RUHR
ECONOMIC PAPERS

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#857

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

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Editors

Editorial Office

Ruhr Economic Papers #857

Responsible Editor: Thomas Bauer

ISSN 1864-4872 (online) – ISBN 978-3-86788-993-3

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Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/86788993
ISSN 1864-4872 (online)
ISBN 978-3-86788-993-3

Birgit Zeyer-Gliozzo[1]

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Abstract

The automation of work tasks due to technological change increases the pressure on employees whose workplaces consist largely of such activities. Further training is an important way of adapting skills and enabling the performance of tasks that cannot be automated and are required in modern labour markets. Therefore, it should help to reduce the number of substitutable tasks performed and the risk of automation. These returns to training are highly relevant, but as yet little studied. Using data from the German National Educational Panel Study (NEPS), this paper examines the effect of formal, non-formal and informal training on work tasks and the automation probability for workers at risk of automation. The results show that non-formal and informal training in the form of media use actually helps to reduce the intensity of routine tasks. The effects of training on analytic, interactive and manual tasks as well as the probability of automation differ depending on the type of training, but are in many cases not significant. Furthermore, the results indicate that the impact of training on tasks partly varies with the degree of computerisation, a change of job and the level of education.

JEL-Code: I26, J24, M53, O33

Keywords: Further training; returns to education; automation; job tasks

July 2020

1 Birgit Zeyer-Gliozzo, RUB. – I am grateful to Martin Werding for helpful comments. – All correspondence to: Birgit Zeyer-Gliozzo, Ruhr-Universität Bochum, Gebäude GD E1/273, Universitätsstr. 150, 44801 Bochum, Germany, e-mail: birgit.zeyer@rub.de

1 Introduction

Many studies analysing the impact of technological change on labour markets reveal massive changes in the task content of jobs (e.g. Autor et al. 2003; Spitz-Oener 2006; Oesch and Rodriguez 2011; Bachmann et al. 2018). Since the 1970s, substitutable manual and cognitive routine tasks lose considerably in importance while analytic and interactive non-routine tasks, which are considered to be complements to computers, gain in importance. Some of these trends seem to have flattened out since the mid-2000s (Autor and Price 2013). One reason could be that task changes due to the introduction of computer technologies have already taken place in many areas. However, recent technological advances especially in artificial intelligence enable the automation of further tasks, which were not considered as substitutable so far, like for example truck driving (Brynjolfsson and McAfee 2014; Frey and Osborne 2017). This progress may cause another wave of task change in the near future.

Education and further training are considered to be of great importance in this context, both in science (Autor 2015, p. 27; Nedelkoska and Quintini 2018; Heß et al. 2019) as well as in politics (Bundesministerium für Arbeit und Soziales and Bundesministerium für Bildung und Forschung 2019). It can help workers to keep up with technological transformation and new qualification as well as task demands. This is particularly important for employees with a high share of tasks that can be automated (already or in the near future). This group of workers is most at risk of facing wage or job losses due to technological change. Further training could empower them to perform more tasks that are complemented by new technologies and less tasks that are substitutable. A successful task change, either within the same job or in connection with a job change, could be one way for this group to counteract job and wage losses through digitisation.

So far, however, there is only little research that examines the extent to which training actual helps workers to change the task content of their job and therefore raise their complementarity to computers and reduce their risk of being replaceable. Instead, much of the literature on individual benefits of training pays attention to the impact on wages, productivity, employability and mobility (for an overview, see Hansson (2008) or Grip and Sauermann (2013), the latter focusing on wages and productivity). To the best of my knowledge, there are only three articles analysing the impact of training on job tasks or the automation risk of workers. Using German WeLL Data from 2007-2010, Tamm (2018) found a significant effect of training participation on the amount of interactive non-routine tasks performed. Görlitz and Tamm (2016) analysed data from interviews with training voucher recipients in Germany in 2010/2011 and concluded that participation in training significantly increases the scope of analytic non-routine tasks carried out. None of these studies found a significant negative effect of training on the amount of substitutable routine tasks. Nedelkoska and Quintini (2018) focused on the automation risk according to Frey and Osborne (2017) and estimate the automation probability of workers against the background of further advances in artificial intelligence and mobile robotics. They showed, based on data of the German BIBB/BAuA Employment

Survey 2012, that requalification leads to occupational skills with a lower risk of automation than the first qualification. However, they only considered formal trainings. Training activities that do not lead to a formal qualification are therefore not taken into account, although participation in non-formal training activities is far more common among adults than participation in formal learning activities (Cedefop 2015, p. 58). Moreover, their approach does not measure changes in the tasks composition of the job actually performed.[1]

No previous study has investigated the effect of informal training, i.e. little structured learning such as learning with a computer program or learning from colleagues, on job tasks or the automation probability, even though informal learning plays an important role in the development of adults skills (Grip 2015). In addition, informal learning activities make up a significant proportion of adult learning activities and are practiced almost as often as non-formal ones. German data of the Adult Education Survey (AES) from 2016 shows that 43% of the 18 to 64-year-olds perform informal learning activities (Kaufmann-Kuchta and Kuper 2017), whereas 50% participated in non-formal (Bilger and Strauß 2017) and only 10% in formal learning activities (Kuper et al. 2017).[2] In addition, no research has examined the role of computer use and job change for the impact of training on jobs tasks. Does training increase the complexity of computer use? Is a change in job tasks due to computerisation stronger if it is accompanied by further training? Does a change of tasks in connection with training take place within jobs or is it associated with a change of job? This is of particular interest, as it is often argued that modern machines will not replace whole jobs but either just single tasks (e.g. Arntz et al. 2016). Accordingly, it should be possible for at least some employees to keep jobs by shifting tasks. The main purpose of this article is to analyse the returns to formal, non-formal and informal training of workers at risk of automation (high share of routine tasks/ high automation probability according to Frey and Osborne (2017)) in terms of changes in the composition of tasks performed in their (on-going or new) jobs.

This paper contributes to the literature on tasks and automation by providing important insights into the mechanisms for changing individual job tasks in the context of digitisation. More specifically, the role of learning activities is examined with respect to adaptations to new requirements in times of technological change. In addition, the results contribute to the research on returns to training. This paper is the first to investigate the effect of informal training on the task content of jobs as well as the automation risk of workers. So far, there have been only few studies on the returns to informal training in general (Rüber and Bol 2017), partly because of the difficulties of (uniform) measurements (Bassanini et al. 2007, p. 189f.). Comparing the impact of formal, non-formal and

[1] The analyses of Nedelkoska and Quintini (2018) are at occupational level. They compare the automation risk of the first occupational qualification with the automation risk of the new qualification that is acquired with a requalification. They calculate the differences by looking at the task characteristics of the two ISCO categories corresponding to the respective qualifications (Nedelkoska and Quintini 2018, p. 113).

[2] Also, participation in formal training decreases considerably with age. The proportion of participation in formal learning activities is only 6% in the age group between 30 and 34 years, and even less in the older age groups (Kuper et al. 2017, p. 156).

informal training on changing job tasks could provide important policy implications. It can help to understand which specific types of learning activities should be promoted in order to support workers to keep up with technological change. In addition, understanding the link between job change and the effect of training on tasks can help to explain the lower training participation of workers at risk of automation, as outlined in recent research (Heß et al. 2019). As employers often bear the costs of training, the fact that a change in the structure of tasks within the workplace is much less frequent than in connection with a change of employer could provide a possible explanation. Finally, the effects of training on tasks and the risk of automation have so far only been analysed for all workers. Since the number of jobs with a high intensity of routine tasks is decreasing, it is very important to analyse the impact of training for workers with a high proportion of these tasks, as it is precisely this group that has to adapt to technological change. Accordingly, the results presented here contribute to examining the extent to which further training activities have an effect for the most important target group in the context of digitisation.

