.108*** (0.030)	
Parental SES 5				0.110*** (0.029)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variable immigrant background.

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Table 1b. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. Sweden.

Men	Model 1	Model 2	Model 3	Model 4	Model 5
Cognitive skills (4 domain composite)	0.015 (0.016)		0.015 (0.016)	0.019 (0.016)	-0.410* (0.239)
Non-cognitive skills (extraversion)	-0.021 (0.019)		-0.017 (0.019)	-0.015 (0.019)	0.368 (0.268)
Non-cognitive skills (conscientiousness)	0.028* (0.017)		0.030* (0.017)	0.036** (0.017)	-0.410 (0.254)
Non-cognitive skills (emotional stability)	0.027 (0.018)		0.027 (0.018)	0.030* (0.018)	-0.102 (0.271)
Automation risk		0.014*** (0.005)	0.013*** (0.005)	0.011** (0.005)	0.023*** (0.007)
Cognitive skills * Automation risk					0.011* (0.006)
Non-cogn. skills (ext.) * Automation risk					-0.010 (0.007)
Non-cogn. skills (con.) * Automation risk					0.011* (0.006)
Non-cogn. skills (em.) * Automation risk					0.003 (0.007)
Parental SES 1				0.195*** (0.050)	
Parental SES 2				0.127*** (0.042)	
Parental SES 3				0.134*** (0.039)	
Parental SES 5				-0.037 (0.083)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variable immigrant background.

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Table 1c. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. The Netherlands

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (3 domain composite)	-0.013* (0.007)		-0.009 (0.006)	-0.008 (0.006)	-0.008 (0.006)
Non-cognitive skills (extraversion)	0.004 (0.006)		0.007 (0.006)	0.008 (0.006)	0.005 (0.006)
Non-cognitive skills (conscientiousness)	-0.003 (0.006)		-0.003 (0.006)	-0.006 (0.006)	-0.002 (0.006)
Non-cognitive skills (emotional stability)	-0.010 (0.006)		-0.007 (0.006)	-0.006 (0.006)	-0.009 (0.006)
Automation risk		-0.074*** (0.005)	-0.075*** (0.005)	-0.071*** (0.005)	-0.074*** (0.006)
Cognitive skills * Automation risk					0.000 (0.005)
Non-cogn. skills (ext.) * Automation risk					-0.005 (0.006)
Non-cogn. skills (con.) * Automation risk					0.003 (0.005)
Non-cogn. skills (em.) * Automation risk					-0.005 (0.005)
Parental SES 1				-0.014 (0.019)	
Parental SES 2				-0.030 (0.019)	
Parental SES 3				-0.009 (0.019)	
Parental SES 5				-0.017 (0.020)	

Continued.

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Table 1c cont. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. The Netherlands

Men					
Cognitive skills (3 domain composite)	-0.001 (0.006)		0.000 (0.006)	0.001 (0.007)	0.001 (0.007)
Non-cognitive skills (extraversion)	-0.008 (0.007)		-0.010 (0.007)	-0.010 (0.007)	-0.010 (0.007)
Non-cognitive skills (conscientiousness)	-0.009 (0.007)		-0.008 (0.007)	-0.006 (0.007)	-0.007 (0.007)
Non-cognitive skills (emotional stability)	0.006 (0.007)		0.006 (0.007)	0.012 (0.007)	0.002 (0.007)
Automation risk		-0.058*** (0.009)	-0.060*** (0.009)	-0.060*** (0.009)	-0.064*** (0.009)
Cognitive skills * Automation risk					0.000 (0.009)
Non-cogn. skills (ext.) * Automation risk					0.000 (0.010)
Non-cogn. skills (con.) * Automation risk					-0.002 (0.010)
Non-cogn. skills (em.) * Automation risk					0.016 (0.010)
Parental SES 1				-0.017 (0.022)	
Parental SES 2				-0.003 (0.021)	
Parental SES 3				0.014 (0.021)	
Parental SES 5				0.009 (0.021)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and MBO3.

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Table 1d. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. Germany

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (mathematics)	0.040* (0.018)		0.002 (0.001)	0.041* (0.018)	0.038 (0.066)
Non-cognitive skills (extraversion)	0.024 (0.015)		0.002 (0.001)	0.023 (0.015)	0.017 (0.059)
Non-cognitive skills (conscientiousness)	0.014 (0.016)		0.002 (0.001)	0.012 (0.016)	0.049 (0.061)
Non-cognitive skills (emotional stability)	-0.011 (0.016)		0.002 (0.001)	-0.010 (0.016)	-0.035 (0.058)
Automation risk		0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.002)
Cognitive skills * Automation risk					0.000 (0.002)
Non-cogn. skills (ext.) * Automation risk					0.000 (0.001)
Non-cogn. skills (con.) * Automation risk					-0.001 (0.002)
Non-cogn. skills (em.) * Automation risk					0.001 (0.001)
Parental SES 1				0.084 (0.044)	
Parental SES 2				0.054 (0.079)	
Parental SES 3				0.088* (0.039)	
Parental SES 5				0.105* (0.049)	

Continued.

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Table 1d cont. Results of linear regression models on annual earnings 1 year after graduation. Only graduates with upper-secondary school vocational degree. Germany

Men					
Cognitive skills (mathematics)	0.050*** (0.012)		0.050*** (0.012)	0.051*** (0.012)	0.154* (0.067)
Non-cognitive skills (extraversion)	-0.006 (0.013)		-0.006 (0.013)	-0.006 (0.013)	-0.022 (0.074)
Non-cognitive skills (conscientiousness)	0.010 (0.012)		0.010 (0.012)	0.012 (0.012)	0.039 (0.072)
Non-cognitive skills (emotional stability)	0.038** (0.012)		0.038** (0.012)	0.038** (0.012)	0.087 (0.073)
Automation risk		-0.001 (0.002)	0.000 (0.002)	0.000 (0.002)	0.001 (0.002)
Cognitive skills * Automation risk					-0.003 (0.002)
Non-cogn. skills (ext.) * Automation risk					0.000 (0.002)
Non-cogn. skills (con.) * Automation risk					-0.001 (0.002)
Non-cogn. skills (em.) * Automation risk					-0.001 (0.002)
Parental SES 1				-0.054 (0.036)	
Parental SES 2				-0.156** (0.056)	
Parental SES 3				-0.039 (0.031)	
Parental SES 5				-0.068 (0.038)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and abitur.

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Table 2a. Results of linear regression models on annual earnings 1 year after graduation. All graduates. Finland

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (GPA)	0.027*** (0.006)		0.029*** (0.006)	0.029*** (0.006)	-0.047*** (0.022)
Automation risk		-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.004*** (0.001)
Cognitive skills * Automation risk					0.002** (0.001)
Parental SES 1				-0.029 (0.022)	
Parental SES 2				-0.014 (0.014)	
Parental SES 3				-0.016 (0.013)	
Parental SES 5				-0.009 (0.013)	
Men					
Cognitive skills (GPA)	-0.030*** (0.008)		-0.031*** (0.008)	-0.025*** (0.008)	0.148** (0.039)
Automation risk		-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.007*** (0.001)
Cognitive skills * Automation risk					-0.005*** (0.001)
Parental SES 1				0.010 (0.034)	
Parental SES 2				0.051* (0.021)	
Parental SES 3				0.122*** (0.020)	
Parental SES 5				0.109*** (0.019)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and years of education.

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Table 2b. Results of linear regression models on annual earnings 1 year after graduation. All graduates. Sweden

Men	Model 1	Model 2	Model 3	Model 4	Model 5
Cognitive skills (4 domain composite)	0.021*** (0.005)		0.015*** (0.005)	0.019*** (0.005)	-0.331*** (0.050)
Non-cognitive skills (extraversion)	0.006 (0.006)		0.012* (0.006)	0.013** (0.006)	0.147** (0.063)
Non-cognitive skills (conscientiousness)	0.020*** (0.006)		0.023*** (0.006)	0.025*** (0.006)	-0.119** (0.057)
Non-cognitive skills (emotional stability)	-0.016*** (0.006)		-0.016*** (0.006)	-0.014** (0.006)	-0.155*** (0.059)
Automation risk		0.028*** (0.002)	0.029*** (0.002)	0.029*** (0.002)	0.032*** (0.002)
Cognitive skills * Automation risk					0.010*** (0.001)
Non-cogn. skills (ext.) * Automation risk					-0.004** (0.002)
Non-cogn. skills (con.) * Automation risk					0.004** (0.002)
Non-cogn. skills (em.) * Automation risk					0.004** (0.002)
Parental SES 1				0.027 (0.018)	
Parental SES 2				0.023* (0.014)	
Parental SES 3				0.030*** (0.011)	
Parental SES 5				-0.023* (0.013)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and years of education.

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Table 3a. Results of linear regression models on annual earnings 10 years after graduation. Only graduates with upper-secondary school vocational degree. Finland

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (GPA)	0.040*** (0.009)		0.040*** (0.009)	0.041*** (0.009)	-0.070 (0.044)
Automation risk		-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)
Cognitive skills * Automation risk					0.003* (0.001)
Parental SES 1				-0.087 (0.054)	
Parental SES 2				-0.007 (0.027)	
Parental SES 3				-0.034 (0.026)	
Parental SES 5				-0.013 (0.025)	
Men					
Cognitive skills (GPA)	0.057*** (0.006)		0.057*** (0.006)	0.055*** (0.006)	0.171*** (0.040)
Automation risk		-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.002* (0.001)
Cognitive skills * Automation risk					-0.003** (0.001)
Parental SES 1				-0.022 (0.034)	
Parental SES 2				-0.038* (0.018)	
Parental SES 3				-0.079*** (0.017)	
Parental SES 5				-0.046** (0.016)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variable immigrant background.

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Table 3b. Results of linear regression models on annual earnings 10 years after graduation. Only graduates with upper-secondary school vocational degree. Sweden

Men	Model 1	Model 2	Model 3	Model 4	Model 5
Cognitive skills (4 domain composite)	0.029*** (0.009)		0.027*** (0.009)	0.024*** (0.009)	0.240 (0.158)
Non-cognitive skills (extraversion)	0.035*** (0.011)		0.039*** (0.011)	0.040*** (0.011)	0.019 (0.170)
Non-cognitive skills (conscientiousness)	0.010 (0.010)		0.012 (0.010)	0.014 (0.009)	-0.120 (0.164)
Non-cognitive skills (emotional stability)	-0.017* (0.010)		-0.017* (0.010)	-0.015 (0.010)	-0.197 (0.176)
Automation risk		0.014*** (0.003)	0.016*** (0.003)	0.014*** (0.003)	0.010** (0.005)
Cognitive skills * Automation risk					-0.005 (0.004)
Non-cogn. skills (ext.) * Automation risk					0.000 (0.004)
Non-cogn. skills (con.) * Automation risk					0.003 (0.004)
Non-cogn. skills (em.) * Automation risk					0.005 (0.004)
Parental SES 1				0.021 (0.028)	
Parental SES 2				0.015 (0.023)	
Parental SES 3				0.043* (0.022)	
Parental SES 5				0.052 (0.048)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variable immigrant background.

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Table 3c. Results of linear regression models on annual earnings 10 years after graduation. Only graduates with upper-secondary school vocational degree. The Netherlands

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (3 domain composite)	-0.009 (0.007)		-0.003 (0.007)	-0.004 (0.007)	-0.000 (0.007)
Non-cognitive skills (extraversion)	0.029*** (0.007)		0.027*** (0.006)	0.027*** (0.007)	0.029*** (0.006)
Non-cognitive skills (conscientiousness)	0.004 (0.006)		0.007 (0.006)	0.006 (0.006)	0.007 (0.006)
Non-cognitive skills (emotional stability)	-0.007 (0.006)		-0.006 (0.006)	-0.006 (0.006)	-0.008 (0.006)
Automation risk		-0.045*** (0.005)	-0.048*** (0.005)	-0.049*** (0.005)	-0.052*** (0.005)
Cognitive skills * Automation risk					0.012** (0.006)
Non-cogn. skills (ext.) * Automation risk					0.009* (0.005)
Non-cogn. skills (con.) * Automation risk					-0.001 (0.005)
Non-cogn. skills (em.) * Automation risk					-0.005 (0.005)
Parental SES 1				-0.044** (0.020)	
Parental SES 2				0.008 (0.019)	
Parental SES 3				-0.006 (0.019)	
Parental SES 5				0.041** (0.020)	

Continued.

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Table 3c cont. Results of linear regression models on annual earnings 10 years after graduation. Only graduates with upper-secondary school vocational degree. The Netherlands

Men					
Cognitive skills (3 domain composite)	0.019** (0.008)		0.020** (0.008)	0.020** (0.008)	0.021** (0.009)
Non-cognitive skills (extraversion)	0.014* (0.008)		0.013* (0.008)	0.012 (0.008)	0.010 (0.009)
Non-cognitive skills (conscientiousness)	0.003 (0.008)		0.004 (0.008)	0.005 (0.009)	0.003 (0.009)
Non-cognitive skills (emotional stability)	-0.001 (0.008)		-0.001 (0.008)	-0.000 (0.009)	-0.001 (0.009)
Automation risk		-0.024*** (0.010)	-0.022** (0.010)	-0.016 (0.010)	-0.020* (0.010)
Cognitive skills * Automation risk					-0.004 (0.011)
Non-cogn. skills (ext.) * Automation risk					0.013 (0.011)
Non-cogn. skills (con.) * Automation risk					0.005 (0.011)
Non-cogn. skills (em.) * Automation risk					-0.002 (0.011)
Parental SES 1				-0.004 (0.025)	
Parental SES 2				-0.015 (0.024)	
Parental SES 3				-0.008 (0.023)	
Parental SES 5				0.030 (0.023)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and MBO3.

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Table 4a. Results of linear regression models on annual earnings 10 years after graduation. All graduates. Finland

	Model 1	Model 2	Model 3	Model 4	Model 5
Women					
Cognitive skills (GPA)	0.023*** (0.006)		0.023*** (0.006)	0.024*** (0.006)	0.007 (0.021)
Automation risk		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
Cognitive skills * Automation risk					0.000 (0.001)
Parental SES 1				-0.018 (0.021)	
Parental SES 2				0.014 (0.013)	
Parental SES 3				0.001 (0.013)	
Parental SES 5				0.010 (0.012)	
Men					
Cognitive skills (GPA)	0.022*** (0.004)		0.022*** (0.004)	0.020*** (0.004)	0.091*** (0.022)
Automation risk		-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001* (0.001)
Cognitive skills * Automation risk					-0.002*** (0.001)
Parental SES 1				0.010 (0.019)	
Parental SES 2				0.002 (0.012)	
Parental SES 3				-0.034** (0.011)	
Parental SES 5				-0.009 (0.011)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and years of education.

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Table 4b. Results of linear regression models on annual earnings 10 years after graduation. All graduates. Sweden

Men	Model 1	Model 2	Model 3	Model 4	Model 5
Cognitive skills (4 domain composite)	0.036*** (0.005)		0.032*** (0.005)	0.030*** (0.005)	0.002 (0.044)
Non-cognitive skills (extraversion)	0.025*** (0.005)		0.029*** (0.005)	0.028*** (0.005)	-0.051 (0.053)
Non-cognitive skills (conscientiousness)	0.021*** (0.005)		0.023*** (0.005)	0.024*** (0.005)	0.101** (0.049)
Non-cognitive skills (emotional stability)	-0.033*** (0.005)		-0.033*** (0.005)	-0.032*** (0.005)	-0.158*** (0.050)
Automation risk		0.017*** (0.002)	0.020*** (0.002)	0.019*** (0.002)	0.020*** (0.002)
Cognitive skills * Automation risk					0.001 (0.001)
Non-cogn. skills (ext.) * Automation risk					0.002 (0.001)
Non-cogn. skills (con.) * Automation risk					-0.002 (0.001)
Non-cogn. skills (em.) * Automation risk					0.004** (0.001)
Parental SES 1				-0.030* (0.016)	
Parental SES 2				-0.030** (0.012)	
Parental SES 3				-0.003 (0.010)	
Parental SES 5				0.042*** (0.012)	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, and *** p<0.01. All models also include the variables immigrant background and years of education.

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Appendix 1

Automation risks of vocational training programs and early careers in the Netherlands

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Abstract

This paper analyzes the effects of automation risks of educational fields on early career development of secondary vocational education (VET) graduates in the Netherlands. We make use of longitudinal register data on educational field, employment status, and wages from Statistics Netherlands for the entire Dutch population, and predicted probabilities of automation risks by Frey & Osborne (2017) which are matched on educational field. We further match unique large-scale survey data which include detailed information on cognitive skills and personality traits. These data allow us to analyze the moderation effects of cognitive skills and personality traits on individual's resilience in the labor market to automation risks. We find that automation risks are not significantly related to labor force participation. However, automation risks are negatively associated with earnings. We further find no significant moderation with cognitive skills but do show that personality traits impact the resilience of individuals towards automations risks.

Keywords: Automation risks, Career paths of individuals, Cognitive skills, Personality traits

JEL-codes: E24, J22, J24, J31, O31

1. Introduction

Throughout developed countries there is a looming fear of a further increasing employment and income polarization due to automation (Autor 2015; Goos, Manning, and Salomons 2009, 2014). New technologies that augment human and physical capital enable firms to automate routine tasks, which were previously performed by medium skilled workers (Autor and Dorn 2013) and increase the relative demand for higher-skilled labor (Katz and Autor 1999). Indeed, the share of labor in national income fell in a large number of countries (Karabarbounis and Neiman 2014). So did employment and wages in medium skilled occupations (Autor 2015; Goos et al. 2009, 2014). Wages for abstract tasks, on the other hand, have increased, which has created a polarization on the labor market (Böhm 2020).