This paper is organised as follows. Section 2 deals with a closer description of the different forms of training activities. In addition, it provides a theoretical background resting on the task-based approach by Autor et al. (2003) and on human capital theory (Becker 1964). Section 3 describes the data and methodology used for this study. The analyses will be based on the German National Educational Panel Study (NEPS), starting cohort adults (Blossfeld et al. 2011) and use fixed-effects estimations to reduce problems of selectivity into training. Section 4 presents the findings. The paper closes with a brief summary and discussion of the results in section 5.

2 Background and Theory

For my purposes, it is necessary to clarify exactly what is meant by further training. Previous German studies mostly defined it as the resumption of organised learning after completion of an initial education phase, usually marked by the entry into full employment (Deutscher Bildungsrat 1970, p. 197). Following Eurostat (2016), one can distinguish between different types of training:

- **Formal training**: institutionalised, intentional learning planned by public organisations and recognized private institutions, which leads to officially recognised qualifications.
- **Non-formal training**: institutionalised, intentional learning planned by an education provider, e.g. learning in courses or seminars.
- **Informal training**: intentional, but little organised and little structured learning.

Training can be further differentiated according to content (professional, general), location, source of funding, initiator or employment status (Bellmann and Leber 2017; Gnahs and Reichart 2013; Schiersmann 2007). In this paper, formal training as well as job-related informal and non-formal training of employees at risk of automation (high rate of routine tasks = 75th percentile or above / automation probability > 70%) are considered.

Why can it be assumed that further training can help with the restructuring of work tasks? To explain this, the task-based approach, first developed by Autor et al. (2003), will be illustrated in more detail. The main idea is that jobs consist of a bundle of tasks and that output is not achieved through qualification itself but the use of various skills for the execution of these job tasks. The impact of computerisation is considered to take place at the level of job tasks as computers substitute for certain types of tasks, while they complement other types of tasks. It is assumed that rule-based routine tasks can be decomposed into clear rules and therefore performed by computers by following programmed code. Thus, routine tasks are substitutable by machines and will be less performed by humans when computer prices will fall. Simple calculations are an example for cognitive routine tasks or repetitive assembly line tasks for manual routine tasks. In contrast, analytic and interactive non-routine tasks are instead complemented by computers and rise in demand. These tasks cannot be fully described by explicit rules for computer-based execution and, on the other hand, often use routine inputs. Managing people or doing research belongs to this type of tasks. Manual non-routine tasks like janitorial or care services can neither be complemented nor substituted by computers, and workers performing them are not directly affected by technological progress.

The classification of tasks varies between papers. For example, Spitz-Oener (2006) or Antonczyk et al. (2009) directly follow the assignment of tasks suggested by Autor et al. (2003); Acemoglu and Autor (2011) rearrange the relevant categories as non-routine cognitive, routine and non-routine manual tasks; Akçomak et al. (2016) only differentiate between routine and non-routine tasks; Nedelkoska and Quintini (2018) refer to analytic, social and manual tasks.[3] In any case, the basic idea that jobs are understood as a bundle of tasks and that the effects of computerisation on jobs take place at this level has proven empirically very useful in these articles.

Autor et al. (2003) make further assumptions regarding which workers are performing which types of tasks. They assume that workers have different productivity endowments in performing routine and non-routine tasks and that they choose their tasks due to comparative advantages. Therefore, labour supply for different tasks responds to changes in the relative wages for analytic and interactive non-routine and routine tasks as well as to changes in the relative efficiency at analytic and interactive non-routine vs. routine tasks. If the wage for non-routine tasks rises relative to the wage for routine tasks or if workers get more productive in performing non-routine tasks in relation to routine tasks (for example through the implementation of more computers), marginal workers would reallocate their job tasks from routine to non-routine.

In this paper, training is assumed to be one mechanism to increase relative

[3] The last classification in particular makes it clear that the theoretical framework itself can be transferred to different task categorisations.

productivity in non-routine tasks versus routine tasks, thereby restructuring the task supply. There are several reasons why one might expect this. 1. It is presumed, that better qualified workers have a comparative advantage in fulfilling analytic and interactive non-routine tasks vs. routine tasks (Autor et al. 2003, p. 1309). Following the human capital theory (Becker 1964), qualification is part of a person's human capital. Investments in human capital, such as further training, increases the level of human capital and makes workers more productive. Therefore, it is plausible that training raises qualification and thus the relative productivity in performing non-routine tasks in relation to routine tasks. 2. Against the background of human capital theory, workers and firms only invest in training if the expected returns exceed the expected costs. Therefore it is plausible that they invest in trainings for performing tasks which will remain, or increase, in demand in the future. So training should not only raise qualification and, hence, productivity in general but especially for performing non-routine tasks.

In sum, it is assumed that training increases the relative productivity in analytic and interactive non-routine vs. routine tasks. If so, training should have a negative effect on the amount of routine tasks and would have a positive effect on the amount of analytic and interactive non-routine tasks performed. This should be especially the case for marginal workers. Marginal workers are workers who already have a relative high productivity in non-routine tasks compared to routine tasks. In the context of theory, these should be the better educated workers within the group of routine workers.

In the popular (albeit also criticised) article from Frey and Osborne (2017) about the automation risk of workers in the United States in the next few decades, the authors recognised that advances in artificial intelligence and mobile robotics will expand the scope of tasks that can be performed by modern machines. Therefore, some of the tasks that Autor et al. (2003) described as non-routine will become routine in the near future. They developed three so-called engineering bottlenecks that characterise the new limits of what is technically feasible: perception and manipulation tasks or tasks of social intelligence or creative intelligence. Based on a workshop with IT experts from Oxford, they identified 70 out of 702 occupations from the O*NET database that can be fully automated, or not automated at all, given the latest technological advances.[4] They then applied a classification methodology using variables on the engineering bottlenecks to predict the automation probability for all 702 occupations. Some authors, like for example Nedelkoska and Quintini (2018), made use of the information on automatability of jobs and repeated the analyses at an individual level. They used information on job tasks in the Programme for the International Assessment of Adult Competencies (PIAAC) data that fits to the engineering bottlenecks to estimate the automation probability for people working in the 70 hand labelled jobs. Using the calculated coefficients, they then estimated the automation probability of all others.

[4] The O*NET data provide standardised descriptions of occupations in the USA (O*NET Resource Center 2020) and are frequently used in research on job tasks.

Since the technological development is progressing rapidly (Brynjolfsson and McAfee 2014) and a change in work tasks in the sense of the task-based approach seems to be flattening out recently (Autor and Price 2013), it is considered important in the present study to also examine the effect of further training on the automation risk with regard to the engineering bottlenecks. In this way, returns to training are analysed in the context of the most modern technological advances. To achieve this, Nedelkoska and Quintini's (2018) procedure described above can be followed to calculate the automation risk at an individual level (see below). Against the background that employers and workers will only invest in training tasks which will raise in demand in the near future, training should have a negative impact on the likelihood of automation. Furthermore, if one assumes that better qualified people have a comparative advantage in the execution of (complex) social and creative tasks, this also leads to the assumption that training reduces the risk of automation due to engineering bottlenecks.

At the beginning I argued that training is particularly important for those workers who perform many tasks that can be automated. Considering the approaches reviewed in this chapter, it can further be assumed that training will help only this group of workers to achieve a significant change in their job tasks. For people who already perform a large number of non-routine tasks, it is likely that training will help them become more productive in these tasks. However, it is likely that they already had a comparative advantage in performing these tasks prior to further training. It is therefore not expected that this group will experience significant changes in the task structure of their jobs as a result of further training. This underlines the relevance of focusing on employees with a high risk of automation.

3 Data and methodology

3.1 Data

For the following analyses, data of the NEPS starting cohort adults (SC6, Version 10.0.1) is used (Blossfeld et al. 2011). This dataset provides longitudinal data on educational processes and competence development during the life course of adults (aged 20 and older). The study is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg and there are currently 9 waves that have been collected annually since 2009/2010. The analyses in this paper are based on wave 3 (2011/2012) and wave 7 (2015/2016) as they contain specific information on job tasks.[5]

The sample is restricted to individuals who participated in wave 3 and 7, aged between 27 and 60 in wave 3, who were in dependent employment in both waves and have no missings in relevant variables. The final sample consists of 3,198 individuals.

For the measurement of tasks which correspond to the task-based approach by Autor et al. (2003), Matthes et al. (2014) developed an instrument which

[5]For the sake of simplicity, I will only refer to the years 2011 and 2015 below.

was included in the NEPS questionnaire in the waves 3 and 7. Most questions address how often the respondents are performing specific tasks, with answers ranging from 1 ("always/very often") to 5 ("very seldom/never"). For example, for manual tasks the question was asked how often one has "to stand continuously for at least 2 hours on an average working day"; or for interactive tasks how often one has to "teach or train other people" (Matthes et al. 2014, p. 292f.). Some tasks like use of mathematics, reading, writing or use of computers are measured with dichotomous response categories, stating whether certain activities are carried out or not. Thereby, several questions were used for one task, which differed with respect to the complexity.[6] From these items, a variable can be formed which measures the complexity in the execution of the respective task. The different task variables can be used to calculate task-indices for the following task-types: Analytic, interactive, manual, routine and autonomy tasks (see table 1). The category of autonomy tasks is not used in the following analyses. The task indices are built by first recoding the single items so that high values reflect high occurrence or complexity (values 0 to 4). Secondly, the corresponding items for an index are summed up and the mean value is calculated. The result is standardised to the range between 0 to 1. Out of this, a "routine intense" variable was generated, which is 1 for all people who's index lies above the 75. percentile of the routine-distribution (this idea is based on Heß et al. (2019)).[7]

[Table 1 around here]

To calculate the probability of automation I follow Nedelkoska and Quintini (2018), who made use of the approach of Frey and Osborne (2017). They assigned the 70 jobs which were manually labelled as automatable or not automatable in O*NET to occupations in ISCO-08.[8] I adopt this assignment (for details see Nedelkoska and Quintini (2018, p. 121 f.)). For classification, they used a logistic regression model estimating the latent probability of automation as a function of job tasks on an individual level. Their analyses are based on PIAAC data of 2011/2012 and 2014/2015. The data used to fit the model consists of people working in jobs that were hand-labelled in the first step. For the regression, they had to find PIAAC variables describing job tasks that reflect the engineering bottlenecks identified by Frey and Osborne (2017), i.e. perception and manipulation, creative intelligence and social intelligence. Table 2 provides an overview of the variables that Nedelkoska and Quintini (2018) used to measure the engineering bottleneck tasks, as well as the selected variables in NEPS for the present analyses.

[Table 2 around here]

[6] Here is an example of a question about writing activities: "As part of your occupation, do you write texts which are five pages long or longer?" The next question (filtered to the answer before) is: "As part of your occupation, do you write texts which are twenty five pages long or longer?".

[7] The task variables are calculated at individual level and not at the level of occupations.

[8] 7 jobs were not transferable when transferred to ISCO-08, so only 63 jobs were used.

Table 3 shows the results of the logistic regression I carried out. The coefficients point in the right direction and are significant for most variables referring to manual and interactive tasks. Most coefficients of the variables referring to tasks involving creative intelligence are not significant and sometimes have an unexpected sign, with the exception of "variety of requirements: can learn sth. new".

[Table 3 around here]

This indicates that the NEPS task items (which are based on the task-based approach by Autor et al. (2003)) are not perfectly suitable for mapping tasks demanding creative intelligence. Thus, the estimated probability of automation may be biased upwards because the performance of creative intelligence tasks is not sufficiently reflected by the data. Nevertheless, the results indicate that the probability of automation is predicted at least as well as in Nedelkoska and Quintini (2018) (referring to the area under the ROC curve). In the last step, the estimated coefficients are used to predict the automation probability for all workers based on their job tasks.

Based on the definition provided above, further training is the resumption of learning after having completed an initial educational phase. The problem in measuring formal training is the distinction between formal initial education and further formal training. How can the end of the first phase of education be empirically measured? Age could be a broad indicator, but will probably lead to misclassifications due to the very different starting ages of full employment (people in Germany who have completed an apprenticeship usually enter full employment earlier than people who initially study). For this reason, a different approach is chosen that takes advantage of the detailed information about the educational career of the respondents in NEPS. The "initial education phase" is separated from a "second education phase" by examining when the gap between the start of a new educational activity and the end of the previous educational activity first exceeded 15 months.[9] Military service and vocational preparation schemes are counted as educational activities (since the interruption by a military or civilian service does not mean the completion of the first phase of education, but often only an interruption after school). All subsequent educational activities after this first gap, i.e. attendance of schools, universities, technician or master schools or the completion of vocational trainings are then assigned to the second education phase and therefore to formal training (military service and vocational preparation activities are not taken into account at this stage). Two variables are generated that indicate whether and how many such formal training activities have been completed between waves 3 and 7.

[9]The gap of 15 months was chosen because a gap of this magnitude probably no longer represents a "mere break". The main regressions in table 7 and 8 were also carried out for larger (20 and 24 months) and smaller gaps (6 and 12 months). The regression results are almost identical to those reported here (across all types of tasks and the probability of automation, the maximum difference between the new coefficients for formal training and those given here is 0.006).

Data on non-formal further training is collected in NEPS through various question modules. The following information is used for the present analyses: The module *spCourse* contains information about training courses during episodes of employment, unemployment, parental leaves, military/civilian service or gap episodes. Information about training participation since the last interview, the total number and total duration of courses as well as detailed information about up to three trainings were collected. Here, only training courses during episodes of employment are taken into account. The second module which provides information about non-formal trainings is *VocTrain*. Some of the trainings reported there, more precisely training courses for obtaining licenses, can also be classified as further training(FDZ-LIfBi 2019, p. 98). For reasons of comparability with the other non-formal trainings, only courses that started during an employment phase are taken into account. Two non-formal training variables were generated. First a variable that tells if a person participated in non-formal further training between wave 3 and 7. Second a variable indicating the number of courses attended between wave 3 and 7.[10] A third variable is generated to test how sensitive the results are with respect to whether only completed training courses or the general attendance of training courses are counted. This variable is 1 if (at least) one further training has been completed between waves 3 and 7.

In order to operationalise informal learning activities, information from employees on "Visit of special trade fairs or congresses", "Visit of special lectures" and "Use of any computerized learning programs, learning CDs or DVDs or similar materials" is used. The respective informal learning activity is only taken into account if it was carried out for professional or professional and private reasons. A dichotomous variable was constructed to indicate whether a person had carried out (at least) one of these informal training activities between wave 3 and 7. There is no information about the scope of informal training activities.