While this literature on the labor-market consequences of technology is extensive, most of these studies relate automation and labor market outcomes on a macro-level (one exception being Nedelkoska and Quintini (2018) who find a negative correlation of automation risk and individual wages). The aim of this paper is to fill in this gap in the literature by analyzing the effects of automation risks of educational fields on individual vocational education to work trajectories and wage growth in the Netherlands.

We ask the following research questions:

i. To what extend do automation risks affect early career paths and wage growth of VET graduates?
ii. Can cognitive skills and personality traits explain these possible differences in labor market outcomes as a consequence of automation risks?

The Netherlands provide an excellent case study, due to the availability of high-quality data, to answer these questions. Concerning external validity, we expect that our analyses, however, might provide us with a lower bound estimate of the effects of automation risks on early careers. First, unemployment rate and income inequality are among the lowest in Europe. Second, the Netherlands have a highly skilled labor force, have been an early adopter of internet (Worldbank 2020) and have the largest share of inhabitants with above basic digital

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skills in the EU (Eurostat 2020). Finally, the occupational structure in the Netherlands is estimated to have a comparatively low risk of automation (Nedelkoska and Quintini 2018).

Previous studies indicated that medium-skilled workers are the ones most affected by the polarization caused by technological change (Autor 2015; Goos et al. 2009, 2014). Therefore, we focus on graduates from vocational education (VET). VET graduates might initially have an advantage over graduates with general education through smoother entrances into the labor market (Ryan 2001). However, the specificity of their skills makes them less flexible to (technological) changes on the labor market (Forster, Bol, and van de Werfhorst 2016; Hanushek et al. 2017). Moreover, young people might be especially affected by automation because as labor market outsiders, they not yet have attained insider protection of unions and employment protection (Lindbeck and Snower 2001).

The degree to which automation risks affect individual labor market outcomes of VET graduates depends heavily on the educational field. However, and opposite to what can be seen in aggregate effects of automation, even within education fields, some VET graduates will suffer more from automation risks than others. Potential moderator effects are cognitive skills and personality traits. This is due to that a large number of empirical studies show that cognitive skills and personality traits are powerful determinants of human capital investments, wages, and many other aspects of social and economic life (e.g., Borghans et al. 2008; Deming 2017; Heckman, Stixrud, and Urzua 2006; Murnane, Willett, and Levy 1995; Roberts, Walton, and Viechtbauer 2006). The importance of personality skills in relation to automation is shown by a growing body of empirical studies that investigated the effects of computers on the relative valuation of personality traits in the labor market during recent decades. For example, Borghans et al. (2014) show that more extensive use of computers has actually increased the demand for and the wages of people with better "people skills". Moreover, employment and wage premia have increased disproportionately in occupations that require both high levels of cognitive skills and personality traits (Weinberger 2014). At the same time, they decreased in occupations with more routine type of tasks which can be more easily automated (De La Rica, Gortazar, and Lewandowski 2020).

We contribute to the literature in the following ways. First, as mentioned before, most studies on technological changes estimate aggregated employment and wage effects. Instead, we analyze the effect of automation risks on young individuals' career paths and wages. Something which has not yet been done in the literature of school-to-work transitions, earnings, and vocational training (e.g., Körvers et al. 2011; Hanushek et al. 2017; Middeldorp, Edzes, and van Dijk 2018). So far, this research line has mostly focused on early career differences between vocational and general education and between programs. We add to this by estimating a measure of automation risk per educational program and focusing on within differences in vocational education programs with respect to individual career and wage trajectories.

Second, in contrast to the literature on technological change, automation and job tasks (Arntz, Gregory, and Zierahn 2016; Autor 2015; Autor, Levy, and Murnane 2003; Frey and Osborne 2017; Nedelkoska and Quintini 2018), we do not focus on automation risks of occupations but of educational programs. The advantage of this is that we do not have to deal with potential selection into occupations based on changed employment opportunities due to substitution of workers by machines.

Third, our article adds to the literature of cognitive skills and personality traits and their effects on individual's labor market and education outcomes (Borghans et al. 2008; Brunello and Schlotter 2011; Deming 2017; Heckman et al. 2006). We add to this literature by analyzing whether cognitive skills and personality traits serve as compensatory resources in overcoming automation risks within educational fields.

Finally, we employ excellent data to answer our research questions. We make use of longitudinal register data on diplomas earned, monthly employment status, and monthly wages from Statistics Netherlands for the entire Dutch population. We measure the automation risk of VET programs using the weighted average of the most frequent occupations for each VET program in the labor force and their predicted probabilities of automation by Frey & Osborne (2017). These data allow us to follow the early career of young VET graduates into the labor market for 10 years and to identify the role automation risks might have had on these career paths. We further match unique large-scale survey data from the Voortgezet Onderwijs Cohort Leerlingen (VOCL'99) study which include detailed information on cognitive skills and personality traits (Kuyper, Lubbers, and Van der Werf 2003). These data allow us to analyze the moderation effects of cognitive skills and personality traits on individual's resilience to automation risks.

Our main finding is that automation risks are not statistically significantly related to labor force participation, while they are significantly negatively associated with hourly wages, but not with wage growth over time. We find no significant direct moderation of automation risk by cognitive skills. Personality traits, however, do change the resilience of individuals towards automations risks. The negative relation between automation risk and earnings is stronger for individuals who score high on the agreeableness scale, and weaker for individuals who are more open to experience. The relative importance of personality traits for dealing with automation risks are in line with recent studies that show the increasing relevancy of soft skills development for success on the labor market (Balcar 2016; Cubel et al. 2016; Heckman et al. 2006; Mueller and Plug 2006).

The remainder of the article is setup as follows. We first deduce hypotheses. We then further describe the data and the operationalization of the variables used. We present our results in two steps. First, we explore the different VET-to-work trajectories and use these trajectories as dependent variables in a multinomial logistic regression. Secondly, we model wage growth during the early career using a multilevel growth-curve model.

2. Theory

2.1. Automation and labor market outcomes

The task approach to automation distinguishes routine from non-routine tasks and manual from cognitive tasks with routine-manual tasks being the easiest to codify and thus the most likely to be substituted for by computers (Autor et al. 2003). Recently, this has been brought into question. Today, and in the near future, more and more non-routine tasks can and will be performed by computers (Brynjolfsson and McAfee 2011). This is addressed by the approach of engineering bottlenecks put forward by Frey and Osborne (2017) who define the risk of automation of an occupation by judging which skills machines cannot yet easily perform. These are the perception and manipulation of complex objects as well as creative and social intelligence. In the light of rapid development in machine learning, the authors then estimate

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that a substantial share of employment (in the United States) is at risk of automation in the near future.

What does that mean for young people who enter the labor market? Labor market entrants are considered as outsiders (Lindbeck and Snower 2001). As outsiders, they have yet to attain the protection of unions, collective bargaining schemes, higher wages, and tenured contracts. Hence, young people will be the last to be hired and the first to leave. With regards to automation, this might mean a stop of new hires and the subsequent replacement of the workforce by machines. Because an education with a high risk of automation will be less demanded on the labor market, its wage returns are likely to decrease as well.

Following this, we expect that young people who have graduated from a vocational education program with a high estimated automation risk, will, on average, have a less successful early career. Meaning, we expect automation risk to correlate (1) positively with following a trajectory of long joblessness/NEET, (2) negatively with starting wages, and (3) negatively with wage growth.

In addition to these direct effects of automation risk, it is to be expected that the degree to which automation risks of education programs affects graduates, will differ depending on their cognitive skills and personality traits. We will lay out this reasoning in the following section.

2.2. *Moderation by cognitive skills and personality*

We expect that individuals with higher cognitive skills are more able to adapt to new technologies. We base our expectation on the intuition that "cognition is essential in processing information, learning and in decision-making" (Borghans et al. 2008) and that lower educated workers are less likely to participate in further training (Bassanini et al. 2007; Fouarge, Schils, and de Grip 2013). In addition, workers whose jobs are the most likely to be substituted by machines, are the least probable to receive further training (Ehlert 2020; Nedelkoska and Quintini 2018). Those who have higher cognitive skills, however, might be more able and willing to still follow trainings. Hence, we expect that higher cognitive skills reduce (moderate) the negative effect of automation risk on labor market outcomes.

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In addition to cognitive skills, personality traits may offer another mechanism of moderation of automation risks. Personality traits are commonly considered to be "relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (Roberts et al. 2006). From this follows that individuals who share similar personality traits will respond similarly to technological challenges. As personality differs between people, so will their reactions to automation risks.

Personality traits are commonly organized in five domains (e.g., Big Five; Five-Factor Personality Inventory): extraversion, agreeableness, conscientiousness, emotional stability (reverse coded neuroticism), and autonomy (openness to experience) (Hendriks, Hofstee, and De Raad 1999; McCrae and John 1992).

Conscientiousness is the personality trait often considered most salient on the labor market (Borghans et al. 2008). Conscientiousness can be described with being efficient, organized, planful, reliable, responsible, and thorough (McCrae and John 1992). Conscientious people agree with items such as "does things according to plan", and negatively on items such as "does things at the last minute" (Hendriks et al. 1999). Based on this, we expect that conscientious people are better able to cope with technological changes at work because of their efficient and planful way of working. Conscientiousness is also related to shorter unemployment durations (Uysal and Pohlmeier 2011) and higher wages (Almlund et al. 2011). Hence, conscientious people are likely better able to plan ahead and thus avoid the negative externalities of automation on the labor market.

Emotional stability (or reverse coded neuroticism) is also often related to educational and occupational success (Borghans et al. 2008). Neuroticism describes people as anxious, unstable, worrying, self-defeating, thin-skinned, and vulnerable (McCrae and John 1992). Emotional stable people agree to statements like "readily overcomes setbacks" and "can take his/her mind off his/her problems" and disagree with statements like "invents problems" and "has crying fits" (Hendriks et al. 1999). On the labor market, neuroticism predicts fewer and lower status job offers and longer unemployment duration (Baay et al. 2014; Uysal and Pohlmeier 2011). People who score high on neuroticism might tend to prefer and adapt better to positively affective, stable work environments that are predictable and frictionless (Bode et al. 2019). Hence, experience to automation risks can be expected to have a more distorting effect on the behavior of individuals who score high on this trait.

Openness to experience (autonomy) is described as being artistic, imaginative, curious, and following unusual thought processes (McCrae and John 1992). Open individuals are therefore expected to be better equipped to adapt to novel situations or environments that provide opportunities to engage their intellectual capacities, such as new technologies. In our data, this trait is called autonomy. Autonomy significantly correlates with openness to experience (Hendriks et al. 1999). Autonomous is measured with items such as “can easily link facts together”, and “thinks quickly” and negatively loads on items such as “follows the crowd” (Hendriks et al. 1999). Hence, openness (autonomy) is likely to reduce the strength of the negative relation between automation risks and labor market outcomes.

Extraversion describes people as active, assertive, energetic, enthusiastic, and outgoing (McCrae and John 1992). An extraverted person “loves to chat” and “slaps people on the back”, while an introverted person “avoids company” (Hendriks et al. 1999). Extraversion is a desirable trait for employers, especially for higher-level positions and outgoing persons are more likely be working in managerial rather than working class positions (Jackson 2006). We expect that people who score higher on extraversion are better able to cope with automation risks because of their sociability which gives them an edge over current technology.

Finally, agreeableness is associated with characteristics of sympathy, altruism, tendermindedness, and compliance (Costa & McCrae, 1992). A more agreeable person “is willing to make compromises” and would not “impose[s] his/her will on others” (Hendriks et al. 1999). Individuals who score high on agreeableness might be less likely to shift jobs as they stronger value the relationship with their current employer, and hence, might feel obliged to stay at their firm despite negative technological shocks. Moreover, the natural inclination to make compromises might be negatively correlated to the job conditions negotiated when applying for a job. Agreeableness is therefore likely to exacerbate the negative association with automation risks.

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3. Data

We use a unique combination of survey and register data for our analyses on the relationship between automation risks and wages. We use the Voortgezet Onderwijs Cohort Leerlingen (VOCL'99) survey collected from a random sample of pupils in the first year of secondary education in 1999 (Kuyper et al. 2003). The survey was held among 10% of all graduates from primary education in 1999 and gives us access to personality traits and cognitive skills, which are not available in register data. Sampling was done on the school level. From 1144 school locations in the Netherlands, 246 were randomly selected and out of these, 126 school locations agreed to participate. Within these 126 school locations, there were 825 first grade classes with 19,391 pupils, representing about 11% of that school entry cohort (Van Berkel 1999). Data were collected from three sources: schools delivered background information on their pupils, pupils filled out questionnaires and ability tests, and additional questionnaires were taken home by the pupils to be filled out by parents (in 147 cases by care takers).

We further use register data from Statistics Netherlands (Bakker, van Rooijen, and van Toor 2014) which give us access to measures such as diplomas earned, socioeconomic activity over time, wages, employment contracts, and working hours. We merge them on the individual level using the encrypted personal identifier. Merging them gives us the advantage of both survey and administrative data.

From the VOCL sample, we select young people who have attained a diploma from MBO levels 3 and 4 between 2006 and 2012 (N = 5,588), where the modal graduation year is 2007. We do not include Levels 1 and 2 as they are not considered a full degree within the Dutch education system.[7] To each diploma, we subsequently merge an estimated automation risk based on Frey & Osborne (2017).[8]

In our analyses we control for basic demographics. These include gender and immigration background, which stem from register data of Statistics Netherlands.

[7] The match of automation risks of occupations to educational fields is not possible for higher or lower educational levels due to a too low number of fields.
[8] Automation risks stem from the analysis by Frey & Osborne (2017) because it is the automation risk estimation which is most relevant for our observation period from 2006 until today.

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We perform listwise deletion on key variables of interest so that our final analytical sample is N = 3,420. The majority of the missing data stems from the personality and cognitive ability items as well as the parental background questionnaire in the VOCL. For the sequence analysis and multinomial regression, the sample size is N = 3,266 as we exclude observations with more than 10% missing states over the ten-year observation period.

4. Operationalization of Measurements

We use the following variables in our analyses. Descriptive statistics of all variables are presented in Table 1, and the distributions of some of the key variables are shown in Figure A1.1 in Appendix 1.1.

Automation risk: We make use of the predicted probability of automation by Frey and Osborne (2017). The automation risks from Frey and Osborne (2017) were originally estimated on the Standard Occupational Classification (SOC) 6-digit level and then merged to ISCO 4-digit codes, which were in turn collapsed to ISCO 2-digit level. Using Data from the Dutch labor force surveys from 2006-2008, we subsequently calculated a weighted average of the automation risk of the most frequent 50% of ISCO 2-digit occupations within each Dutch education code (ONR). By this, we construct a measure of automation risk for each VET program. We then split this variable in tertials.

Monthly activity sequence: The monthly activity is obtained by merging two datasets from the Dutch administrative data (Bakker et al. 2014). The first includes calendar data on the main economic activity based on the main source of income. While it is theoretically possible to receive a larger income from social welfare than from employment in practice this is seldom the case and the employment would have to be low income/low workhours for this to happen. The original variable has twelve states: (1) employee, (2) director/major shareholder, (3) self-employed, (4) other self-employed, (5) recipient of unemployment insurance, (6) recipient of welfare, (7) recipient of other social benefits, (8) recipient of illness and disability benefits, (9) recipient of pension, (10) (not yet) pupil/student with income, (11) (not yet) pupil/student without income, (12) other without income. We combine states 1-4 into ‘Working’, states 5-9 & 12 into ‘NEET’, and states 10-11 into ‘Education’. We further separate ‘Working’ into ‘A’ and ‘B’ to capture the volatility of the career. The first contract after leaving VET will be ‘A’, the

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second contract will be 'B', the third contract again 'A' and so on. The second dataset includes calendar data on registration in publicly funded education. We combine the information from both datasets to distinguish secondary education from further education. We merge the two variables, whereas we let education overwrite other states. Primary education, practical education, and secondary education are grouped together as "Secondary Education and below". The other states represent the three main types of further education in the Netherlands, upper secondary vocational education (MBO), university of applied science (HBO), and research university (WO).

Log hourly wage: We calculate the hourly wage from the Dutch register data which include wages and working hours of different contracts per month. We sum up all contracts per person-month, divide the wage by four weeks and then by working hours per week to arrive at hourly wages. In some cases, likely accounting errors, values for wages were negative. We code these values as missing. We do the same with for hourly wages that are lower than the minimum wage for 19-year-olds in 2006 (3.86€) and higher than three standard deviations above the mean. We then deflate these nominal wages to real wages by dividing yearly values by their corresponding yearly customer price index (2015 = 100) and finally take the natural logarithm.

Cognitive skills: The VOCL'99 study included a test of cognitive abilities in three domains: math (Cronbach's $\alpha = .83$), language (Cronbach's $\alpha = .74$), and information processing (Cronbach's $\alpha = .79$) (Kuyper et al. 2003). Values were imputed by CBS for students who only finished two of the three subdomains (Kuyper et al. 2003). No test data is available for students who did not finish any subdomain test (N = 1216) and students who only finished one subdomain (N = 36). The test is comparable to the test used by the Dutch education system to track pupils into general and vocational schooling tracks (the so called CITO test). Values of the CITO test were also included in the VOCL data, however with higher rates of missing data. Both tests correlate highly, $r = .82$, $p < .01$. Both tests also correlate highly with the tracking advice given ($r = .78$, $p < .01$; $r = .82$, $p < .01$). To aid interpretation we standardize the score to the sample mean after listwise deletion.

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Personality traits: We make use of the Five Factor Personality Inventory (FFPI) which was part of the VOCL'99. It consists of 100 items to measure the factors Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Autonomy. Responses were collected on a five-point scale from 1 (not at all applicable) to 5 (entirely applicable). Observations were excluded if less than 70% of items were answered, responses were corrected for positive answering bias (acquiescence; 'yea-saying'), and missing values were imputed by the student's personal mean on the answered items per factor pole (Hendriks et al. 1999). Whether personality measured at age twelve is informative of events and choices several years later deserves further attention. The stability of personality over the lifespan and especially in early life phases is still subject to debate. Personality (normatively) matures during adolescence and stabilizes after young adulthood (Roberts and DelVecchio 2000; Roberts et al. 2006). However, evidence is mixed on precisely which personality traits change and, if at all, at which rate, time, or direction (Klimstra et al. 2012; Soto and Tackett 2015). Personality traits might not even change substantially after involuntary job loss (Anger, Camehl, and Peter 2017). We are thus confident that personality measured at age twelve is a valid measure of personality traits in the context of the school to work transition. First, early measurements ensure that our analyses are likely not to be inflated by reverse causality. Second, evidence of group-level changes does not imply intra-personal changes and can for instance be related to normative trends over the lifespan (Roberts et al. 2006). Thus, while on average a cohort might mature with age, not everyone in that cohort will change at the same rate, time, or direction, if at all. Evidence on intra-personal stability is less extensive, but generally confirms maturation and plateauing after young adulthood (Terracciano, McCrae, and Costa 2010).

MBO Level: From the education registers, we can distinguish MBO Level 3 from Level 4 and code them as a binary variable.

Field of Education: We separate educational programs by service/blue collar orientation. We consider the fields (1) Education, (2) Humanities and Arts, (3) Social sciences, Business and Law, (4) Science, Mathematics and Computing, (7) Health and Welfare, and (8) Services as services and the remaining fields (5) Agriculture and Veterinary, and (6) Engineering, Manufacturing and Construction, as blue collar.

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Gender: We use the variable provided in the register data to distinguish women (coded as 1) from men (coded as 0).

Immigration background: The country of birth of pupils and parents was obtained from Dutch register data. We distinguish between pupils with two Dutch born parents (coded as 0) from pupils who with at least one foreign born parent or who themselves were not born in the Netherlands (coded as 1).

5 Empirical models

We first use sequence analysis to explore the different trajectories from vocational education into the labor market. We observe these post-VET trajectories from the month of graduation from VET (MBO3/4) until ten years after. Then, we model the probability to a specific trajectory using multinomial logistic regression models. The model includes tertials of automation risk, standardized cognitive ability, and standardized personality traits. They also include variables to account for the educational differences within the VET system. First, a dummy for the overall orientation of the graduated VET program, either blue collar or services, and second, a dummy for the education level, either MBO3 or MBO4. We also include dummies for gender and immigration background.

In addition to the type of early career, automation risk is expected to influence wages earned and the rate of wage growth in the early career. We expect that a VET program with a higher automation risk would result in a lower starting wage and slower wage growth. We also expect these effects to be moderated by personality traits and cognitive abilities. In the following section, we test these hypotheses using growth curve modeling (GCM).

In essence, GCM are two-level multilevel models. In this case, multiple time-observations (level 1) nested within individuals (level-2). This strategy allows us to observe the role of time-invariant variables (such as the estimated automation risk of an education) on the development of wages. The basic specification can be written as:

$$y_{ti} = \beta_0 + \beta_1 YEARS_{ti} + \beta_2 AUTORISK_i + (\mu_{0i} + \mu_{1i} + \varepsilon_{ti})$$

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Where the hourly wage y at time t for the individual i is regressed on a linear term for years since graduating VET and the time-invariant variable of the estimated automation risk of VET programs. The random part of the equation (in brackets) includes the random intercept (μ_{0i}), the random slope for linear time (μ_{1i}) and the person-specific residual error term (ε_{ti}).

6 Results

Results of the sequence analysis and clustering are shown in Figure 1. It provides us with descriptive evidence on the main trajectories after graduation of the VET students in the Netherlands. We find four clusters that represent different typical trajectories after VET in the Netherlands. First, we find the largest cluster Stable Employment, 36.5% of our sample follow this trajectory. Next, we find a cluster we name Employment changes (30.2%), which includes trajectories that are more often interrupted and change employers more often. Hence, about 66% of the graduates find employment after graduation, of which slightly more than half is stable employment. The third cluster is Further Education (29.2%) and represents a very common way to stream from MBO4 into HBO Bachelor programs. 4.1% follow a trajectory predominantly described by time spent neither in employment, nor education (NEET).

Table 2 shows the marginal effects of the multinomial logistic regression that models the probability to follow one specific cluster. We find that, on average, graduates from VET programs with a medium level of automation risk have a slightly higher probability to follow Further Education and a lower probability to follow Stable Employment than graduates from a low automation risk VET program. However, and refuting our hypotheses, a high automation risk VET program is not associated with an increased probability to follow any specific trajectory, compared to low automation risk VET programs. We had expected that a higher automation risk would increase the chance to follow a re-education or NEET trajectory.

We also estimated a multinomial logistic regression that models the probability to follow one specific clusters in which we additionally included interaction terms between the different levels of automation risk and cognitive skills and personality traits. Based on this multinomial logistic regression, Figure 2 shows the predicted probabilities to follow the four clusters for the interaction terms of different levels of automation risk over cognitive skills and personality

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traits. None of these interaction terms are statistically significant. This implies that cognition and personality traits do not play a role in the relation between automation risks and early career trajectories after VET education. As we did not find a clear relation between automation risks and early career trajectories in the first place, this is not surprising.

However, these results do not imply, that automation risks do not play a role in early careers at all. Figure 3 shows the average real hourly wage over time for three levels of automation risk. Consistent with our expectations, graduates from a VET program with a high estimated automation risk have lower starting wages than VET graduates from programs with low estimated automation risk. Thus, although automation risks do not seem to affect the probability of getting a job, they do seem to affect the starting wages of VET graduates. The figure also shows that, overall, wages seem to grow quite linearly.

We test the role of automation risks in both starting wages and wage growth more formally, by estimating multilevel growth-curve models. First, we estimate a null model (not shown) without covariates, to decompose the variance into between- and within-person variances. The unexplained variance on the between individual level is .035. The unexplained variance within individuals is .036. The ratio of the between individual variance and the sum of both between- and within-person variance is the intraclass correlation, which in this case is equal to .495, meaning that 49.5% of the total variance can be ascribed to level 2. Put differently, for 49.5%, the differences in real hourly wages between people are due to differences between people and the remaining 50.5% are due to differences within people. The intercept of this null model represents the mean of all intercepts, in this case $e^{2.736}$ = 15.42€.

Next, we add a linear specification of years since graduating from VET (Model GC1) and a random slope of years. The coefficient of years since VET is .039 and statistically significant, meaning that on average, hourly wages in the early career increase by 3.9% or $e^{0.39}$ = 1.03€ per year. By taking into account years since obtaining a VET diploma (MBO3/MBO4) for the first time, we now explain more of the within-person variation, which has decreased to .013. At the same time, the random slope allows for more differences between people. Hence, the intraclass correlation has increased to 78%. As we add variables to the fixed part of the model, the intraclass correlation decreases as we explain more between-person differences.

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To test our hypothesis that automation risk decreases hourly wages, we add to the model our measurement of automation risk of VET programs. Model GC2 shows, that medium- and high-risk programs are associated with lower hourly wages as compared to VET programs that have a low automation risk. Specifically, we find that a medium-risk program reduces hourly wages by 7.8% ($p < .001$) on average and that high-risk programs reduces hourly wages by 10.2% ($p < .001$). Therefore, we can accept the hypothesis that automation risk of VET programs is associated with lower wages.

To model wage growth, we add an interaction term of time and automation risk (Model GC3). Contrary to our expectations, but consistent with Figure 3, VET programs with a medium automation risk are significantly associated with a .005% higher wage growth ($p < .01$) as compared to programs with a low automation risk. Based on Figure 3, this seems to be driven by a higher wage growth in the period 5-7 years after graduation. Except for these years, wage growth seems to be linear to that of those graduated from programs with low and high automation risks. Also contrary to our expectations, but in line with Figure 3, high automation risk VET programs are not significantly associated to wage growth ($p = .301$). This leads us to reject the hypothesis that automation risks of VET programs negatively affect wage growth in the early career. The absence of a clear wage growth effect might be explained by collective agreements made on the sectoral level. Whereas starting wages depend more on the supply-demand relation in the year of graduation, wage increases thereafter are, for those not changing jobs, mainly determined by wage scales and inflation corrections, which are largely fixed.

In the following models, we therefore focus on explaining differences in overall hourly wages, not growth, by leaving out the interaction term. In Model GC4 (Table 4), we add a battery of socioeconomic and demographic control variables. We find that women (vs. men), persons with an immigration background (vs. NL-born with two NL-born parents), graduates from service-oriented VET programs (vs. blue collar oriented) all have significantly lower starting wages. We also find that graduates from the higher-level VET have lower starting wages than graduates from the lower track (MBO4 vs MBO3). This is likely due to the fact that MBO4 graduates can go on to attend Universities of Applied Sciences (as seen in Table 2).

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In Model GC5, we add interaction terms of automation risk with personality traits and cognitive abilities to estimate the moderating role of cognition and personality traits in the relation between automation risks and wages. For ease of interpretation, the interactions are also presented as marginal effects plots in Figure 4. In all plots we see the level effect of automation risk we have observed before: lower automation risk VET programs (solid blue line) are associated with higher average wages than medium (dashed red line) and high automation risk (dash-dotted green line) VET programs. For cognition and personality traits that we hypothesized to compensate automation risks, we should observe a convergence of wages of those educated for occupations with low, medium and high automation risks towards the right side of the plots. This would mean that the differences between the levels of automation risk become smaller with higher scores on cognitive skills, or extraversion, conscientiousness, emotional stability and autonomy. On the other hand, as we expect high scores of agreeableness to exacerbate the negative association with automation risks, we expect to see a divergence towards the right side of the plot for this trait.

We do find some visual evidence of convergence, however, that is also driven by the slight (non-significant) negative slope of cognitive skills for low automation risk VET programs. For agreeableness, we find indeed evidence of divergence, or rather a convergence towards dominance. Meaning, that with a higher agreeableness, we find higher average hourly wages for low automation risk VET programs, but lower average hourly wages for medium automation risk VET programs. For high automation risk VET programs, hourly wages do not significantly change with agreeableness. For autonomy (openness), we find some visual evidence of convergence: with higher autonomy, average hourly wages increase for medium automation risk VET programs, but not for lower or higher automation risk VET programs. We also find some visual evidence for convergence for emotional stability. Higher emotional stability is associated with lower wages for those who graduated a low automation risk VET program, while it is associated with higher wages for those who graduated a medium and high automation risk VET program. For extraversion, we find that higher extraversion benefits those with low automation risk VET programs, but not those with lower medium and higher automation risk VET programs. For conscientiousness, we do not find any difference in the slopes of automation risks.

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7 Conclusion

We set out to explore the role of automation risk in the early career of VET graduates in the Netherlands. First, we found four post-VET trajectories. However, automation risk did not explain the allocation of graduates to these trajectories. This suggests that the automation risk of VET programs is not (yet) driving young graduates out of employment. Second, we show that there are lower wage returns to educations which are expected to be more easily automated. However, wage growth is not affected by this. This might be because we only look at the first ten years of the career. Moreover, in the Netherlands, wage growth is largely determined by collective agreements made on the sectoral level. Whereas starting wages depend more on the supply-demand relation in the year of graduation and demonstrated skills, wage increases thereafter are, for those not changing jobs, mainly determined by wage scales and inflation corrections, which are largely fixed.

Moreover, we found that personality traits, specifically autonomy (openness to experience) and emotional stability, can compensate partly for a higher automation risk with regards to hourly wages, while cognitive skills have no significant interaction effect. This suggests that these personality traits make VET graduates more resilient to automation risks. Higher levels of agreeableness, however, are associated with significantly lower hourly wages of graduates of VET programs with a high automation risk.

Our results are of great importance for the literature on the impact of technological change on labor market outcomes, as we did focus on medium-skilled workers who are the ones most affected by the polarization caused by technological change (Autor 2015; Goos et al. 2009, 2014). We showed the degree to which automation risks depend on educational fields, as well as that even within education fields, some VET graduates will suffer more from automation risks than others. Moreover, our paper adds to the recent empirical literature that show that cognitive skills and personality traits are powerful determinants of human capital investments, wages, and many other aspects of social and economic life (e.g., Borghans et al. 2008; Deming 2017; Heckman, Stixrud, and Urzua 2006; Murnane, Willett, and Levy 1995; Roberts, Walton, and Viechtbauer 2006), by providing further evidence that personality skills in relation to automation play also a vital role in compensating the negative effects of automation.

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Tables and Figures

Table 1 Summary statistics

	Freq.	%
Time constant variables		
Estimated automation risk		
Low	1,385	42.4
Medium	862	26.4
High	1,019	31.2
Early career trajectory		
Employment changes	987	30.2
Further Education	954	29.2
NEET	134	4.1
Stable Employment	1,191	36.5
Level of diploma		
MBO3	1,104	33.8
MBO4	2,162	66.2
Field of diploma		
Blue collar	718	22
Services	2,548	78
Migration background		
No	2,847	87.2
Yes	419	12.8
Gender		
Male	1,592	48.7
Female	1,674	51.3
Parental homeownership		
Owned	2,320	71
Rented w/ subsidies	320	9.8
Rented	626	19.2
Parental Education		
Lower	898	27.5
Secondary Education	1,675	51.3
University	693	21.2
N (Person-years)	30770	
N (Persons)	3,266	

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Table 2 Multinomial logistic regression of early career trajectories on automation risk of VET programs and socioeconomic variables

	Employment Changes	Further Education	NEET	Stable Employment
Automation risk, ref. cat.: Low risk				
Medium	0.03	0.05*	0.01	-0.08***
High	-0.00	0.02	-0.00	-0.01
Cognitive Ability & Personality				
Cognitive skills	-0.01	0.03***	-0.01	-0.01
Emotional Stability	-0.01	0.00	-0.01*	0.01
Extraversion	0.00	-0.01	-0.01	0.01
Conscientiousness	0.01	-0.00	0.00	-0.01
Agreeableness	0.00	0.01	-0.00	-0.01
Autonomy (Openness)	-0.01	0.02*	0.00	-0.01
Field of diploma, ref.cat.: Blue Collar				
Services	-0.01	0.09***	0.01	-0.09***
Gender, ref.cat.: Male				
Female	-0.02	-0.07***	0.04***	0.05*
Immigration backgr., ref.cat. No				
Yes	-0.01	0.07***	0.04***	-0.10***
Level, ref. cat.: MBO3				
MBO4	-0.14***	0.32***	-0.02***	-0.16***
N (Persons)	3266			
BIC	7884.848			
McFadden Pseudo R^2	0.0868			

Coefficients represent average marginal effects; * p <0.05 ** p <0.01 *** p <0.001

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Table 3 Random-effects growth curve models

DV: Real log hourly wage	GC1	GC2	GC3
Intercept	2.565***	2.618***	2.620***
Automation risk, ref. cat.: Low risk			
Medium		-0.078***	-0.093***
High		-0.102***	-0.097***
Years since VET	0.039***	0.039***	0.039***
Years since VET X			
Medium			0.005**
High			-0.001
Variance components			
Between	0.048***	0.045***	0.045***
Within	0.013***	0.013***	0.013***
Random slope (Years)	0.001***	0.001***	0.001***
Covariance intercept-slope	-0.003***	-0.003***	-0.003***
BIC	-28211.0	-28379.2	-28374.2
ICC	0.780	0.772	0.772
N (Person-years)	30770	30770	30770
N (Persons)	3420	3420	3420

$*$ $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

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Table 4 Random-effects growth curve models

DV: Real log hourly wage	GC4	GC5
Intercept	2.740***	2.728***
Years since VET	0.039***	0.039***
Automation risk, ref. cat.: Low risk		
Medium	-0.122***	-0.120***
High	-0.129***	-0.123***
Cognitive Ability & Personality		
Cognitive skills	-0.003	-0.006
Emotional Stability	0.001	-0.011*
Extraversion	0.008*	0.017***
Conscientiousness	0.000	0.000
Agreeableness	0.002	0.022***
Autonomy (Openness)	0.005	-0.007
Interaction terms		
Medium X Cognitive skills		0.017*
Medium X Emotional Stability		0.021*
Medium X Extraversion		-0.017*
Medium X Conscientiousness		0.000
Medium X Agreeableness		-0.050***
Medium X Autonomy (Openness)		0.027**
High X Cognitive skills		-0.005
High X Emotional Stability		0.022**
High X Extraversion		-0.016*
High X Conscientiousness		0.001
High X Agreeableness		-0.020*
High X Autonomy (Openness)		0.014
Gender, ref.cat.: Male		
Female	-0.017*	-0.019*
Immigration backgr., ref.cat. No		
Yes	-0.033**	-0.032**
Field of diploma, ref.cat.: Blue Collar		
Services	-0.090***	-0.078***
Level, ref. cat.: MBO3		
MBO4	-0.015*	-0.018*
Housing ownership, ref. cat. Owned		
Rented w/ subsidies	-0.019	-0.021
Rented	-0.010	-0.009
Parental education, ref. cat. Low		
Secondary Education	-0.007	-0.008
University	-0.007	-0.008
Variance components		
Between	0.043***	0.043***
Within	0.013***	0.013***
Random slope (Years)	0.001***	0.001***
Covariance intercept-slope	-0.003***	-0.003***
BIC	-28404.9	-28341.2
ICC	0.764	0.761
N (Person-years)	30770	30770
N (Persons)	3420	3420