To measure the use of computers at work, NEPS records whether the respondents are using computers at all and what type of activities they carry out on the computer. This information can be bundled in a variable on the complexity of computer usage: No computer usage at work, normal computer usage (no use of standard software, use of standard software, use of specific software) and complex computer usage (use of program functions of standard software, use of program functions of specific software, use of programming languages). From this, a variable is created about the change of computer use between wave 3 and 7 (no change, more complex computer use, less complex computer use).

Table 4 presents summary statistics for the whole sample as well as for routine intense and not routine intense workers. It is apparent that, on average, routine intense workers are more often woman, have more frequently a low or middle and less often a high level of education, are more often in a temporary work contract and use computers less often and in less complex ways than not routine intense workers. Furthermore, the table shows that almost one in three

[10] It is not possible to calculate the total duration of all courses when using the trainings from *VocTrain*, because there only information about the start and end date is recorded. Instead, information about the total course duration in *spCourse* is provided in hours.

routine intense workers has an automation probability of over 70%, compared to only 8% of not routine intense workers.

[Table 4 around here]

Figure 1 illustrates the task intensity, automation probability and complexity of computer usage by education group. In line with the task-based approach, which assumes a comparative advantage of highly qualified individuals in performing analytic and interactive tasks, high skilled workers have the highest values in these task indices and have the lowest index value in routine tasks. The literature on job polarisation states that routine tasks are mainly performed by middle skilled workers (which leads to job polarisation as a result of technological change; e.g. Goos and Manning 2007). This is not reflected in the data here. Rather, there seems to be a linear relationship between the index of routine tasks and the level of qualification in the sense that the more highly qualified a person is, the fewer routine tasks are performed. A similar pattern can be seen in the estimated probability of automation. From the figure we can see that (apart from complex computer use) the higher the level of education, the more computer use is pronounced. However, almost half of the employees without vocational training also have normal computer use at work. There are almost no employees with a university or college degree who do not use a computer at work. The most striking result that emerges from this figure is that slightly more people from the lowest education group report complex computer use than from the middle education group.[11]

3.2 Estimating the returns to training

A crucial problem in estimating the returns to training is selectivity into training (Bassanini et al. 2007, p. 254 f.). The following equation models human capital returns y_{it} (in the present analyses, job tasks or the probability of automation) as a function of investments in human capital T_{it} (training), a vector of controls $\boldsymbol{x}_{it}$ and the error term ε_{it} :

$$y_{it} = \alpha T_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{1}$$

When using ordinary least squares (OLS) estimators, the explanatory variables must be uncorrelated with the error term in order to obtain unbiased coefficients. Thus, if there are unobserved characteristics such as ability or motivation that have a positive impact on human capital investment and a positive effect on returns to human capital investments, OLS would lead to positive biased results (Wooldridge 2013). For example, it is very plausible that more motivated or

[11] Two possible explanations are examined: does the result come from the fact that there are workers in this group who are completing a vocational qualification (e.g. studies) and use computers in a complex way? In total there are 13 persons in training among those without a professional degree, but only about 8% of them have complex computer use. Or is it due to a more complex computer use of younger (aged 20-49) compared to older (aged 50 or older) workers in this group? Again, this is not the case; the older group even shows a higher proportion of individuals who have complex computer use.

able people are more likely to receive further training and that, at the same time, employers tend to adapt the work tasks of these people in the event of technological change rather than looking for new workers.

The training literature has followed different approaches to address this problem, such as using fixed-effects (FE) estimations (Pischke 2001; Booth and Bryan 2005; Frazis and Loewenstein 2005; Albert et al. 2010), counter factual research designs (Leuven and Oosterbeek 2008; Görlitz 2011) or estimations with instrumental variable (Kuckulenz and Zwick 2003). The NEPS data does not contain any variables that can be used to create a counter factual research design.[12] In addition, it is difficult to find appropriate instrumental variables that correlate with training, but not with training returns. However, the panel structure of the NEPS data and the time variation of training and tasks can be used to carry out FE estimations. For this purpose, the error term is divided into an individual, time-constant error term a_i and an idiosyncratic error term u_{it}.

$$y_{it} = \alpha T_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + a_i + u_{it} \tag{2}$$

This equation is averaged over time for each individual. Then in the FE model the averaged values for each t are subtracted from equation (2) (Wooldridge 2013), yielding:

$$(y_{it} - \overline{y}_i) = \alpha(T_{it} - \overline{T}_i) + (\boldsymbol{x}_{it} - \overline{\boldsymbol{x}}_i)'\boldsymbol{\beta} + (u_{it} - \overline{u}_i) \tag{3}$$

As a result, all time-invariant variables drop out of the equation, as does the time constant error term a_i. Consequently, the FE estimation allows for a correlation between time-invariant unobserved variables (captured in a_i) and the explanatory variables.

In order to obtain unbiased estimates, the main assumption of an FE estimation is that the explanatory variables are strictly exogenous. There must be no correlation between the idiosyncratic error u_{it} and the explanatory variables over all time periods. Measurement errors, time-varying, unobserved heterogeneity and reverse causality can lead to a violation of this assumption (Brüderl 2010, p. 992). The last point in particular could pose a problem in the present analyses. It may well be that an employee is entrusted by his employer with new tasks (for various reasons, e.g. individual promotion or structural changes) and is then expected to acquire the necessary skills through further training. This seems plausible, especially with regard to informal learning activities, which can be one form of familiarisation with the new tasks. However, the problem seems less likely with increasing levels of institutionalisation and structure of training. Qualifications acquired through formal training are often a prerequisite for the exercise of certain tasks or professions and should therefore generally be acquired beforehand. In addition, the employer needs information to assess whether the employees are able to perform the new tasks or are able to learn how to perform them. Especially in the case of workers who have previously carried out many

[12]This was done in the literature with information about non-participation in training due to random events of individuals who wanted to participate in training

routine tasks, the employer is likely to have only partial information about their ability to engage in analytic or interactive tasks. To ensure the quality of the output, it seems sensible to first have employees successfully complete a course to prepare them adequately for a change of tasks. Nevertheless, possible reverse causality should be taken into account when interpreting the results, especially the estimates for informal training. Particularly in this case, the results should more be interpreted as correlations rather than as a causal relationship between training and tasks.

4 Results

4.1 Training participation and task change

The first set of analyses examines the average learning activities of routine intense and not routine intense workers as well as the task change between 2011 and 2015. Table 5 presents data on the participation in formal, non-formal and informal training for routine intense and not routine intense workers. In line with the above-mentioned results from the German AES data of 2016, the most common form of training between 2011 and 2015 is non-formal training (65%) followed by informal training (between 30% and 38%).[13] Only 4% of the adult workers participated in formal training. Comparing routine intense workers and those who are not routine intense shows, as expected from previous studies (e.g. Heß et al. 2019), that routine intense workers participated less frequently in further training. About half of the routine intense workers took part in non-formal further training, while 70% of the non-routine intensive workers did so. There is also a difference in the number of further trainings attended. Among those who attended further training at all, the average number of non-formal training courses between waves 3 and 7 is 3.16 for routine intense workers and 4.32 for not routine intense workers. While similar patterns can also be seen for informal training activities, they do not seem to apply to formal training courses in which 4% of employees in both groups participated. Among the persons who have participated in formal training (140 in total), about 88% have attended only one course (this proportion is about 24% for non-formal training). The maximum number is 3. Due to the small variation, only the dummy variable for formal training is included in the regression models.