* p <0.05 ** p <0.01 *** p <0.001

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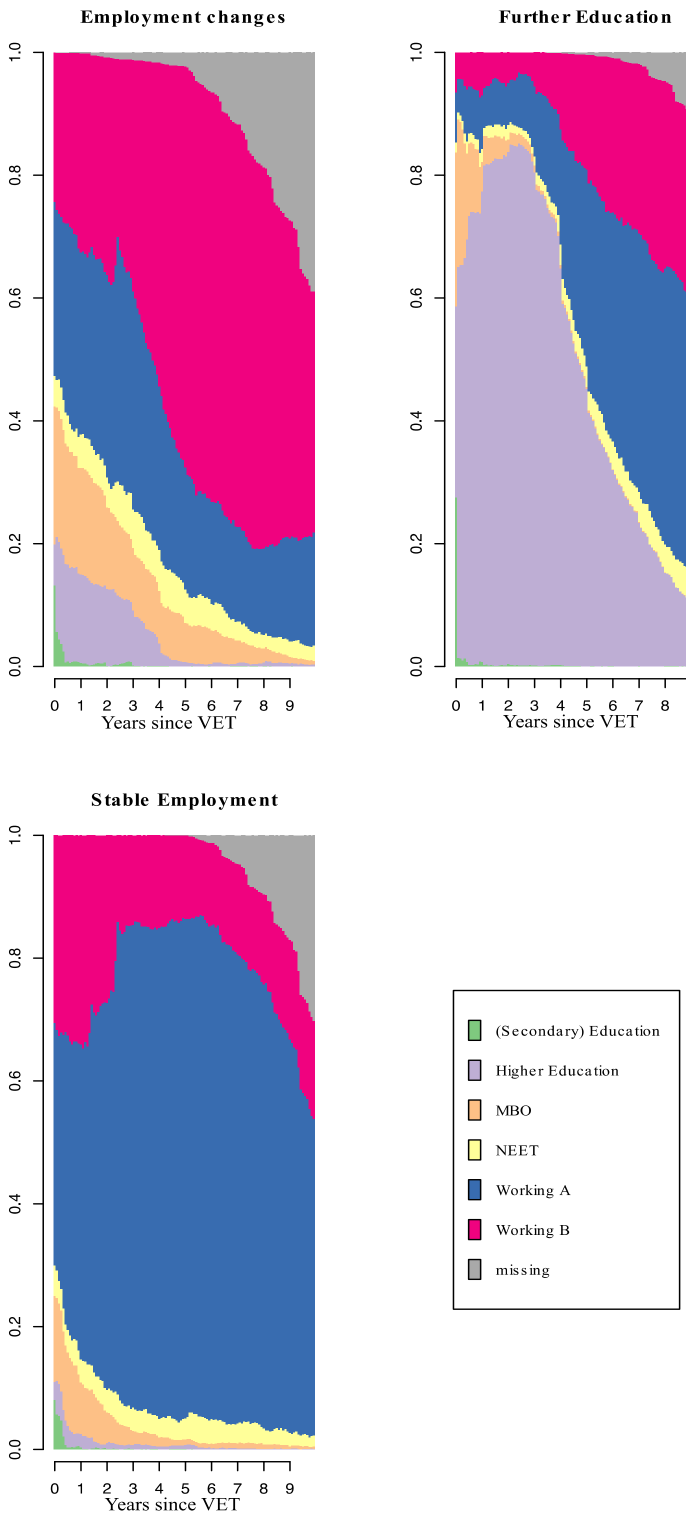
Figure 1 Sequence distribution plot of four typical post-VET trajectories.



Note: Trajectories as obtained from optimal matching and cluster analysis. Monthly states are mutually exclusive. Simultaneous enrollment in education overwrites possible working activities. Working states 'A' and 'B' represent different contracts, where the first contract after graduation is A, the second B, the third again A and so on.

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Figure 2 Interactions of automation risks with cognitive skills and personality traits to predict cluster membership

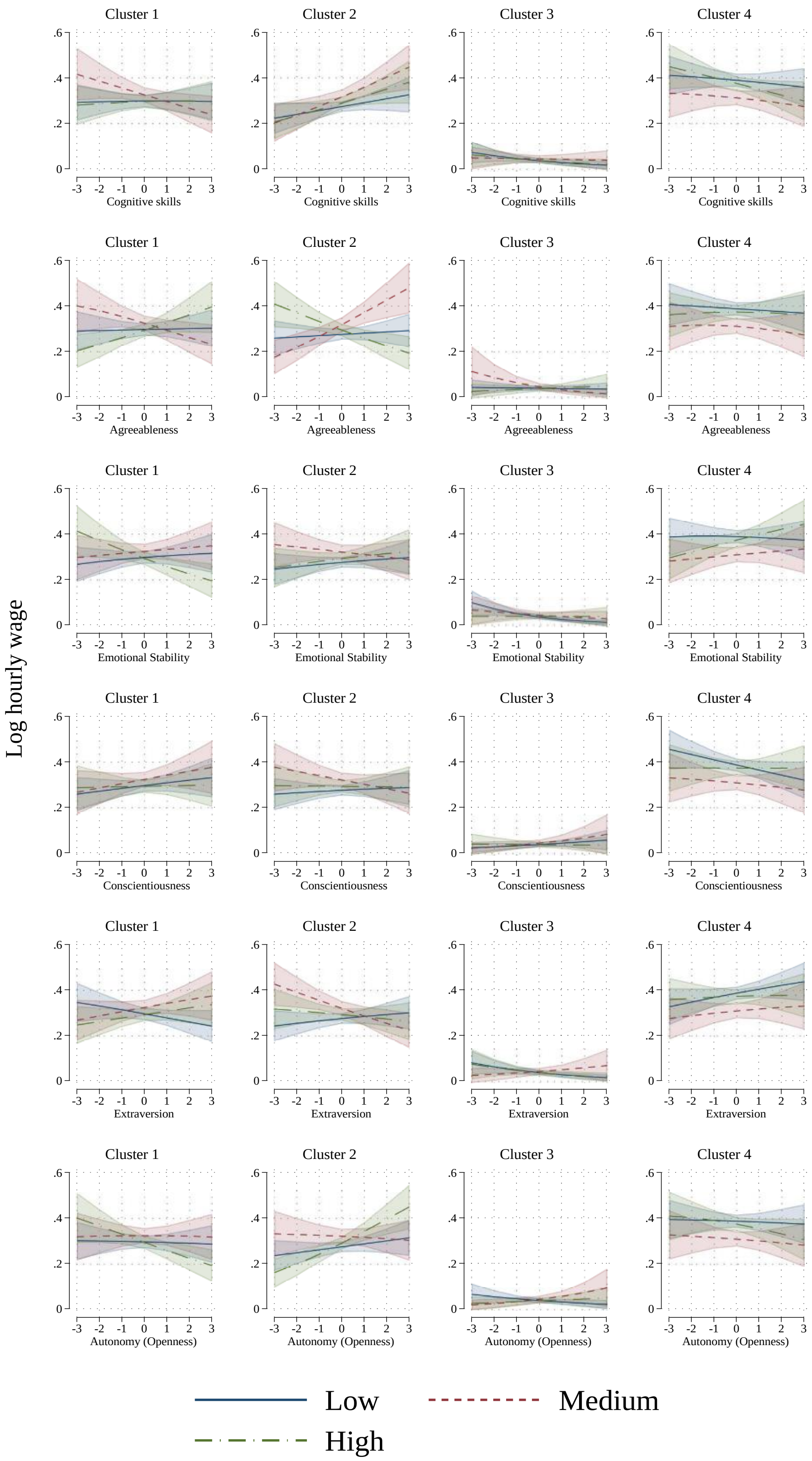

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Figure 3 Average wage profiles of vocational education graduates by tertials of automation risk

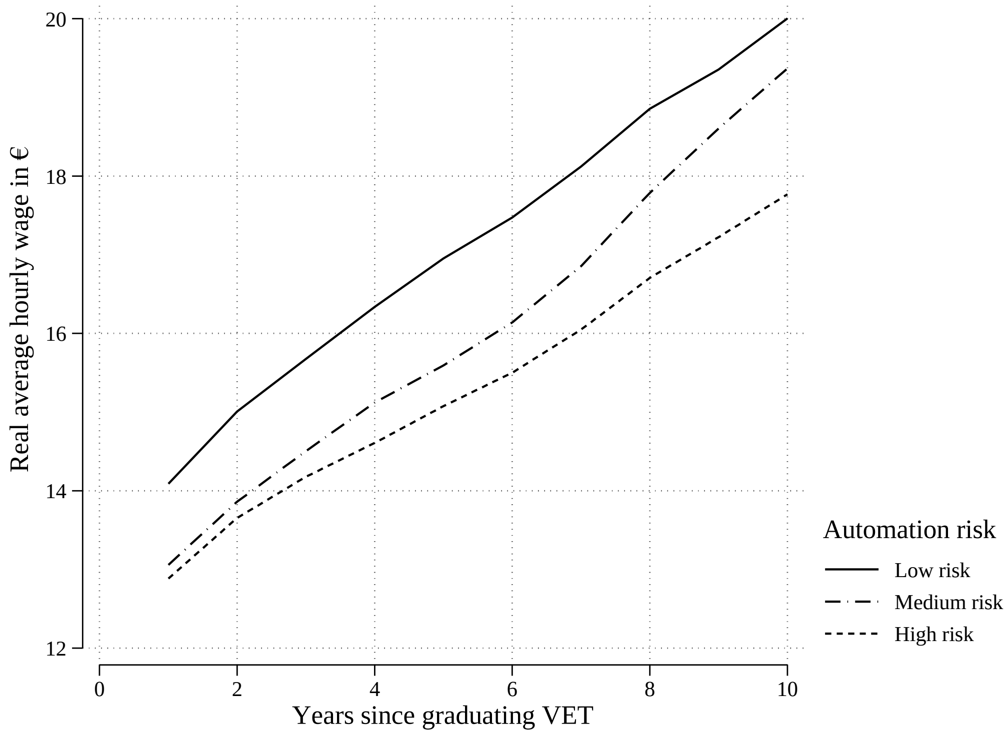

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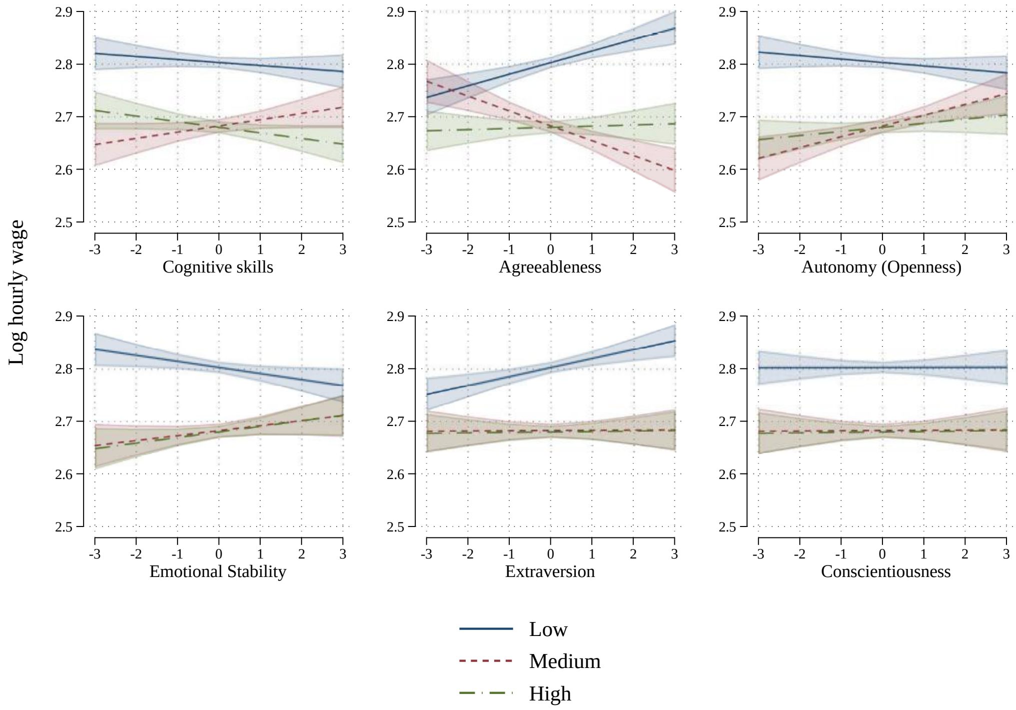
Figure 4 Interactions of automation risks with cognitive skills and personality traits to predict log hourly wage



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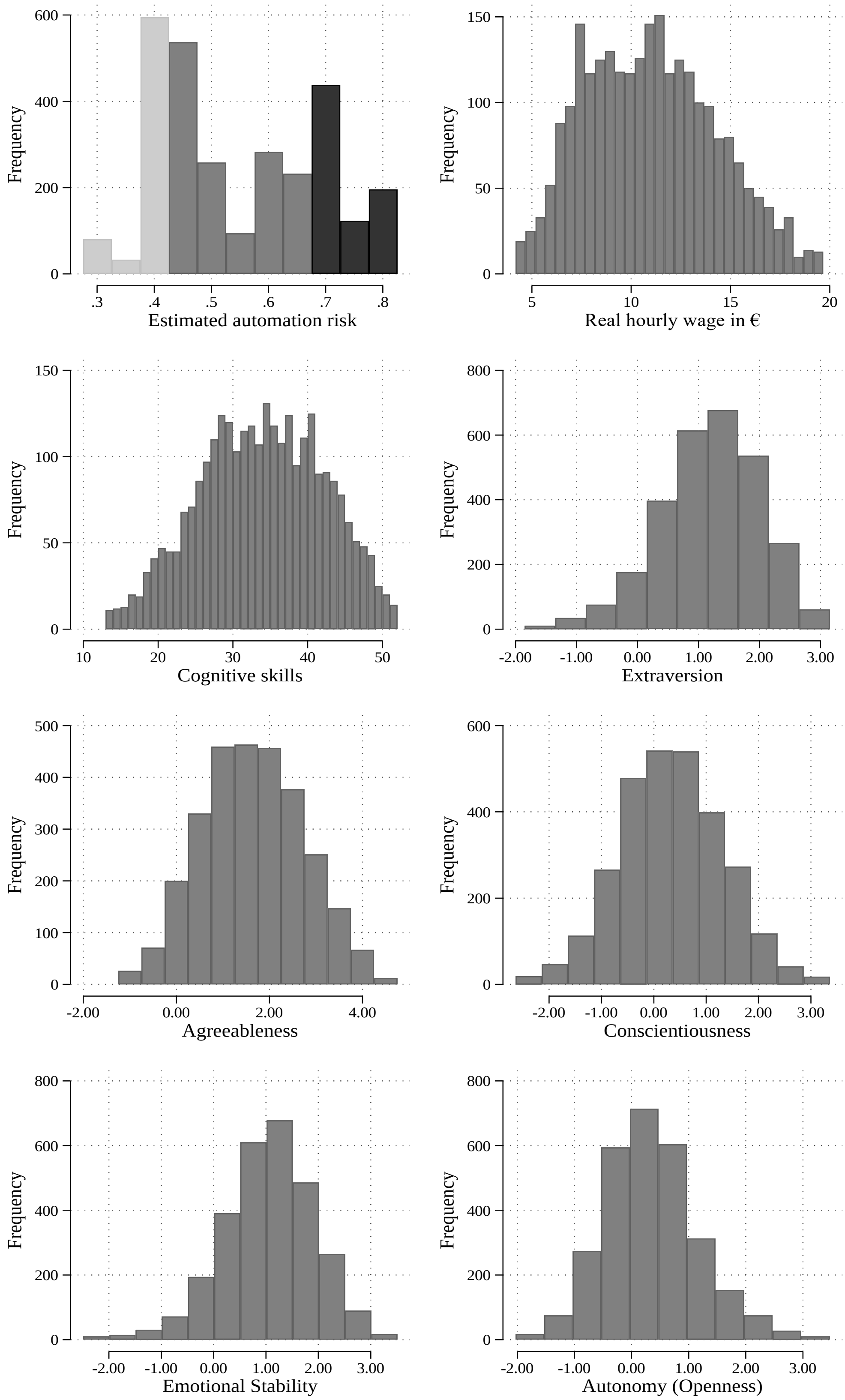
Appendix 1.1

Figure A1.1 Distributions of main variables of interest before standardization



Note: Frequencies < 10 not shown

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Appendix 2

Educated for bad years to come?
Precariousness in the short and the long run for those who are educated for occupations with high automation risks in Sweden

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Abstract

Using Swedish registry data, the chapter sheds light on consequences of automation risks, in terms of risks of ending up in precarious economic situations after examination from 98 specific educational tracks. Automation risks are derived from occupational automation risks. First, there is a high and almost linear association between automation risks and years of education. Second, vocational tracks for men, compared to women, have considerably higher automation risks. There is only limited support for the idea that precariousness is associated with automation risks but in general the results indicate that years of schooling is of substantially larger importance.

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1. Introduction

Automation of work tasks is not something new and some early examples of automation is the introduction of Spinning Jenny in the textile industry at the end of the 18th century and the assembly line in manufacturing in the early 20th century. An early Swedish invention that led to a drastic decline of one occupation was the automatic AGA-lighthouse introduced in 1905 that eventually made lighthouse keepers redundant. What is claimed to be new with the automation of the late 20th and the 21st century is that also advanced non-routine work tasks, both cognitive and manual, can be automated through usage of machine learning and robotics (including artificial intelligence) – sometimes together referred to as computerization (Frey and Osborne 2017).