[Table 5 around here]

Table 6 and figure 2 provide an overview about the change in task intensity, automation probability and computer usage between 2011 and 2015. It is apparent from the table that the change in tasks over those four years was not particularly pronounced. Between 2011 and 2015, no significant and relevant differences in the intensity of the analytic, interactive and manual tasks were

[13] Looking only at completed training courses in the respective waves, the share of persons who participated in training courses between waves 3 and 7 drops slightly to 63% (all), 47% (routine intense) and 69% (not routine intense).

found among all employees. This is in line with the literature, which finds a deceleration of task change according to the classification by Autor et al. (2003). The average intensity of routine tasks rose significantly in the meantime. This is somewhat unexpected. Comparing routine intense and not routine intense workers, a different picture emerges. It can be seen that those who carried out a lot routine tasks in 2011 did less of these on average after four years. In contrast, the routine intensity of the group that was not intense in 2011 has increased. This also becomes clear when looking at the proportion of workers who are classified as routine intense. 29% of those originally routine intense were no longer so in 2015, while 18% of those who were not routine intense in 2011 were routine intense in 2015. Among this group, the average probability of automation also increased significantly from 39 to 42%, while it did not decrease significantly among routine intense workers, but was still at a higher level of 55% in 2015. A small but slightly significant increase in interactive tasks of routine intense workers (and a decrease in this task type for not routine intense workers) can also be detected.

[Table 6 around here]

Turning now to the change of computer usage, it can be seen that the number of employees who either do not use computers at work or have a complex computer use decreased on average, while normal computer use increased between 2011 and 2015. The reduction in complex computer use could be explained by the fact that software is becoming increasingly intelligent and user-friendly, thus reducing the need for complex adaptations, e.g. via program functions. This pattern is basically visible across all groups.

The task change of training participants and non participants among routine intense workers is shown in figure 2. What stands out are the large differences in the intensity of different types of tasks between training participants and non-participants that already exist in 2011. Routine intense workers who did not attend non-formal training courses between 2011 and 2015 had a higher intensity in routine tasks and manual tasks, a higher automation probability and were less intense in analytic and interactive tasks compared to those, who did participate in training. Perhaps these differences can be explained by educational background, as many studies indicate that higher educated people are more likely to take part in further training than lower educated people (e.g. Arulampalam et al. 2004; Bassanini et al. 2007; Albert et al. 2010). It may also be the case that unobserved factors influence participation in further training and the structure of work tasks, such as intelligence or motivation. This would underline the relevance of the estimation strategy used. Another striking result is the differences in task changes between training participants and non-participants. It is apparent that trained routine intense workers experienced a greater reduction in routine tasks than those who did not participate in training. Moreover, the scope of analytic tasks increased for this group, while those who were not trained performed slightly fewer analytic tasks in 2015 than in 2011. The probability of automation of the trained employees also decreased, albeit only slightly, while the probability of employees who had not undergone further training remained essentially the same.

[Figure 2 around here]

Taken together, the descriptive results suggest that workers at risk of automation participate less often in training, that the task change between 2011 and 2015 is not very pronounced and that there seems to be an association between training and task change of routine intense workers. Since this relationship may be influenced by other factors, multivariate analyses are discussed in the next step.

4.2 Returns to training

FE regression analyses are used to estimate the effect of training on tasks and the automation probability of workers in routine intense occupations or with a high automation probability (> 70%) in 2011. Table 7 shows the effect of computerisation and training on the amount of routine tasks. The results in column 1 confirm the negative relationship expected from the task-based approach between computer use and the scope of routine tasks. Workers who experienced an increasingly complex computer use between 2011 and 2015 performed significant less intense routine tasks in 2015. The coefficient decreases slightly when controlling for training. This could be interpreted to mean that further training is a mechanism (albeit not a very strong one) for the change in tasks caused by digitisation. The relationship is still negative but no longer significant if one controls for having a temporary contract, hours of work, work experience and having a child in the household.

Column 2 shows that non-formal and informal training in the form of media use significantly reduce the amount of routine tasks for workers at risk of automation. On average, after participation in non-formal training between 2011 and 2015 the amount of routine tasks decreased by 0.03 index points. With each further training, the index is reduced by additional 0.01 points. Routine intense workers who made use of any computerised learning programs, learning CDs or DVDs or similar materials (informal learning) between 2011 and 2015 subsequently had a 0.03 point lower routine index on average. Formal training as well as informal learning in terms of attending special trade fairs, congresses or lectures does not have a significant impact on the amount of routine tasks.[14] The size of the effects does not appear to be very large. However, if one takes

[14] If, instead of a general variable for formal training, variables are used that differentiate according to the type of formal training (e.g. vocational training, university studies, master craftsman/technician training, courses with an association/chamber, doctoral studies/habilitation, and so on), different effects are seen. Formal training in the form of a course at an association/chamber and master craftsman/technician training has a significant negative effect, university studies have a slightly significant positive effect, vocational training has no significant effect. However, the number of cases is too small (association/chamber: 10, master craftsman/technician: 8, university studies: 19, vocational training: 31) to make reliable statements.

into account that the overall change in tasks between 2011 and 2015 was not very pronounced, they are nevertheless not negligible. For example, a change of 0.03 routine index-points accounts for more than half of the total average change in this task type between 2011 and 2015 for routine intense workers (see table 2). The coefficients do not change much when control variables are included and are still significant (column 3). For sensitivity analyses, a variable is created that becomes 1 if at least one non-formal training was *completed* between 2011 and 2015. The results in column 4 show an average decrease in routine intensity by 0.04 points if routine intense workers completed at least one training between 2011 and 2015.[15]

[Table 7 around here]

The second set of analyses examines the impact of computerisation as well as training on analytic, interactive and manual tasks, the automation probability (for people with a high automation probability in 2011) and the increase or decline of the complexity of computer use. First of all, from the data in table 8 it is apparent that the change in tasks is related to the increase in the complexity of computer use in the expected direction. More complex computer use has a significant positive effect on the amount of analytic and interactive tasks and a negative effect (not significant) on manual tasks and the automation probability.[16] Table 8 shows that, on average, non-formal training has significant positive effect on the amount of analytic tasks, but not on any other task type. Routine intense workers who received non-formal training between 2011 and 2015 experienced an increase in the intensity of analytic tasks by 0.02 points (significant at the 10% level). The amount of interactive and manual tasks seems to be unaffected by any type of training. There is a significant negative correlation between informal training and changes in the probability of automation. Employees with a high automation probability in 2011 who used media and lectures for learning in the following four years have on average a 0.04 point lower probability of automation than before. This accounts for about 30 % of the total change for these workers.[17] Surprisingly, formal training and informal training (media use) have a significant positive impact on the likelihood of less complexity in computer use in 2015. Given the descriptive results and the decreasing average number of people not using a computer, it is likely that this effect reflects a positive impact of training on the likelihood of switching from complex computer use to normal computer use. A change of job only seems to have a significant positive effect on the probability of increasing complexity in

[15] For comparison: if one only includes the dichotomous variable for participation in non-formal training between 2011 and 2015 in model 3, the coefficient is 0.042.

[16] If, as in table 7, the variables are introduced step by step to determine the extent to which training is a mechanism for changing tasks through computerisation, it can be seen that the coefficients of increased complexity of computer use do not change with the inclusion of the training variables (except for analytic tasks, but only marginally). When the control variables are included, the coefficients for analytic and interactive tasks and the probability of automation decrease somewhat more (results can be provided on demand).