A recurrent theme in the history of automation is the belief that jobs will disappear and not be replaced with a corresponding number of new jobs. Although there is indeed unemployment in a number of European countries from decades back in time the lion's share of unemployment is probably related to business cycles as it fluctuates. At least it is premature to claim that there is ever-increasing unemployment caused by automation; we have not seen it yet in any case (Autor 2015, but see Kim et. al. 2017). Hence, another possibility is that automation opens up for new opportunities in the labor market which sometimes is referred to as "creative destruction" using Schumpeter's words (see World Bank 2019, OECD 2019).

Much research in this area is oriented towards trends at the macro level. With the usage of micro level data, it is also possible to study the consequences of automation risks at the individual level. In this chapter we will use Swedish registry data to follow individuals across time after examining from school and universities to explore whether those who are educated for work tasks that are likely to be automated are overrepresented in a precarious economic situation in the short as well as in the long run. Moreover, we will investigate whether skills such as cognitive ability and an attractive personality/having high non-cognitive skills are able to counteract the potential higher risk of ending up in precariousness when being educated for work tasks that are at high risk of being automated. The time period of the analyses covers 1997-2012, which is a period characterized by economic growth as well as a shorter recession before 2010, when unemployment also increased for a few years.

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2. Automation risks from macro to micro analyses

The point of departure for this paper is research that has attempted to assess the risk of automation, or more specifically computerization, in occupations where Frey and Osbornes study (2017, published in 2013 originally) stands out as the most influential. Frey and Osborne assess the risk of automation in occupations by, first, using expert judgements for 70 occupations and then O*net data to identify bottle necks to computerization. Second, this is followed by a probabilistic classification of around 700 occupations. They concluded that especially low wage occupations with low skill requirements face the highest risks for computerization and more specifically that: "…in short, generalist occupations requiring knowledge of human heuristics, and specialist occupations involving the development of novel ideas and artifacts, are the least susceptible to computerisation". Using the framework of Frey and Osborne there has been assessments in a number of countries of the proportion of occupations that are at risk of computerisation (e.g. Frey et. al. 2016).

In Sweden Fölster's (2014) results suggest that around half of all jobs in Sweden could be automatized in 20 years which is somewhat more than in the U.S.. Fölster also argues that Sweden has relatively high wages for many of the occupations with high automation risks, as well as a relatively regulated labor market, which may increase the risk of automatization of these occupations in Sweden compared to the U.S.. It is worth mentioning that Fölster's results are based on the Frey and Osbornes classification of automation risks. Hence, it assumes that occupations are similar between Sweden and the US. and have similarities in automation risks. It is close to impossible to know to what extent this holds true but, first, technologies are hardly nation-specific but most likely diffused in the world. Second, as long as the Frey and Osbornes measures are used for around the same years it could be argued that the automation risks would be similar.

Nonetheless, a critique against the approach of Frey and Osborne is found in Walsch (2018) where it is indicated that the original expert judgements for the initial 70 occupations may have been somewhat on the higher side in assessing automation risks, compared with another expert panel used. Moreover, an approach based on assessing the automation risks, with a work tasks approach instead of an occupationally based approach, gives substantially smaller automation risks which suggests that there is a variation of automation risks in occupations

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(Arntz et. al. 2016). In all, it may be the case that assessments of automation risks are over-estimated when using the Frey and Osborne approach. However, the Frey and Osborne measures may still be meaningful as a way to assess relative automation risks in occupations although the exact level of automation risk in an occupation can be settled first in retrospect. Hence, the assessment that half of all jobs will disappear in the upcoming 15-20 years in Sweden could be somewhat exaggerated. Potentially more important; such a macro analyses based on the distribution of occupations in a country says little, if anything, on what will happen at the individual level. Although it could be the case that many occupations become redundant in the future, due to automatization, they may be replaced by new and perhaps better jobs (C.f. OECD 2019, World Bank 2019). Going back to the light house example, most lighthouse keepers probably found other jobs when the occupation disappeared in the dynamic economy of the first decades of the 20th century.

One way to gain a deeper insight in how individuals face the consequences of automation risks is to follow individuals after examination from school/university and study if those educated for work tasks that are at risk of becoming automatized have higher risks of ending up in unemployment and precarious economic situations. It may even be the case that automatization opens up new possibilities at the individual level with new types of jobs in the same industry or in other industries. This paper contributes with such micro analyses for the case of Sweden by deriving automation risks of specific educational tracks from Frey and Osbornes automation risks of occupations. The over-all idea is that skills are learnt during education which typically lead to employment in a number of occupations with similarities in work tasks. However, some educational tracks are too general to lead to similar occupations. Hence, the analyses are restricted to educational tracks that typically lead to occupations with similar automation risks. Skills are accumulated through schooling and through work experience, as suggested in human capital theory (Becker 1964), but there are also skills that to a large extent are learnt prior to schooling, sometimes labelled cognitive and non-cognitive skills (the latter being close to personality), that can be useful in the labor market (Heckman et. al. 2006, Kautz et. al. 2014). The importance of non-cognitive skills has been highlighted in recent research (see Kautz et. al. 2014 for a review) and for our purpose we may assume that both cognitive and non-cognitive skills may enhance opportunities for those educated for occupations with high automation risks as they may take advantage of other skills than those

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learnt at school/university. Such skills are likely to be more of a general kind than skills learn at school/university and may therefore counteract negative effects of being educated for occupations with high automation risks.

Going back to the critique of the Frey and Osborne approach above, first, in the upcoming analyses we need not to assume that automation risks are realistic in terms of levels just that the risks are of varying magnitudes between occupations. Hence a macro analyses with the aim to predict how many jobs that will disappear future wise is arguably more in need of realistic levels than the kind of micro analysis that are carried out in this chapter. Second, an occupationally based approach seems intuitively sound as educational tracks, if focusing on the more specific ones, typically lead to specific occupations. Therefore, it seems plausible to derive automation risks from occupations held after certain educational tracks. However, a direct work task approach could also be possible in future research when the relevant information is available.

3. Research questions and hypotheses

The research question of this paper is: What are the short- and long-term consequences of automation risks for labor market precariousness? More specifically two hypotheses are formulated:

H1: Individuals who are educated for performing work tasks that are at high risk of automation have higher risks of ending up in precarious labor market situations in the short run or/and the long run.

H2: For those who face such high automation risks the risk of ending up in precarious labor market positions are lower for those with advantageous personality traits and high cognitive ability.

Since automation risks, but also cognitive ability, are highly associated with years of education we adjust for years of education in the models. We conduct separate analyses for the genders. Besides adjusting for years of education separate analyses for both those with upper secondary vocational education and tertiary education is conducted. This is done both as a sensitivity test but also to study if automation risks are associated differently with precariousness for those with different educational backgrounds.

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4. Data and analyses

For the analyses we have access to Swedish registry data where individuals can be followed from examination and up to ten years after examination. The first step in the analyses is to link automation risks to specific educational tracks (329 different) through automation risks at the occupational level. Individuals examined from 1996-2007 are followed in registers from two years after exam up to nine years after exam until the year 2012 (the last year available). The restriction in follow-up time to nine years is chosen as it is probably the case that there is a growing variation in skills over time as individuals gain skills differently across time and not only from schooling (if individuals go back to school/university they are excluded from the data and censored). The first year after exam is excluded as there may be more variation in the first year before having ended up in an occupation that matches the education. As a very detailed educational variable is used in order to capture different skills a large population is required and this data covers 3,7 million person-years with valid occupational information.

Since some educational tracks are general and do not lead to a specific set of skills, and subsequent typical occupations, a selection criterion is used so that educational tracks that lead to occupations with a large variation in automation risks are excluded from the analyses. First, 15 educational tracks are removed because they cover only 20 individuals or less each and, hence, are seen as too small to produce reliable estimates of automation risks. Second, a criterion is used so that the inter-quartile range (IQR) in automation risks for each educational track is required to be less than 15 percent. This means that if the value of the 75th percentile minus the value of the 25th percentile is more than 15 percent for specific educational tracks individuals with such a track are excluded. Somewhat less than one third of the educational tracks have an inter-quartile range below 15, which means a reduction of tracks to 98 from 314. This means that many general tracks are excluded and in fact all exams below secondary school (up to 9 years of schooling), but also some general tracks at higher educational levels.

Although the requirement of the IQR to be below 15 percent is arbitrary it comes close to requiring that the 25th and the 75th percentile correspond to the same category of automation risks that are used below in the analyses (less than 30 percent, 30-60 percent, more than 60 percent). All tracks with an IQR below 15 meet this criterion and additionally 21 tracks meet

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only this ‘category criterion’ and not the IQR less than 15 percent criterion. Hence, in the analyses, as a sensitivity test we also rerun the analyses with the less restrictive sample which cover around 84 percent more individuals. Finally, individuals who examine relatively late in life are excluded as they may have left school earlier but are examined later for different reasons (the sample is restricted to those aged 16-30 when examined).

The occupational automation risks are taken from Frey and Osborne (2017), and then matched to the international occupational coding ISCO-88 using a cross-walk from the occupational code of the US, i.e. SOC (Hardy et. al. 2018). As there often are several SOC codes for each ISCO-88 code (three-digit level) the median automation risk for each ISCO-88 code was used. The median was used instead of means to reduce the risk of small SOC occupations to bias the automation measure downwards or upwards. Finally, when estimating automation risks of educational tracks means were instead used to make a measure of the average automation risks. The measures of Frey and Osborne (2017) correspond roughly to the same time period as being investigated in this chapter. There is most likely a time variation in automation risks of occupations, e.g. the work tasks of truck drivers quite recently became perceived as being possible to automatize.

In the next step of the analyses the average automation risks of educational tracks, constructed in the first step, is used to analyze the risk of ending up in a precarious situation in the short respectively in the long run from 1997 to 2012. Both dependent variables define a precarious situation as having annual earnings from tax records below 100 k SEK (roughly corresponding to 10 k Euros) for three out of five years in the very start of careers, i.e. in one to five years after, or in the subsequent period, i.e. six to ten years after examined from school/university (as far as the individual has not returned to school/university). To have earnings below this cut-off point means not being gainfully employed or self-employed for most individuals – at least not for an entire year. However, for some it may indicate part-time work. By setting the criterion to three out of five years we lower the risk to include temporary low earners in the group with a precarious situation.

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4.1 Measures of cognitive ability and personality

For men born from 1966 to 1978 we have access to military enlistment/conscription data on cognitive ability and personality collected around the age of 18 which is prior to leaving school and university for most individuals. Enlistment was mandatory for men in these birth cohorts although exceptions were made (See Bihagen et. al. 2017). In practice, in order for these birth cohorts to be followed after examination before 30 years of age (see age restriction above) only those being examined at age 30 in the 1966 cohort are included (i.e. in 1996), and for the 1978 cohort those examined at age 18-29 are included where the oldest can be followed for five years up to 2012.

The first measures of interest capture cognitive ability through four tests aimed to measure induction, verbal comprehension, spatial ability and technical comprehension. A general dimension is derived out of the measures using factor analysis (by the military), ranging from 1 to 9.

The second set of measures are based on interviews by a psychologist. This interview lasts approximately 20 minutes and results in four measures intended to indicate social maturity (extraversion, having friends, taking responsibility, independence), psychological energy (perseverance, ability to fulfil plans and to remain focused), intensity (the capacity to activate oneself without external pressure, the intensity and frequency of free-time activities), and emotional stability (the ability to control and channel nervousness, tolerance of stress, and disposition to anxiety). The measures partly cover well-known personality traits referred to as the big five but they are not identical to them (see Bihagen et. al. 2017, Mood et. al. 2012). For the current analyses these indicators are summed up to an index, ranging 1-20, as they have similar associations with the outcomes of the analyses. Both the personality index as well as cognitive ability index are z-standardized (mean 0, sd 1).

4.2 Models

The analyses are based on OLS-regressions with the binary outcomes of economic precariousness as dependent variables (described above). Models using logistic regressions give similar results but an OLS-regression framework offer some advantages when it comes to comparing associations across models and are, hence, preferred here (Mood 2010). The focus

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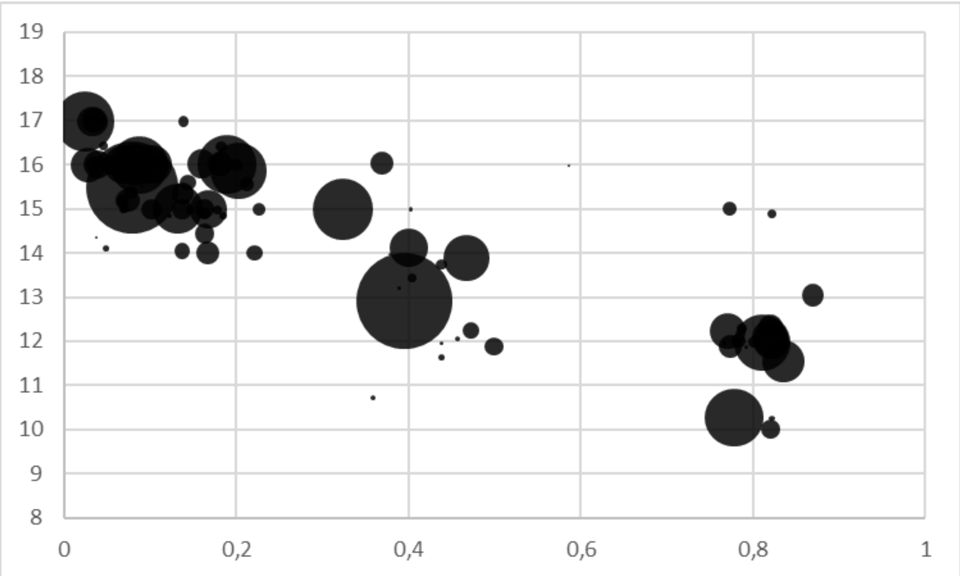
is on the associations with automation risks. In order to use the complete data-set the regressions are first conducted for all individuals examined from school and university 1996-2007, with valid earnings in the first 5 years after examination (including zero-earnings) or/and the subsequent 6-10 years after examination up to the year 2012. Second, data is restricted to men born from 1966 to 1978 with valid enlistment
data.

In the first model results are adjusted for age (linear and squared). In the second model controls for years of education are included (as categories). Then for those with enlistment data controls for cognitive ability and personality are added (model 3). Finally, interaction terms between automation risks and cognitive ability (model 4) or interaction terms with personality are added (model 5).

5. Results

In Diagram 1 the average automation risks for 98 educational tracks are plotted by average years of education. In line with Frey and Osborne (2017) it is obviously the case that there is a strong and almost linear association between years of education and automation risks. Moreover, outliers tend to be relatively small.

Diagram 1 Average automation risks (x) by years of education (y) for 98 educational tracks (bubble areas represent sizes of educational tracks)



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Based on the results visualized in Diagram 1, it is possible to create a trichotomy from the automation risks where automation risks between 30 and 60 percent are used as a middle category. In Table 1 this categorization of automation risks is cross-tabulated by groups of educational tracks, i.e. all tracks, vocational upper secondary tracks and university tracks. The latter two make up almost all of the 98 tracks of the first column since theoretical tracks at the upper secondary level have too much variation in automation risks to be included in the analyses. Once again, there is a clear association between length of education (where the vocational ones are 11 or 12 years, and university from 14 years) and automation risks, where those with vocational education rarely have low automation risks at all while those with university education seldom face high automation risks. There is a remarkable gender difference when it comes to vocational tracks where as much as 96 percent of these end up in the high automation risks for men whereas 91 percent of these end up in the middle automation risks for women.

Table 1 Automation risks by educational groups (in percent)

Men			
	All 98 tracks	Vocational tracks	University tracks
Low auto, <0.30	29,8	0,0	90,4
Mi. auto, 0.30-0.60	5,2	4,2	6,6
High auto >0.60	65,0	95,8	3,0
	100,0	100,0	100,0
N	85.646	56.150	28.176
Women			
	All 98 tracks	Vocational tracks	University tracks
Low auto, <0.30	63,2	0,0	81,7
Mi. auto, 0.30-0.60	34,1	91,0	17,6
High auto >0.60	2,7	9,0	0,7
	100,0	100,0	100,0
N	77,517	16.552	59.929

In Table 2 cross-tabulations between automation risks and economic precariousness are shown. Both in the short and the log run there is an overrepresentation of those with middle and high automation risks with precarious situations. It is clear that the association is not completely linear but rather that those with the lowest automation risks have lower risk for economic precariousness than those with middle and high automation risks. Substantially more women than men end up in precarious situations and since unemployment is not more

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common among women than men in Sweden we may assume that part-time work and low wages are factors behind this gender difference.

Table 2 Economic precariousness in the first five years after examination and in the consecutive five years by automation risks (in percent)

Men				
	low auto	middle auto	high auto	N
prec. in 1-5 yrs	2,6	7,7	8,6	5.780 (of 85.646)
prec. in 6-10 yrs	2,0	5,6	5,8	1.852 (of 38.930)
Women				
	low auto	middle auto	high auto	N
prec. in 1-5 yrs	8,9	18,9	17,5	9.750 (of 77.517)
prec. in 6-10 yrs	8,5	19,6	17,7	4.138 (of 31.259)

In Table 3, separately for men and women, regression coefficients (OLS) are shown for having a precarious economic situation in the first five years after examination for all, and also separate for those with vocational education and university education. For men, when including all 98 educational tracks, we see the expected positive association between automation risks and precariousness, where especially those with low automation risks have the lowest risks of precariousness (see m1_all). However, when controlling for years in education this association is reduced substantially (m2_all). Moreover, the regression for vocational education shows a similar small association with high automation risks (m1_voc; for those with vocational education no control for years of education was used and the group with low automation risk was too little to produce a plausible coefficient). For those with university education automation risks are only weakly (if at all) associated with precariousness (m1_uni). In all, this suggests that it was rather years of education than automation risks that affected precariousness. Going over to the results for women the results are quite similar in the first model where especially those with low automation risks have lower risks (m1_all), but when controlling for years of education (m2_all), and in the separate model for those with university education (m1_uni), there are lower risks for precariousness both for those with low automation risks and those with high automation risks. For those with vocational education there is no significant association with automation risks. In all, hypothesis 1 is only weakly supported.

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Most of the results for precariousness in the first five years are replicated when using the long-term measure for men – precariousness in the period six to ten years after examination (see Table 4, compare panel 1 and 3 – only automation risk coefficients are shown). For women, however, the results are more like those for men in these analyses – most of the associations disappear when controlling for years of education and there is no longer a negative association with high automation risks in model 1 (except for women with vocational education). The results are basically similar with the less restrictive sample (with more educational tracks included, described above). However, there is a somewhat stronger support for hypothesis 1 since the negative associations for women with high automation risks disappear or are reversed to positive associations in these analyses with partly the exception for women with tertiary education where the association is still negative for precariousness in the short run (see panel 2 and 4 in Table 4). In short, there is some support for hypothesis 1 but the results are somewhat dependent on which selection criteria are used. However, irrespective of criteria used the associations of automation risks are considerably reduced when controlling for years of education.

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Table 3 Having a precarious situation in the first five years after examination for men and women (OLS-regressions)

	Men					Women				
	m1_all	m2_all	m1_voc	m1_uni	m2_uni	m1_all	m2_all	m1_voc	m1_uni	m2_uni
low auto. r.	-0.065***	-0.015**	-	0.001	-0.008*	-0.100***	-0.051***	-	-0.066***	-0.050***
	(0.005)	(0.006)	-	(0.004)	(0.004)	(0.003)	(0.004)	-	(0.003)	(0.003)
mi auto. r.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
high auto.	0.024***	-0.010*	-0.013*	0.001	0.008	-0.016*	-0.038***	-0.018	-0.040**	-0.031*
	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.015)	(0.015)
edu_10yrs		0.109***					0.059***			
		(0.007)					(0.011)			
edu_11yrs		0.079***					0.126***			
		(0.005)					(0.012)			
edu_12yrs		0.000					0.000			
edu_13yrs		-0.092***					-0.053***			
		(0.008)					(0.012)			
edu_14yrs		-0.138***			-0.013***		-0.194***			-0.030***
		(0.008)			(0.003)		(0.010)			(0.005)
edu_15yrs		-0.130***			0.000		-0.164***			0.000
		(0.008)					(0.008)			
edu_16yrs		-0.123***			0.009***		-0.216***			-0.052***
		(0.008)			(0.003)		(0.009)			(0.003)
du_17yrs		-0.119***			0.011**		-0.250***			-0.085***
		(0.009)			(0.004)		(0.010)			(0.005)
edu_18yrs		-0.079			0.045		-0.300			-0.139
		(0.064)			(0.041)		(0.188)			(0.171)
edu_20yrs		-0.082**			0.038		-0.239***			-0.081
		(0.031)			(0.019)		(0.059)			(0.053)
Constant	-0.547***	-0.948***	-1.925***	0.047	0.175	0.700***	-1.018***	-3.400***	-0.261	-0.821***
R-squared	0.01	0.03	0.01	0.00	0.00	0.02	0.04	0.02	0.01	0.02
N	85646	85646	56150	28176	28176	77517	77517	16552	59929	59929

Comments: *p<0.05 **p<0.01 ***p<0.001. Standard errors in parenthesis.

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Table 4 Having a precarious situation in the first five years, and in the consecutive five years for men and women. Sensitivity tests for the coefficients of automation risks (OLS-regressions)

	Men					Women				
	m1_all	m2_all	m1_voc	m1_uni	m2_uni	m1_all	m2_all	m1_voc	m1_uni	m2_uni
3 of 5										
low auto. r.	-0.065***	-0.015**	-	0.001	-0.008*	-0.100***	-0.051***	-	-0.066***	-0.050***
	(0.005)	(0.006)	-	(0.004)	(0.004)	(0.003)	(0.004)	-	(0.003)	(0.003)
high auto. r.	0.024***	-0.010*	-0.013*	0.001	0.008	-0.016*	-0.038***	-0.018	-0.040**	-0.031*
	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.015)	(0.015)
3 of 5										
no select										
low auto. r.	-0.045***	-0.037***	-	-0.028***	-0.035***	-0.045***	-0.037***	-	-0.028***	-0.035***
	(0.002)	(0.002)	-	(0.001)	(0.002)	(0.002)	(0.002)	-	(0.001)	(0.002)
high auto. r.	-0.022***	-0.008***	-0.033***	0.017***	0.019***	-0.022***	-0.008***	-0.033***	0.017***	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
3 of 6 to 10										
low auto. r.	-0.059***	-0.018*	-	-0.006	-0.007	-0.059***	-0.018*	-	-0.006	-0.007
	(0.006)	(0.008)	-	(0.005)	(0.006)	(0.006)	(0.008)	-	(0.005)	(0.006)
high auto. r.	0.024***	-0.002	-0.001	0.002	0.011	0.024***	-0.002	-0.001	0.002	0.011
	(0.006)	(0.006)	(0.008)	(0.009)	(0.010)	(0.006)	(0.006)	(0.008)	(0.009)	(0.010)
3 of 6 to 10										
no select										
low auto. r.	-0.032***	-0.015***	-	-0.015***	-0.014***	-0.032***	-0.015***	-	-0.015***	-0.014***
	(0.002)	(0.003)	-	(0.002)	(0.002)	(0.002)	(0.003)	-	(0.002)	(0.002)
high auto. r.	-0.003	-0.001	-0.011***	0.017***	0.015***	-0.003	-0.001	-0.011***	0.017***	0.015***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)

Comments: Four different regressions are reported, but only the coefficients for automation risks. The upper two have precariousness in the short run (3 out of 5 years after examination) as dependent variable. And the lower two have precariousness in the long run (3 out of years 6 to 10 after examination) as dependent variable. "No select" means that all educational tracks are included even those with a large variation in automation risks. *p<0.05 **p<0.01 ***p<0.001. Standard errors in parenthesis.

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In Table 5 the results for men with enlistment data, for whom we have access to information on cognitive ability and personality, are reported. First of all, there is somewhat of a weaker positive association between automation risks and precariousness in the first five years for this sample compared to the larger sample presented in Table 3. Moreover, controlling for years of education reduce these associations to non-significant levels and cognitive ability and personality only reduce them slightly. There is a substantial interaction effect between high automation risks and personality (model 4), and to some extent between automation risks and cognitive ability (model 5). Hence, a beneficial personality/non-cognitive skills and cognitive ability reduce the risk of having a precarious situation for those with high automation risks. This could also be formulated in the way that having low cognitive and non-cognitive skills (i.e. a disadvantageous personality) is associated with a precarious situation especially for those educated for an occupation with high automation risks. However, this is not seen in the separate analyses for educational groups while especially personality has relatively high associations for those with vocational education (see Table 6). Thus, it seems like the interaction effect(s) between automation risks and personality is mainly due to personality being of high importance to avoid a precarious situation in the group of those with vocational education. Once again, the findings are replicated with the long-run measure of precariousness (not shown in tables). Personality has a stronger negative association again than cognitive ability and especially so for the group with vocational education. The results are also basically similar with the less restrictive sample, but with a somewhat stronger association between automation risks and precariousness for the first model.

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Table 5 Having a precarious situation in the first five years for men with measures including personality and cognitive ability. OLS-regressions.

	m1_all	m2_all	m3_all	m4_all	m5_all
low auto. Risks	-0.020***	-0.006	0.004	-0.056	0.009
	(0.006)	(0.007)	(0.007)	(0.031)	(0.020)
mi auto. Risks	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
high auto. Risks	0.049***	0.014	0.009	0.149***	0.085***
	(0.007)	(0.008)	(0.008)	(0.031)	(0.019)
Personality			-0.028***	-0.024*	-0.027***
			(0.002)	(0.009)	(0.002)
cognitive ability			-0.004***	-0.003**	0.003
			(0.001)	(0.001)	(0.004)
personality*low auto				0.016	
				(0.010)	
personality*high auto				-0.047***	
				(0.010)	
cognitive ab.*low auto					-0.002
					(0.004)
cognitive ab.*high auto					-0.017***
					(0.004)
Constant	0.317***	-0.653***	-0.498***	-0.370*	-0.462**
R-squared	0.04	0.05	0.05	0.06	0.06
N	25269	25269	25269	25269	25269

*p<0.05 **p<0.01 ***p<0.001. Standard errors in parenthesis.

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Table 6 Having a precarious situation in the first five years for men with measures including personality and cognitive ability, separately for those examining from vocational education and university. OLS-regressions.

	m3_voc	m4_voc	m5_voc	m3_uni	m4_uni	m5_uni
low auto. risks	-0.246	-0.231	-0.205	-0.005	-0.021	0.010
	(0.326)	(0.326)	(0.327)	(0.005)	(0.026)	(0.018)
mi auto. Risks	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
high auto. risks	0.017	0.066	0.076	0.013	0.020	0.025
	(0.016)	(0.076)	(0.043)	(0.009)	(0.048)	(0.030)
				(0.000)	(0.000)	(0.000)
Personality	-0.070***	-0.055*	-0.070***	-0.008***	-0.012	-0.008***
	(0.007)	(0.024)	(0.007)	(0.002)	(0.008)	(0.002)
cognitive ab.	-0.009***	-0.009***	0.006	0.000	0.000	0.003
	(0.003)	(0.003)	(0.011)	(0.001)	(0.001)	(0.003)
personality*lo auto		-			0.005	
		-			(0.008)	
personality*hi auto		-0.017			-0.002	
		(0.025)			(0.015)	
cognitive ab.*lo auto			-			-0.003
			-			(0.003)
cognitive ab*hi auto			-0.016			-0.002
			(0.011)			(0.006)
Constant	-0.656	-0.697	-0.724	-0.008	0.010	-0.028
R-squared	0.03	0.03	0.03	0.00	0.00	0.00
N	7838	7838	7838	16839	16839	16839

*p<0.05 **p<0.01 ***p<0.001. Standard errors in parenthesis.

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6. Concluding discussion

The impact of automation on employment may be both positive and negative from the perspective of workers. Automation may lead to a decline of jobs with poor working conditions and a rise of more advanced jobs but the consequence may at the same time be a declining number of jobs and an increase of unemployment. This paper contributes with empirical findings using Swedish registry microdata and by deriving automation scores for 98 specific educational tracks using Frey and Osbornes (2017) occupational scores, and by studying the risks of ending up in economic precariousness in the short and the long run after examination. The findings of this paper indicate that a substantial part of the association between automation risks and precariousness is due to educational length. In other words, the findings indicate that, to a large extent, it is not high automation risks that leads to low earnings but rather short education. Moreover, for women it turns out that the association between automation risks and precariousness is not completely linear when adjusted for educational length: both low and high automation risks give smaller risks for precariousness at least in the short run. Hence, high automation risks are associated with precariousness, as suggested by hypothesis 1, but this association does not hold when it is adjusted for educational length.

For men who completed military enlistment we were also able to study the impact of cognitive ability and personality/non-cognitive ability, measured before examination, for precariousness after examination. First, there was some support for hypothesis 2, that such cognitive and non-cognitive skills reduce the risk for those with high automation risks. However, by large this is not seen in the separate analyses for the educational groups of vocational education and university education. It seems rather that especially non-cognitive skills reduce the risk of precariousness for those with upper secondary vocational education irrespective of automation risks.

All in all, the results suggest that skills in terms of years of education and gender are of pivotal importance when analyzing individual level outcomes of automation. Men with vocational education is a group that stands out as having very high automation risks, while for those with university background automation risks are small but relatively high for women. Methodologically, it seems like it is possible to derive automation risks for educational tracks.

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However, many educational tracks, even when distinguishing very specific tracks, appear to lead to quite different occupations and they are probably too general to make accurate assessments of the risk of automation. Hence, this approach appears to be most appropriate for a limited selection of educational tracks.

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Appendix 3

Are you becoming more like your parents?
Testing counter-mobility and relative risk aversion on career movements

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1. Introduction

Technological development is transforming many jobs and tasks. These transformations put pressure on keeping individual skills and credentials up to date. This, in turn, could increase the importance of these skills in occupational attainment, and thus weaken or even make irrelevant the direct effect of social origin, net of educational attainment. Previous research offers contradictory evidence on this argument. On one hand, inequalities in both educational and occupational attainment have been proven to be persistent across societies and generations, recent evidence highlighting direct intergenerational linkages between social origin and occupational attainment (Bernardi & Ballarino 2016; Gugushvili et al 2017; Passaretta et al 2018). On the other hand, technological changes and globalisation have transformed the labour markets by modifying the skills and tasks of various jobs, creating a need for constant updating of skills, a diminishing of some manual jobs and creation of new technology-related jobs during the recent decades (Goos et al. 2014; Gregory et al 2016; Haslberger 2019; Spitz-Oener 2006). As a result, technological changes in the labour market may have shifted inequalities and processes of both intra- and inter-generational occupational mobility, by influencing the need and motivation for job changes and career movements due to shift in skills and tasks. Further, the increased emphasis on individual skills in the labour market is hypothesised to make family background irrelevant as proven skills rather than class or networks determine individual job allocation.

This paper tests this argument and examines the influence of social origin on individual career movements throughout early careers, and how technological changes influence in these associations. Specifically, we analyze how class mobility over the early career is influenced by exposure to automation risk in one's occupation, by parental class, and the interaction between the two. Our analysis of detailed annual occupational information from the Finnish register data between 2004-2017 makes the following contributions. First, we combine intra- and inter-generational mobility and provide information on nuanced processes of intergenerational occupational attainment by demonstrating in-detail information on individual careers. Second, we assess arguments of the career destabilizing role of technological change and automation risk and ask whether exposure to automation risk in an occupation has a strong enough effect to increase career mobility between classes (and not only jobs and occupations). Class boundaries are commonly considered less permeable than those between jobs, firms and occupations. Can technological change break them? We also combine perspectives from intergenerational class mobility research and literature on the career effects of technological change to analyse whether those exposed to automation risk are more or less likely to move to their parents' class. Our analytical approach extends from traditional event history analyses or destination-specific multinomial analyses by applying multinomial conditional logit regression modelling, that allow to include earlier career position and parental class position with the destination class position with various constraints in the model. By moving beyond analyses of social origin and occupational attainment, measured only at one point in adulthood, to analysis of career development our analysis also provides an additionally nuanced test of hypotheses of the diminishing relevance of social origin in times of technological change.

2. Skills, career and mobility

Educational attainment and work experience are two of the most important determinants of occupational attainment in modern labour markets (Van der Velden & Wolbers 2007). Career development takes place particularly during the first 15 years in the labour market (Härkönen and Bihagen 2011) and occupational status maturity is generally reached around age 30-40. Occupational attainment at this age has consequently been used to measure occupational 'destination' in social mobility research. While large part of career mobility research has focused on one's career with the changes between entry job status and matured status, recent studies have acknowledged the longitudinal and life-course factors in occupational attainment (Bukodi & Goldthorpe 2011; Jacob & Klein 2019; Manzoni et al 2014). Individual career paths can vary largely by individual characteristics and motivations, but career movements, upward and downward, take place most likely in the early years of the careers (Hillmert 2011; Härkönen & Bihagen 2011).

As education is the main provider of individual skills, how well these skills are matched in the labour market is important for career mobility. Wolbers (2003) demonstrated that those who have a poor job match (in regard to their education), have more unstable labour market attainment as they seek different jobs and vocational training more often. Further, Groes et al

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(2015) found that people with either low or high wages within the occupations tend to move to occupations that pay even less (low-earners) or more (high-earners), arguing that low match-specific productivity pushes them to move to jobs and occupations that are more suitable for their skills and perceived ability. In support of this, Bachmann et al (2020) found that voluntary change of occupation result more often among people with higher earnings. These findings can also indicate how individuals may need to keep up with the technological changes of their job, reflected in the earnings divide within the occupation, and if not, may experience lower wages and thus higher probability for career movements.

Recent advanced technological changes and innovations have altered occupations throughout industries and skill level, resulting in replacement of tasks and skills, transformation of jobs and higher demand of skilled labour (Acemoglu & Autor 2011; Frey & Osborne 2017). Although the technological changes have not reduced the overall number of jobs, they do affect occupational structures and occupational skill requirements, which, in turn, can influence career mobility. First, technology and computerisation has increased the amount of new machinery, programs, and a new sets of occupational tasks. Thus, in order to keep up in individual labour market attainment, one needs to obtain new skills and qualifications, or update current skills (Spitz 2004). An unsuccessful skill attainment process may result in job changes. Second, some tasks, particularly manual and routine tasks, have become obsolete due to technology, automation or robotisation, reducing the job opportunities for those with this kind of skill set (Frey & Osborne 2017; Jaimovich & Siu 2012; Vermeulen et al 2018). In order to avoid unemployment due to lack of job opportunities, particularly within some specific sectors and occupations, individuals may be forced to move jobs, organisations or industries in order to maintain their labour market activity. Third, technological change also creates new tasks and jobs, such as coding, digital marketing and jobs using social media, with new skill sets required (Autor 2015; Gregory et al 2016; Vermeulen et al 2018).

Although the literature on the impact of technological change on career mobility has primarily focused on movements between jobs, regions and sometimes, occupations, we argue that mobility induced by exposure to automation risk may also increase mobility across class lines, even if they are frequently considered less permeable:

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(H1) Automation risk is positively associated with class mobility over the career.

Beyond the general impact of automation on career movements, we expect class-specific results in this association, because technology and automation have impacted different occupational sectors to different degrees.