[17] Employees with a high probability of automation in 2011 experienced an average reduction in their automation probability by 0.13 points.

computer use (table 8 column 5). At the same time, a change of the occupation of routine intense workers is significantly correlated with an increase in analytic and interactive tasks and a decrease in the probability of automation (table 8 column 1, 2 and 4). There seems to be a relatively large time effect on the scope of the interactive tasks. On average, the index of interactive tasks of routine intense workers decreased by 0.2 points between 2011 and 2015, even when controlling for all other variables. This is surprising in light of recent research on the increasing importance of social interactions in the labour market (Deming 2017).

[Table 8 around here]

4.3 Heterogeneity of training returns

In section 2 it was argued that the impact of training on tasks should be greater for marginal workers, i.e. those with a higher relative efficiency in non-routine tasks compared to routine tasks. These should be highly skilled routine intense workers. To test this assumption, interaction effects between training and a university (or university of applied science) degree were included in the regression (see table 10 in appendix C). With regard to changes in routine, analytic and interactive tasks, the results show that the effects of non-formal training are indeed stronger for highly skilled workers, although the difference is not significant. In contrast, informal and less structured learning seems to be more helpful for workers with lower educational attainment. The impact of informal learning in the form of media use on analytic tasks and in the form of attending lectures on interactive tasks is significantly lower for highly skilled workers than for workers without a university degree. The most surprising result is that non-formal training has a positive effect on the probability of automation for employees with a university degree, whereas the effect is negative (but not significant) for less qualified employees. The difference between the two groups is significant. Overall, the results are not consistent and therefore cannot support the assumption that the effect of training on tasks is greater for high skilled routine intense workers.

The final results in table 9 show whether the effects of training on tasks are different for individuals with an increased complexity of computer use (columns 1-5) or who changed jobs (columns 6-10) between 2011 and 2015. Here, interaction variables between training and increasing complexity of computer use or job change have been included in the regression equations. The first five columns indicate whether a change in work tasks due to the interaction of computerisation and training is stronger than if only one of the two occurs. On average, a more complex computer use which is accompanied by informal learning in the form of media use (i.e., at the computer) is shown to have a strong significant negative effect on the amount of routine tasks. Routine intense workers who switched to more complex computer use in the workplace between 2011 and 2015 and learned informally using media, had a routine index that was on average 0.16 points lower than before. An increase in the complexity of computer use or informal learning activities alone had no effect on the scope of routine tasks. As with the routine tasks, it is shown that a more complex use of computers accompanied by informal training with media has a (weak) significant positive effect of 0.12 points on the scope of interactive tasks and a significant negative effect of 0.24 points on the probability of automation.[18] What can be said about the impact of non-formal training on tasks? On average, employees who used more complex computers and participated in non-formal training performed 0.05 index points less manual tasks in 2015 than in 2011. The significant negative effect of non-formal training on routine tasks does not seem to be affected by whether or not computer use has changed. This is different for analytic tasks. The training coefficient (which represents the effect of training for workers who did not increase their computer use, if the interaction coefficient is neglected) is smaller and no longer significant. The interaction effect is positive, which means that non-formal training combined with more complex computer use increases the intensity of analytic tasks. However, this effect is not significant. No significant interactions were found for formal training.

[Table 9 around here]

The results on whether or not the effect of training on work tasks is stronger in combination with a job change are shown in columns 6-10. It can be seen that routine intense workers who changed employers between 2011 and 2015, but did not participate in any non-formal training, performed on average 0.07 index points less analytic tasks than before (significant at the 5% level). However, when the job change was accompanied by non-formal training activities, the amount of analytic tasks remained the same due to the significant positive interaction term. A similar pattern is seen for manual tasks, where a change of job or participation in non-formal training alone have a positive (though not significant) impact on the scope of this type of task. However, employees who changed jobs *and* participated in at least one non-formal training performed on average 0.03 index points fewer manual tasks than before. For all other types of training and tasks, a change of employer does not seem to have an influence on the impact of training on tasks.

Column 10 reveals that attending formal training in combination with a job change has a major significant negative impact on the automation probability of workers. Employees with a high automation probability in 2011 had a 0.22 point lower probability of automation after changing jobs *and* attending formal training. Informal training in the form of media use in combination with a change of job seems to have a similar, though somewhat weaker, effect. The most surprising aspect of the results is that non-formal training in combination with a change of job has a positive, albeit marginal, effect on the automation probability of employees (0.01 points). One reason for this could be that the training took place at the previous employer and is not recognised by the new employer. Further research on non-formal training is needed to investigate this.

[18] 0.085+0.027+0.007=0.119 & -0.231+0.001-0.009=-0.239

Taken together, the results suggest that computerisation and informal training in form of media use together seems to have a large impact on the change of job tasks. The effects of training on job tasks is generally not affected by a change of employer. Only for manual and analytic tasks it seems important that a change of jobs is accompanied with non-formal training. In contrast, the probability of automation seems to be significantly reduced if (especially formal) training is combined with a job change.

4.4 Robustness of findings

As explained in Section 3.2, measurement errors, time-varying, unobserved heterogeneity and reverse causality can lead to biased coefficients. To address the problem of unobserved heterogeneity, additional control variables can be included in the regression models, namely upcoming promotion and health satisfaction.[19] For example, it may be the case that someone is doing further training for an upcoming promotion in order to prepare for the new tasks. But it could also be that further training leads to a person being promoted. In this case, however, the promotion might be the reason for a change of tasks and not the further training. Similarly, an improvement or deterioration in health status can influence both training behaviour and the job tasks carried out. The results (see table 11 in appendix C) show that the coefficients of training on routine tasks and the probability of automation are robust to controlling for promotion and health satisfaction. The effect of non-formal training on analytic tasks also remains the same, but is no longer significant ($p = 0.102$). It is therefore possible that other unobserved factors such as career advancement or health may have slightly biased the effect of training on analytic tasks.

5 Summary and Discussion

The main objective of this study was to identify whether formal, non-formal or informal training helps workers at risk of automation to get the task content of their jobs changed in order to perform less substitutable tasks, more tasks that are demanded in current labour markets and having a lower automation probability. Using german NEPS data of 2011/2012 and 2015/2016, FE regression analyses reveal that participation in further training actually helps workers who carry out routine tasks intensively or have a high probability of automation by affecting the structure of tasks in the workplaces as well as the probability of automation. However, the effect of participation in training on

[19]Promotion is measured with a proxy variable that reflects the (self-assessed) probability of promotion in the next 2 years. All persons who indicated in wave 3, 4 or 5 that promotion is likely to occur receive a value of 1 for the promotion variable (in 2015; in 2011 everyone's probability is set to 0). 3 persons in the total sample and 1 person in the sample of routine intense workers had no information on their promotion probability in wave 3, 4 and 5. For this reason, multiple imputations were used to estimate the results based on the same sample as before. The variable on health satisfaction has a value ranging from 0 (completely dissatisfied) to 10 (completely satisfied). There are no missing values in the present sample.

work tasks depends on the learning activity and on the interaction with more complex computer use and a change of employer.