3. Career movements and social origin

To a large extent, the previous occupational mobility literature has focused on career mobility through a few time points (Wolbers 2003) or as a process of progression over the life course (Manzoni et al 2014). However, as occupational attainment is also influenced by individual's background, i.e. parental class and networks, recent literature has linked the individual life course approach with intergenerational occupational inequality, contributing to the cumulative advantage hypothesis (see eg. Hillmert 2011; Jacob & Klein 2019). There is an increasing amount of studies that demonstrate a direct influence of parental resources and family background, net of the mediating impact of education, on offspring's labour market attainment and career advancement that continues throughout individual career (Bukodi & Goldthorpe 2011; Gugushvili et al 2017; Passaretta et al 2018; see also Bernardi & Ballarino 2016 for multiple country examples). However, detailed empirical evidence how parental class is associated with career movements remains scarce. This paper aims to study how career movements are influenced by parental class, focusing on class changes during the early career.

One theory that combines individual career movements with occupational family background factors is counter-mobility. Girod et al (1972) introduced the concept of counter-mobility, that individuals' career movements are drawn by parental occupations throughout the career. These movements would include upward career mobility towards higher parental classes but also downward movements if the person has exceeded parental occupation and then is drawn back towards the origin. One example of counter mobility used in the previous literature is when a person first experiences disadvantage or downward mobility and then moves toward the parental class (Goldthorpe et al 1987). This phenomenon was tested, although it was only weakly linked to counter-mobility, in Germany and the results show that persons who had

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experienced intergenerational educational downward mobility (Diewald et al 2015) were able to compensate for the disadvantage by having slightly more rapid and positive career progression after. DiPrete (2002) points out that this type of counter-mobility would occur most likely in societies where the institutions and the labour market allows rapid improvements from adversity.

Although empirical evidence on counter-mobility is very scarce, some support can be drawn from studies that specifically analyse downward and upward career movements. For example, Bukodi (2017) found that adult education may promote the movements towards parental origin, particularly among the individuals from higher social origins who improve their academic qualifications to maintain the class position or to promote better occupational attainment. Further, Bison (2011) demonstrates that those from higher classes have higher probability for upward career movements, and the likelihood for downward movements has risen slightly if the person moves towards the parental class, particularly among people from the entrepreneurial and lower classes. However, higher levels of educational attainment diminish these differences in downward mobility. Similarly, another example of counter-mobility among persons from lower social origins is given by Bihagen (2007) whose results show that women who had reached the highest class and were from working class origin experienced higher levels of downward mobility, although this was not the case among men.

So, overall counter-mobility addresses career mobility so that if individual attains the same class as the parents, they are more embedded in it and pursue to maintain in that class, or on the other hand, if class is different to parents', individual will take measures that move one's occupational attainment closer to parental occupation. One well-known theory in sociological literature, relative risk aversion (RRA), can be applied to counter-mobility. RRA argues that individuals and families primarily attempt to obtain at least the same class for the offspring as the parents have (Breen & Goldthorpe 1997). This hypothesis has been extensively studied in relation to educational transitions highlighting that at each educational break-point the individual (and the family) will weigh the possible utilities and the probability of success keeping in mind the quantity and quality of educational attainment to achieve at least parental social class (van de Werfhorst 2002; Stocke 2007). Hence, this theory has been tested primarily

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in relation to educational decisions and educational inequalities, often using the highest parental educational attainment as the threshold for individuals to achieve (Davies et al 2002; Tieben 2011). Similarly with the argument of counter-mobility that individuals are found in the parental class, RRA also argues that the utility of achieving higher (educational) positions becomes smaller once the parental position has been reached (Holm & Jæger 2008). However, the idea has not yet been analysed with regard to occupational attainment.

There are two shortfalls in the evidence for RRA in the previous literature. First, obtaining a certain level of education does not automatically guarantee a specific level of socioeconomic status in the labour market. Particularly mid-level educational attainment can have very variable occupational outcomes. This can then reflect different career processes in pursuing the desired labour market status (relative to parental status). However, RRA has not been tested in relation to occupational attainment or career movements, at least to our knowledge. Second, rapid educational expansion has increased the overall level of educational attainment, and has boosted educational mobility, particularly upwards, weakening the argument that attainment beyond parental education has no utility. Also, the extensive adult education systems support attainment of further qualifications after entering the labour market, and thus initial educational attainment may give a limited picture. Further, as social inequalities in educational attainment have weakened in many Western societies due to educational expansion, the focus of intergenerational transmission among individuals may be put to intergenerational transmission of occupational attainment (Pöyliö et al 2018).

Combining the theories of relative risk aversion and counter mobility, which have not been yet been directly tested in relation to career mobility, and drawing from the existing evidence, this study analyses both intra- and inter-generational occupational mobility. Particularly, we examine how career movements, in terms of class, during the first 14 years of the individual careers are influenced by parental class. In light of previous literature, we hypothesise that over the individual careers:

(H2) individual career movements are pulled towards their parental class

(H3) career mobility is lower if individuals are in the same class as their parents

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4. Intergenerational career mobility and technology

While individual labour market attainment is largely influenced by both individual educational attainment and family background, career processes also reflect the structural changes in the society. Particularly important for career movements are the skill and task requirements matching the skilled labour with appropriate jobs. Advanced technologies have altered the organisations of educational institutions and labour markets, increasing the demand for flexible skill sets and promoting innovative career planning (Frey & Osborne 2017; Goos & Manning 2007; Spitz 2004). Many jobs and tasks are experiencing transformations that put pressure on individual skills and credentials in job acquisition, covering all occupational levels from low-skilled jobs to higher prestige occupations with highly specialised skill requirements (Spitz-Oener 2006).

In addition to the changes in individual motivation for career movements described in chapter 2 of this paper, these structural changes can be assumed to influence also the relationship between family background and career mobility. If the skill-biased technological change strengthens the importance of skills, learning and qualifications in labour market attainment, the influence of social origin could be expected to be diminishing or weakening. In other words, technological changes would alter the way jobs are allocated at the labour market, emphasising individual skills over family background. However, this does not say anything about the processes of career movements, particularly in situations where technological changes alter labour market attainment and career progress.

There are two ways in which we argue that technological changes at the labour market influence the intergenerational association of occupations, and particularly career movements in relation to parental class. First, while automation is altering the tasks of occupations, career planning at an early stage becomes more important for positive career advancement and for avoiding unstable careers. While individuals use the resources of their family when planning educational and labour market pathways, parental occupation and class contributes to many aspects of career processes such as occupational aspirations and choice, vocational identity,

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career orientation and development throughout the life course (Whiston & Keller 2004). This would draw the individual career towards the parental class.

Second, when structural settings imply risks or unstable future prospects, such as automation of tasks and jobs, the importance of existing resources, including of family background, strengthens. For example, Tervo (2006) found that when regional unemployment rate is high, individuals from entrepreneurial family backgrounds moved to self-employment, whereas those from wage-earning backgrounds reacted differently. Moreover, if technological changes bring forth unemployment or unstable labour market attainment for the individual, parental occupation can act as a safe haven for resources, such as networks, knowledge and employment. Hence, career movements towards the parental class may be a possible way forward from an unstable situation imposed by technological changes. As a conclusion, we assume that

(H4) High automation risk increases the pulling power of the parental class

5. The Finnish context

This paper benefits from detailed register data from Finland, and the country context is vital when analysing labour market events. Overall, Nordic countries are characterised with high public support, universal policies and benefits, and strong regulations. They are seen as open societies with high social mobility, with free-of-charge educational systems, high gender equality and relative income equality. All of these features influence the volume of voluntary and involuntary occupational movements and in what kind of labour market attainment this results in. Particularly, the matching of jobs with skills acquired from education, and the possibilities to update or upgrade skills (at or outside work), is expected to influence individual career mobility. These are also the aspects in which the recent technological changes have significantly impacted, transforming tasks and increasing the need for continuous learning. Two Finnish welfare state institutions particularly are in the core of how early careers are formed, and how individual motivation and need for career movements might rise.

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First, the educational system shapes and creates the skills and other qualities required for the labour market, but it also provides the official qualifications required for jobs, more so in societies with highly regulated labour. Particularly, the vocational specificity of the educational system influences the labour market outcomes by matching educational qualifications with jobs from the entry point (Wolbers 2007) influencing also later earnings level (Bol et al 2019). In Finland, the first jobs are usually well matched with the educational qualifications (Lindberg 2009). The educational system also influences the inequalities, both in educational and occupational attainment. Finland has experienced a substantial decrease in social inequalities in higher education participation due to educational expansion, including the most prestigious educational programmes (Thomsen et al 2017). As the comprehensive welfare state arrangements ought to provide more equal opportunities for individuals despite family background (Esping-Andersen 2015), the economic resources of the parents' influence educational transitions and outcomes of the children to a lesser degree (Jæger & Holm 2007).

Second, labour market legislation, procedures and contracts influence both the allocation of jobs and occupations, and the possibilities and demand for career movements. Cross-national studies have concluded that employment protection is one of the most important influences on career mobility, as strict regulations can restrict job mobility due to limited turnover (Gangl 2003). Additionally, the relatively strong occupational specificity of the Finnish higher education system results often in people being well matched in their jobs (Lindberg 2009). Both of these can be assumed to influence not only the opportunities for occupational changes, it can also alter the motivation and demand for career movements. Despite these strong institutions, Finland follows the European average in the overall occupational changes, as around 3% of people change occupations in each year (Bachmann et al 2020).

With jobs well matched with educational qualifications in the Finnish labour market due to strong regulations, the changes in skill demand and occupations can be slower than in other contexts. Thus, the impact of technological changes in jobs and occupations in Finland may have resulted in less dramatic or rapid changes. Therefore some of the results of this study might be slightly conservative compared to other more flexible labour markets.

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6. Data

Benefiting from Finnish register data, this paper studies occupational mobility of the 1973-1986 birth cohorts between 2004 and 2017. We start the observation period after people have received their highest formal educational qualification either in 2003 or 2004 but earliest at age 18. If person has obtained only basic education, the graduation year is two years earlier because they have been 16 at the time of graduation and occupational information is measured only from age 18 onwards. Also, the graduation age is capped to 30 years to observe careers that do not have extensive employment experience before obtaining the highest qualification. The occupational information is measured on the last week of each year, and thus to obtain occupational class at time t0 (the beginning of the year), we use occupational information of the previous year. This results in our observation period to start from 2005 onwards. This allows us to examine intergenerational transmission during times when volatility of employment and career movements has increased due to temporal contracts and non-standard employment, but also rapid applications of computing, robotisation and technological innovations in both individual and industrial spheres.

The set analytical starting point after graduation enables us to analyse similar career processes at same time points so that individuals are competing for the same pool of job opportunities, but also so that all individuals are affected by the same societal factors (such as economic downturns) during a similar stage of their early careers. We have dropped those persons who move abroad or die during the observational period, and those for who we do not observe occupational information for any of the years. Also those who do not have any information on parental class throughout their teenage years (i.e. both parents are unemployed, outside the labour force or the information is missing for other reasons when the respondent is a teenager), are not included in the analyses. The total analytical sample consists of 83,651 persons and 1,041,558 person-years.

Our dependent variable is occupational status at the end of each year, measured as the EGP classes (Erikson et al 1979). Although sociological literature has extensively discussed the variability of occupational measures, we consider that a measure of occupational class is the most adequate in this study. Social class demonstrates a more comprehensive socioeconomic

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standing of the individual, and the movements between classes express more significant changes in the labour market positions than job changes or other minor career movements in the occupational hierarchy. It also provides a more valid comparison of parental and offspring labour market positions since occupations and labour market conditions can be very different for the parents and the individuals, but the broader class status of occupations have not changed as much. Parental occupational information is acquired during the person's teenage years with dominance principle where the highest class of the parents is chosen. EGP classes are categorised into five classes: 1) Higher service (EGP I), 2) Lower service (EGP II), 3) Skilled (non)-manual (EGP IIIa+V+VI), 4) Self-employed/farmers (EGP IVabc), 5) Semi-/unskilled (EGP IIIb+VII).

To examine the relationship between career movements, parental class and technological changes, we use a measure of automation risk. This is an indicator of occupational automation risk created by the TECHNEQUALITY project (not released to public yet, see D1.1), measuring the percentage of tasks on which less time will be spent. As there is no specific measure for Finland, the EU-level measure is used, which is coded for 2-digit ISCO08 values. This is matched with the occupations at time t0 (occupational information at the last week of the previous year, forwarded to represent the occupation at the beginning of each observation year). Due to missing information of automation risk for some ISCO08 codes (mainly military occupations), the sample is slightly smaller than the total sample, but only by 0.7 per cent, being 83 062 individuals.

Figure 1 presents the annual means of the occupational automation risk within each EGP class across the observation period. The figure shows clearly the hierarchical nature of automation risk between the EGP classes; the highest average is constantly within the semi-/unskilled class, followed by the skilled (non)-manual class then self-employed/farmers class. This latter one is the only where the mean is slightly decreasing across time, suggesting that the occupational composition within the class changes so that people have moved to occupations with lower automation risk or have changed class. The lowest average over time is within the service classes.

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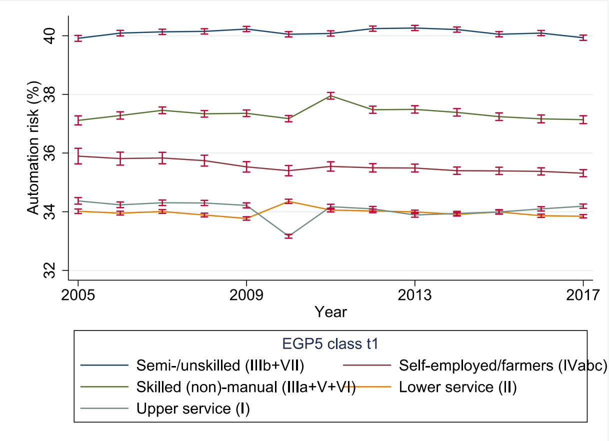
Figure 1 Annual averages of automation risk by EGP class over the observation period



Other variables considered to influence career mobility and occupational attainment are educational attainment, labour market experience and gender. The highest educational degree measures the highest achieved level, obtained before entering the labour market. The Finnish education system has a somewhat dual system on both secondary (vocational/general) and tertiary (applied/academic) levels, so that degrees from the universities of applied sciences mainly result in lower tertiary level degrees, and the ones from academic universities to higher tertiary qualification. These tracks also largely influence labour market attainment and thus it is important to treat them separately. Due to analytical restrictions, the educational categories are coded as years of attainment, resulting in five levels: basic education (9 years), vocational upper secondary (11 years), general upper secondary (12 years), lower tertiary (15 years) and higher tertiary (17 years). Because individuals may have some work experience before graduation we include a cumulative measure of labour market experience from year 2000 onwards, considering a year of experience if main activity has been 'employed' or person has been employed for over six months of that year. Additionally, we include a measure of squared employment experience to obtain the non-linear influence of labour market participation on occupational attainment. The main descriptive statistics of the variables are displayed in Table A3.1 in Appendix 3.1.

Because individual occupational information is obtained only on the last week of the year, some information is missing. As some life events do not alter the class position of an individual in the labour market, the class status has been taken from the previous year in the following

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cases (in order): 1) according to the start and end date of the employment contract 2) if the person was earlier or has remained employed by the same company or governmental institution most of the year 3) if in education after receiving highest educational level and not obtaining a new qualification 4) if the person has been on maternity/paternity/parental leave, 5) if the person was in the army 6) if the person has experienced short-term (maximally two years) unemployment or out of labour market periods 7) if employed the following year. If the person has been out of the labour market for other reasons or experienced long unemployment, the occupational information is missing and the individual is not included in the analysis that particular year or the following year, as we need two consecutive time points to measure career (im)mobility.

7. Methods

Drawing from the core social fluidity model by Erikson and Goldthorpe (1992), and continuing from the applications in Breen (2004), we analyse three-dimensional frequency tables; 1) occupation at time t1, 2) occupation at time t12, and 3) parental class. The association of the first and second factor form the career mobility parameter and the second and third the inheritance parameter. In order to analyse all of these, i.e. career mobility in relation to parental class, with individual covariates and other constraints on the mobility, we employ multinomial conditional logit (MCL) regression. In general, MCL is able to estimate complex intergenerational mobility associations as it uses conditional logit analysis to estimate multinomial logistic model on the dependent variable (Dessens et al 2003; Hendrickx 2000). In other words, the individual destination class (here EGP at the end of the year) is a function of the variation in both individual characteristics and the characteristics specific to the destination alternatives. Further, this approach allows to include various constraints on the outcome and restrictions in the model specification, outside what multinomial or conditional logit separately would allow.

To analyse and test our hypothesis on the association between career mobility and parental class, we apply two effects in separate models; diagonal effects for H2 and post-parental effects for H3. The diagonal effects resemble the mobility models used previously in log-linear analysis of social mobility (Breen 1994). We add dummies for each class that measures if the

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destination class is the same as parental class. With all the other applications in the model that account for the overall intergenerational association and annual career immobility (explained below) these diagonal effects measure the likelihood of individual being in the parental class at the end of each year of their early career. Hence, this part of the model tests if individual career movements are pulled towards their parental class over their careers (H2). Further, we include another constraint for the outcome, a set of dummies for each parental class if the person has been in the parental class already in the beginning of the year (i.e. post-parental effects). This part of the analysis measures the likelihood of career movements at the end of each year of individual careers if the individual is in the parental class in the beginning of the year (H3).

To accommodate the intergenerational association of socioeconomic classes, in addition to diagonal and post-parental effects, we estimate Row and Columns model 2 (RC2) for parental class (Goodman 1979). This scales both the occupational destination and parental class, and calculates the association between these two categorical variables through one parameter (Hendrickx 2000): Further, we allow this association to vary by individual EGP_{t0} class, i.e. the status at the beginning of the year, since the association between the outcome and social origin is somewhat dependent on the status in the beginning of the year.

MCL modelling was first introduced to extend log-linear analysis of two-dimensional mobility tables to individual-level data and to include continuous covariates (Breen 1994). One way is to include interaction terms for each covariate with the dependent variable to ensure variation in the effect of the independent variable across the outcome classes. This is how we control for gender in the analysis. However, in line with human capital theory, our other covariates (educational attainment, employment experience and square of employment experience) affect the individual occupational outcome more directly and thus we apply stereotyped ordered regression (SOR). The SOR model scales the dependent variable according to the effects of the independent covariates, applying linear and multiplicative effects which reduces the parameters of the model (Anderson 1984; DiPrete 1990). The SOR constraint allows the dependent variable to be unordered but also acknowledges that it can be ordered (Hendrickx

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2000). This is particularly important in our model since the EGP classes are not fully hierarchical and ordered measures of classes, but can be considered to be one version of a class scale.

Although MCLR has been mainly applied to capture the complex nature of intergenerational social mobility patterns and associations (Erola et al 2012; Wu & Treiman 2007), we extend it to include also individual career mobility. More precisely, we include a general career immobility parameter, i.e. a dummy variable that measures if the class is the same in the beginning and in the end of the year. This is to control the substantial stability of careers over time and to provide more accurate estimates for the occupational outcomes and for the influence of parental class.

To study the influence of automation on both intra- and inter-generational career mobility, we apply the MCLR models to include a measure of automation risk. Based on the models described above, we create two separate analyses to test hypotheses H1 and H4. First, we include an interaction term between automation risk and career immobility, both as a general career immobility parameter, and as a class-specific immobility variable, without any parental class variables in the models. These results demonstrate how automation risk influences the career movements within each year of the observation period, generally and in each EGP class separately. Second, extending from the model used for H2 studying the pulling power of the parental class, we include an interaction term between automation risk and the class-specific diagonal effect. This model demonstrates how automation risk impacts the pulling power of parental class on individual class destinations.

8. Results

Figure 2 shows the annual percentages for career stability, that is the number of people who do not change class from one year to the next. The percentages are presented by educational attainment groups. Overall, career immobility is lowest during the first years, indicating a high degree of class movements. Also, the educational differences in career immobility seem to be the biggest in the beginning of the careers. There is a drop in career stability in all educational groups around the year 2010, which demonstrates the impacts of the latest financial crisis as the Finnish economy sank into recession, reducing stability and increasing class movements.

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After the recession, career immobility in terms of socioeconomic class seem to be rather stable in all educational groups, immobility stabilising around 90 percent. All this demonstrates that career movements between EGP classes is rather constant, as even after 10 years of entering the labour market, around 10 per cent experience class mobility each year. However, additional analysis show that a third of the 2003-2004 graduation cohort do not experience any change in their EGP class during the first 14 years of their career, which implies that career movements may centre around a smaller group of individuals.

Figure 2 Annual percentages of career stability (no change in class status between the start and end of the year) by educational attainment level

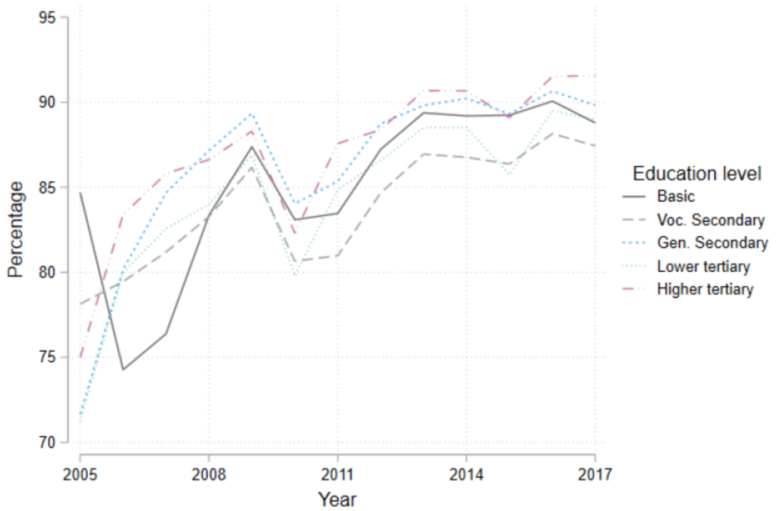

Table 1 presents the interaction effects between automation risk and class immobility (EGP_{t0}= EGP_{t12}) and main effect of immobility within each year throughout the observation period. The results are derived from multinomial conditional logit regression models that include the row and column effects (RC2) on parental class allowed to vary by EGP_{t0}, stereotyped ordered regression (SOR) effects for educational attainment and employment experience, and gender controlled. The Model 1 presents the immobility variable as a dummy – the likelihood of person remaining in the same class from beginning to the end of the year. The interaction effect shows that higher automation risk decreases the overall likelihood of immobility. In other words, higher automation risk increases career movements between classes. This supports our hypothesis (H1) that automation risk is positively associated with career movements.

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Table 1 Interaction effects of automation risk on class immobility within each year, (odds ratios of multinomial conditional logit regression models)

General immobility (ref: EGP_{t0}= EGP_{t12})	Model 1		Model 2	
Interaction effect immobility	0.987***	(0.000)		
Immobility main effect	26.104***	(0.437)		
Class specific immobility (ref: EGP_{t0}= EGP_{t12})				
Semi- or unskilled class			0.983***	(0.001)
Self-employed / farmer			0.996	(0.003)
Skilled (non)-manual class			0.980***	(0.001)
Lower service class			0.968***	(0.002)
Higher service class			1.028***	(0.002)
Main effects of class immobility				
Semi- or unskilled class			22.811**	(0.809)
Self-employed / farmer			184.961***	(19.02)
Skilled (non)-manual class			40.951***	(1.110)
Lower service class			30.456***	(1.953)
Higher service class			4.306***	(0.359)

Note: The models include SOR for education and employment experience, RC2 for parental class and controls for class-specific gender effects.

Model 2 demonstrates the relationship in more detail showing the career immobility results separately for each EGP class. The results show that the negative influence of automation risk in career immobility applies particularly to three classes: semi- or unskilled class, skilled (non)-manual class and lower service class. In these classes the higher automation risk of individuals' occupation increases class mobility. On the other hand, automation risk seems to impact class mobility of those in higher service classes in the opposite way: high automation risk increases the likelihood of immobility, and thus reduces the likelihood for downward mobility of the individuals in higher service occupations with high automation risk. This potentially surprising result does not mean that those in the higher service class experience less occupational mobility, but that the mobility does not cross class boundaries. As automation increases productivity in an occupation, those in the higher service class may benefit from this productivity boost and be able to entrench their advantaged position. Further, the career movements of those in self-employed or farming occupations, are not influenced by automation risk. This can be expected to be due to the very strong immobility of the individuals in this class (see the main effect in Model 2).

Next, we test whether individual careers are pulled towards their parental class over their careers (H2), and whether individuals experience less career mobility if they are in their parental class (H3). For these analyses we conduct two separate multinomial conditional logistic regression models (Table 2). Model 3 demonstrates the results on the pulling power of parental class on career movements (diagonal effects), whereas in Model 4 a variable measuring whether individual is in the same class as their parents (post-parental effects) is included and demonstrates career mobility if one is in the same class as parents. Both models include the row and column effects (RC2) on parental class allowed to vary by EGP_{t0}, stereotyped ordered regression (SOR) effects for educational attainment and employment experience, and gender and general career immobility dummy as control variables.

The diagonal effects in the Model 3 express the pulling power of each parental class for the individual EGP at the end of each year, taking into consideration the RC2, SOR and controlled effects. Thus, the odds ratio demonstrates how likely the individual's destination class (EGP_{t12}) is the same as parental class. And because we control for general immobility (EGP_{t1}=EGP_{t12}), the effect implies the likelihood of moving to the parental class, compared to the those who do not move (reference group). The diagonal effects show that the pulling power social origin is class-specific: it is practically absent in the skilled (non)-manual class (EGP3) and semi-unskilled classes (EGP5), weak for the upper and lower service classes, 12 and 18 per cent respectively, and clearly the strongest among the self-employed/farmers (EGP4) parental class. So, the results provide support for H2 as the career movements are pulled towards the parental class among all of the classes. However, the effect is very small for some classes, which raises class- and occupation-specific questions of the influence of parental class on individual career movements.

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Table 2 Results (odds ratios) of multinomial conditional logit regression (MCLR) on occupational destination (EGP classes)

	Model 3		Model 4	
Diagonal effects (ref: EGP_{t12}!=PEGP)	OR	SE	OR	SE
Semi- or unskilled class	1.068***	(0.012)	1.069***	(0.015)
Self-employed / farmer	1.523***	(0.020)	1.240***	(0.018)
Skilled (non)-manual class	1.056***	(0.012)	1.142***	(0.013)
Lower service class	1.120***	(0.014)	1.201***	(0.015)
Higher service class	1.183***	(0.028)	1.162***	(0.028)
Post-parental effects (ref: EGP_{t12}!= EGP_{t0}!= PEGP)				
Semi- or unskilled class			1.044**	(0.016)
Self-employed / farmer			0.258***	(0.010)
Skilled (non)-manual class			1.401***	(0.031)
Lower service class			1.826***	(0.062)
Higher service class			0.578***	(0.062)
Row and Column effects				
RC2 for parental class	0.982	(0.021)	0.910***	(0.018)
RC2 effect variation by EGP_{t0} (ref: EGP5)				
Self-employed / farmer	0.091***	(0.004)	0.110***	(0.004)
Skilled (non)-manual class	0.692***	(0.016)	0.770***	(0.017)
Lower service class	2.111***	(0.048)	2.198***	(0.047)
Higher service class	1.629***	(0.040)	1.639***	(0.038)
SOR effects				
Educational attainment	1.793***	(0.005)	1.817***	(0.005)
Employment experience	0.917***	(0.007)	0.914***	(0.007)
Employment experience^2	1.005***	(0.000)	1.005***	(0.000)
Controlled covariates				
General career immobility (EGP t1=t12)	18.022***	(0.064)	17.812***	(0.075)
Gender effects (ref. EGP5)				
Self-emp/farmer * Female	0.730***	(0.010)	0.712***	(0.010)
Skilled (non)-manual class * Female	0.785***	(0.008)	0.773***	(0.008)
Lower service * Female	0.747***	(0.008)	0.739***	(0.008)
Higher service * Female	0.336***	(0.005)	0.332***	(0.005)
Constants				
Self-emp/farmer vs Semi-/unskilled	0.395***	(0.004)	0.296***	(0.004)
Skilled (non)-manual class vs Semi-/unskilled	0.248***	(0.004)	0.213***	(0.003)
Lower service vs Semi-/unskilled	0.011***	(0.000)	0.010***	(0.000)
Upper service vs Semi-/unskilled	0.000***	(0.000)	0.000***	(0.000)

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The post-parental effects in Model 4 demonstrate the likelihood for any career movements if the individual class is the same as parental class in the beginning of the year. The odds ratios express the probability to move to another class for each parental class separately, compared to those who are not in the parental class at the beginning of the year. Hence, the results show that career movements are less like likely for those who are in, and whose parents are in the the self-employed/farmers (EGP4) or in the upper service (EGP1) class. Due to the class-specific results, we cannot fully accept or reject H3, as the career mobility is lower only among specific classes if the individual is in the same class as parents. So the hypothesis holds for EGP4 and EGP1 but is rejected for the unskilled class (EGP5) and the middle classes (EGP2-3).

Table 3 Interaction effects of automation risk on parental class diagonal effects within each year, (odds ratios of multinomial conditional logit regression models)

	Model 5	
Automation risk # diagonal effect (ref: EGP_{t12}!=PEGP)		
Semi- or unskilled class	1.000	(0.001)
Self-employed / farmer	0.978***	(0.002)
Skilled worker	0.999	(0.001)
Lower service class	1.018***	(0.001)
Higher service class	1.015***	(0.002)
Main effect of diagonal effects (ref: EGPt12!=PEGP)		
Semi- or unskilled class	1.090	(0.055)
Self-employed / farmer	3.415***	(0.259)
Skilled worker	1.158***	(0.045)
Lower service class	0.567***	(0.024)
Higher service class	0.712***	(0.049)

Note: The model includes SOR for education and employment experience, RC2 for parental class and controls for class-specific gender effects.

Table 3 describes the results of MCL regression models with interaction effects between automation risk and the pulling power of the parental class (i.e. diagonal effects), with the same modelling as the Model 3 in Table 2. The results in Model 5 show class-specific impact of technological changes on career movements in relation to parental class; high automation risk seems to reduce the pulling power of self-employed or farming parental class, but to increase

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the pulling power of service classes. This would suggest that individuals in high automation risk occupations are more prone for upward career movements towards service classes, if their parents are in those classes. Positively, individuals in high automation risk occupations are not drawn towards the semi- or unskilled parental class.

9. Discussion and conclusions

This study unravels new information on the inequalities in the labour market, and how persistent and flexible intra- and inter-generational transmissions can be. The intergenerational advantage in educational and occupational transmissions has been proven to be persistent, despite interventions and promotion of equality of educational opportunity. This paper provides empirical evidence on the mechanisms of intergenerational transmissions of class across individuals' early careers. Overall, the results support both the idea of counter-mobility and relative risk aversion theory by demonstrating, firstly that individual career movements are drawn towards their parental class, and secondly that career movements stagnate if individual is in the parental class. Further, the results indicate that technological changes impact both career movements overall, and the pulling power of the parental class.

One of the main contributions of the results is the class-specificity of them, highlighting the variety of both career mobility and intergenerational association between EGP classes. The pulling power of parental class, that is where individual career movements are drawn towards the parental class, is clearly the strongest among the self-employed/farmers (EGP4) class, followed by the service classes (EGP1-2). Further, the post-parental effects show that the self-employed class have a very strong immobility if both parents and the offspring are in this class, suggesting a very strong generational linkage of entrepreneurial occupations (in line with Bison 2011). The upper service class (EGP1) also demonstrated strong immobility pattern if obtaining the parental class, which is in line with the recent literature on the elites and the persistent intergenerational transmission of advantage, showing how unlikely downward mobility from this class is.

One interesting aspect of the results of this paper is that the pulling power of parental class is particularly weak among the middle class. This could indicate that the parents' middle class

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occupations are not achievable or desired for their offspring anymore. Further, the "post-parental" effect demonstrates that if the offspring is in the parental class, the career movements are still very likely and mobility continues. This could reflect on the more recent changes of these occupations, pushing the individuals to seek employment in other classes.

The results indicate that careers are experiencing substantial amount of mobility and instability in all classes, and this is impacted by family background. Additionally, the role of technological change, measured here as the automation risk of occupations, is found to influence both intra- and intergenerational class mobility. The results support our hypothesis (H1) that automation increases career movements, due to the changes in the labour market, particularly in jobs and tasks. Further, higher automation risk of the individual occupation seems to impact the pulling power of parental class with two opposite impacts: high automation risk is found to reduce the pulling power of those from self-employed or farming background, but to boost it if the parents are in the service classes. Thus, our hypotheses (H4) is supported but only among specific classes.

Even though technology has created the need for new skills, jobs and learning in the labour market – introducing new career movements – these movements are still made towards parental class, promoting particularly upward movements to service classes. Automation not only threatens some jobs and occupations, but also increases productivity. Those in or hailing from the higher service class may be in a specific position to benefit from this productivity increase, which can help them entrench their class position to improve chances of upward mobility. Technological change is therefore not just a threat to many but an opportunity to some, having the potential to increase class inequality.

Even though technology influences the motivation of job changes, this paper examines if these changes in occupational attainment occur also as in changes in class position of the individual. Therefore, some of the results of this study might show a slightly conservative picture of career movements as we focus only on class changes, not job changes (Mayer & Carroll 1987). What our results do not grasp is the probable increase in within-class movements via job changes in search for a better matched job for one's skills and credentials. This is something the increasing technological deformations of the labour market may have a bigger impact on than between-class movements. This, in turn, could increase social and occupational inequalities if some specific groups, e.g. individuals from well-off backgrounds, are able to make successful within-class movements. The analytical framework here is used to examine the big class movements in relation to social mobility, but there are some possibilities to extend it to other outcomes. An interesting one would be to study the movements at occupational level, but the mobility matrix would become extremely large if including multiple years over time. However, these relations and phenomena would be fruitful for future research to explore in order to reveal more in-depth processes between technology, occupational attainment and inequalities.

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Appendix 3.1

Table A3.1 Descriptive statistics of the main variables

Time-constant variables		%			
Parental class	EGP 1	4.3			
	EGP 2	13.9			
	EGP 3	19.5			
	EGP 4	25.7			
	EGP 5	36.6			
Education (highest obtained)	Basic	7.5			
	General upper sec.	7.2			
	Vocational up. Sec.	39.6			
	Lower tertiary	28.9			
	Higher tertiary	16.9			
Gender	Male	52.9			
	Female	47.1			
Time-varying variables (in person-years)					
Class t12 (end of the year)	EGP 1	12.2			
	EGP 2	25.5			
	EGP 3	24.2			
	EGP 4	6.6			
	EGP 5	31.5			
Class t0 (start of the year)	EGP 1	11.9			
	EGP 2	25.2			
	EGP 3	24.4			
	EGP 4	6.1			
	EGP 5	32.4			
Employment experience (yrs)		10.1	3.8	0	18
Automation risk (%)		37.0	7.2	15.78	57.15
		Mean	SD	Min	Max

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