Participation in non-formal training has a significant negative effect on the amount of routine tasks and a significant positive effect on the amount of analytic tasks, whereas the effect on analytic tasks is no longer significant when up-coming promotions and health status are controlled for. Routine intense workers who took part in non-formal further training between 2011 and 2015 had an average routine intensity that was 0.03 points lower than before training, which is a not negligible effect in relation to the overall change in routine tasks during this period (0.05 points). This result is contrary to previous studies which found no effect of non-formal training on the amount of routine tasks (Görlitz and Tamm 2016; Tamm 2018). However, these studies did not focus on workers at risk of automation. As argued in section 2, it can be assumed that training does not have a large impact on the task structure of employees who are not routine intense, as they probably already had a comparative advantage in the performance of non-routine tasks and therefore already carried out these tasks on a large scale.

As mentioned in the literature review, there was no study so far which analysed the effect of informal training on job tasks although informal learning is of great importance for the development of human capital of workers (Grip 2015). This study has revealed that an important mechanism for task change has indeed been left out. The results have shown that informal training, such as the use of computer-based learning programs, learning CDs or DVDs or similar material, has a strong significant negative impact on the scope of routine tasks and the probability of automation as well as a significantly positive effect on the scope of interactive tasks for workers at risk of automation who have experienced increasing computerisation at the workplace. Here, however, it is important to remember the possible reverse causality. Therefore, these results should be interpreted as correlations and not as causal effects.

The investigation of the interaction between training and job change has shown that non-formal training is particularly important in this context. On average, routine intense workers who changed jobs *and* participated in non-formal training performed the same amount of analytic tasks as before, instead of significantly less when changing jobs without non-formal training. A comparable tendency can be seen with regard to manual tasks (in the sense that fewer manual tasks were performed after a job change with non-formal training). At the same time, formal training seems to play an important role for the probability of automation when changing jobs. On average, employees with a high probability of automation (i.e. exceeding 70%) in 2011 had a substantially lower probability of automation after a change of job combined with formal training. This is the only context in which formal training seems to have an impact on the change of tasks or the automation probability of workers at risk of automation.

Taken together, the results partially support the hypotheses made on the basis of the task-based approach (Autor et al. 2003) and human capital theory (Becker 1964). For workers at risk of automation, training seems to have a negative effect on the scope of substitutable tasks and the probability of automation, as well as a positive effect on some tasks with increased demand in the context of digitisation. However, the results suggest that the type and context of training as well as the group that is trained play an important role. With the theories presented above, it cannot be explained why different forms of further training have different effects on the change in tasks. According to human capital theory, formal, non-formal as well as informal training would raise the qualifications, which should result in an increased relative efficiency of non-routine vs. routine tasks. Perhaps the different effects could be explained by the fact that only average effects are considered for non-formal and formal further training. This does not take into account what type of training is carried out. The analyses of informal training, for example, show that those forms involving media use seem to be most relevant. Different effects depending on the organiser, duration, subject and certification (which would be relevant in the context of signalling theory, especially when changing employers) could thus be an explanation. Tamm (2018) has made an important first step by showing clear differences in the effect of further training on job tasks depending on the training content. Therefore, especially non-formal training of communication or soft skills seems to have an impact on the amount of interactive non-routine and cognitive routine tasks.[20] Further studies regarding this point are therefore recommended.

The current results support the conclusion that further training is relevant for employees at risk of automation in order to keep pace with technological change. However, the results show how important it is to take a closer look at these issues when making political decisions. Not every form of further training appears to be helpful. In addition, the target group and the respective context should be taken into account when promoting training activities.

Data availability statement

This paper uses data from the National Educational Panel (NEPS): Starting Cohort Adults, doi:10.5157/NEPS:SC6:10.0.1 The NEPS data were collected from 2008 to 2013 as part of the framework programme for the promotion of empirical educational research, which was funded by the German Federal Ministry of Education and Research (BMBF). Since 2014, NEPS has been collected by the Leibniz-Institut für Bildungsverläufe e.V. (LIfBi) at the Otto-Friedrich-University Bamberg in cooperation with a nationwide network.

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Appendices

A Tables

Table 1: Operationalisation of job tasks according to task-based approach. Items for measuring task dimensions

		Task dimension		
Analytic	Interactive	Manual (physical requirements)	(Non-)routine (task complexity)	Autonomy
Reading	Customer contacts	Standing (at least two hours)	Solving difficult problems	Schedule work activities
Writing	Provide general information	Walking / biking	Learn new things	Choose new task assignments
Mathematics	Counseling (e.g. financial, legal)	Lifting (at least 10 kg)	Get acquainted with tasks	Choose pace of work
	Assistance (personal issues)	Uncomfortable body posture	Unanticipated situations	Decision
	Teaching / training	Heat / cold	Changing work assignments	Involvement
	Deal with candidates / applicants		Perform new tasks	

Source: Matthes et al. (2014, S. 283). *Note*: Work tasks were measured in wave 3 and wave 7.

Table 2: Operationalisation of engineering bottlenecks

Engineering Bottlenecks	O*NET (Frey and Osborne 2017)	PIAAC (Nedelkoska and Quintini 2018)	NEPS
Perception Manipulation	Finger dexterity	Fingers (dexterity)	
	Manual dexterity		
	Cramped work space, awkward positions		Physical exertion: Uncomfortable physical position
Creative Intelligence	Originality	Problem-solving simple	Routine: Reacting to unforeseen situations
		Problem-solving complex	Complexity: Solving more difficult problems
			Variety of requirements: can learn sth. new
			Variety of requirements: wide variety of tasks changing frequently
	Fine arts		
Social Intelligence		Teaching	Interaction: Teaching/training
		Advise	Interaction: Advising
		Plan for others	
		Communication	Interaction: Customer contact
	Negotiation	Negotiate	
	Persuasion		
	Assisting an caring for others		Interaction: Assistance
	Social perceptiveness		Interaction: Job interviews

Table 3: Automability as a function of engineering bottlenecks. Logistic regression

	Automation probability			Automation probability (cont.)			Automation probability (cont.)	
Physical exertion			*Interaction: customer*			*Variety req.: learn*		
rare	-0.401^{*}	(0.17)	rare	-0.202	(0.42)	does rather not apply	0.001	(0.43)
somtetimes	-0.651^{**}	(0.22)	sometimes	-0.637	(0.43)	does rather apply	-0.475	(0.41)
often	-0.935^{**}	(0.20)	often	-0.726^{+}	(0.39)	fully applies	-0.723^{+}	(0.42)
very often	-0.834^{**}	(0.24)	very often	-0.402	(0.38)			
Interaction: advise			*Interaction: interviews*			*Variety req.: tasks*		
rare	-0.071	(0.21)	rare	-0.320^{+}	(0.19)	does rather not apply	0.294	(0.34)
sometimes	-0.411^{+}	(0.23)	sometimes	-0.278	(0.22)	does rather apply	-0.164	(0.34)
often	-0.158	(0.20)	often	-0.192	(0.27)	fully applies	-0.037	(0.36)
very often	-0.042	(0.23)	very often	1.066^{**}	(0.33)			
Interaction: teach			*Complexity: problems*			_cons	1.810^{**}	(0.57)
rare	-0.356^{*}	(0.18)	rare	0.278	(0.25)			
sometimes	-0.538^{**}	(0.19)	sometimes	0.308	(0.24)			
often	-0.428^{*}	(0.21)	often	0.361	(0.25)			
very often	-1.173^{**}	(0.29)	very often	-0.074	(0.29)			
Interaction: assist			*Rout.: unforeseen sit.*					
rare	-0.261	(0.20)	rare	0.196	(0.46)			
sometimes	-0.291	(0.22)	sometimes	-0.109	(0.46)			
often	-0.916^{**}	(0.22)	often	0.016	(0.45)			
very often	-2.655^{**}	(0.30)	very often	0.294	(0.46)			
N	1,509							
Pseudo R^2	0.217							
Correctly classified	74.49%							
Area under the ROC curve	0.805							

Source: NEPS SC6 wave 3, unweighted. *Note*: Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

Table 4: Characterisitics of routine intense workers and not routine intense workers

	All		Routine intense		Not routine intense	
	mean	sd	mean	sd	mean	sd
male	0.50	0.50	0.41	0.49	0.54	0.50
age (years)	45.90	7.98	46.91	7.56	45.49	8.11
child in the household	0.59	0.49	0.60	0.49	0.58	0.49
without prof. degree	0.05	0.22	0.08	0.27	0.04	0.20
professional degree	0.62	0.49	0.75	0.43	0.57	0.50
university degree	0.33	0.47	0.17	0.37	0.39	0.49
hours of work	36.97	12.27	31.84	12.87	39.05	11.39
temporary contract	0.18	0.38	0.20	0.40	0.17	0.37
experience (years)	22.66	8.93	23.59	8.76	22.29	8.98
no computer use	0.14	0.35	0.32	0.47	0.07	0.25
normal computer use	0.59	0.49	0.54	0.50	0.61	0.49
complex computer use	0.27	0.45	0.14	0.34	0.33	0.47
automation prob.	0.44	0.23	0.56	0.22	0.39	0.21
high automation prob.	0.15	0.36	0.31	0.46	0.08	0.27
routine	0.43	0.18	0.66	0.12	0.34	0.11
analytic	0.57	0.22	0.42	0.20	0.63	0.19
interactive	0.47	0.22	0.36	0.20	0.52	0.20
manual	0.29	0.27	0.34	0.28	0.28	0.27
routine intense	0.29	0.45				
N	3,198		922		2,276	

Source: NEPS SC6 wave 3, unweighted.

Table 5: Training participation of routine intense workers and not routine intense workers between 2011/2012 and 2015/2016

	All		**Routine intense**		**Not routine intense**	
	mean	sd	mean	sd	mean	sd
formal training	0.04	0.20	0.04	0.20	0.04	0.21
non-formal training	0.65	0.48	0.49	0.50	0.71	0.45
informal learning: congress	0.30	0.46	0.14	0.35	0.37	0.48
informal learning: lecture	0.38	0.49	0.19	0.39	0.46	0.50
informal learning: media	0.34	0.47	0.20	0.40	0.39	0.49
N	3,198		922		2,276	

Source: NEPS SC6 wave 3 to 7, unweighted.

Table 6: Task change of routine intense workers and not routine intense workers between 2011/2012 and 2015/2016

	All			**Routine intense**			**Not routine intense**		
	2011	2015	diff	2011	2015	diff	2011	2015	diff
routine	0.43	0.45	**	0.66	0.61	**	0.34	0.38	**
analytic	0.57	0.57	+	0.42	0.42		0.63	0.62	**
interactive	0.47	0.47		0.36	0.37	+	0.52	0.51	+
manual	0.29	0.29		0.34	0.34		0.28	0.27	
routine int.	0.29	0.33	**	1.00	0.71	**	0.00	0.18	**
automation prob.	0.44	0.46	**	0.56	0.55		0.39	0.42	**
h. automation prob.	0.15	0.17	*	0.31	0.31		0.08	0.11	**
no computer	0.14	0.13	*	0.32	0.27	**	0.07	0.07	
normal computer	0.59	0.64	**	0.54	0.61	**	0.61	0.66	**
complex computer	0.27	0.23	**	0.14	0.12		0.33	0.28	**

Source: NEPS SC6 wave 3 and 7, unweighted.
Note: Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 7: Fixed effects regression of routine tasks on formal, informal and non-formal training

	(1) routine	(2) routine	(3) routine	(4) routine
non-formal training		-0.028^{*}	-0.026^{*}	
		(0.013)	(0.013)	
num. non-formal training		-0.006^{*}	-0.005^{+}	
		(0.003)	(0.003)	
non-formal training (compl.)				-0.039^{**}
				(0.011)
formal training		-0.016	-0.012	-0.013
		(0.026)	(0.026)	(0.026)
informal training: congress		-0.011	-0.012	-0.012
		(0.016)	(0.015)	(0.015)
informal training: lecture		-0.003	-0.002	-0.004
		(0.014)	(0.014)	(0.014)
informal training: media		-0.026^{+}	-0.023^{+}	-0.024^{+}
		(0.014)	(0.013)	(0.013)
more complex computer use	-0.035^{*}	-0.032^{+}	-0.025	-0.026
	(0.018)	(0.017)	(0.016)	(0.016)
less complex computer use	-0.005	0.001	0.000	0.000
	(0.017)	(0.017)	(0.018)	(0.018)
change of job	-0.047^{+}	-0.043^{+}	-0.039	-0.040^{+}
	(0.024)	(0.023)	(0.024)	(0.024)
change of occupation	-0.016	-0.018	-0.024	-0.022
	(0.030)	(0.029)	(0.028)	(0.028)
wave 7	-0.029^{**}	0.001	0.035	0.040
	(0.006)	(0.008)	(0.077)	(0.078)
controls			x	x
N	1,844	1,844	1,844	1,844
within R^2	0.108	0.143	0.177	0.172

Source: NEPS SC6 wave 3 and 7, unweighted. *Note*: The sample comprises employees who in 2011 had jobs with a high proportion of routine tasks. Controls in model 3 and 4 include having a temporary contract, hours of work, work experience and having a child in the household. Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

Table 8: Fixed effects regression of job tasks, automation probability and the probability of a rising or declining complexity of computer usage on formal, informal and non-formal training

	(1) analytic	(2) interactive	(3) manual	(4) autom. prob.	(5) + comp. use	(6) - comp. use
non-formal training	0.020^{+}	0.016	0.006	-0.016	-0.004	0.024
	(0.012)	(0.012)	(0.014)	(0.019)	(0.028)	(0.025)
num. non-formal	0.000	-0.003	-0.001	0.005	0.003	-0.003
training	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
formal training	-0.030	0.005	-0.001	-0.051	-0.013	0.119^{+}
	(0.028)	(0.024)	(0.032)	(0.060)	(0.062)	(0.070)
informal training:	0.014	-0.014	0.024	-0.032	0.023	0.021
congress	(0.015)	(0.017)	(0.017)	(0.027)	(0.038)	(0.035)
informal training:	-0.009	0.002	0.003	-0.044^{+}	-0.015	0.000
lecture	(0.013)	(0.014)	(0.016)	(0.024)	(0.034)	(0.029)
informal training:	0.013	0.018	-0.002	-0.044^{*}	0.009	0.058^{+}
media	(0.013)	(0.013)	(0.015)	(0.021)	(0.029)	(0.031)
more complex	0.046^{**}	0.042^{**}	-0.026	-0.040^{+}		
computer use	(0.016)	(0.015)	(0.019)	(0.023)		
less complex	-0.031^{*}	-0.014	0.018	0.001		
computer use	(0.015)	(0.015)	(0.017)	(0.024)		
change of job	-0.023	0.001	-0.008	-0.039	0.136^{*}	0.075
	(0.020)	(0.021)	(0.018)	(0.032)	(0.053)	(0.048)
change of occupation	0.055^{*}	0.063^{*}	-0.031	-0.077^{+}	0.013	-0.047
	(0.024)	(0.026)	(0.029)	(0.040)	(0.063)	(0.054)
wave 7	-0.028	-0.206^{**}	-0.100	-0.014	0.030	-0.028
	(0.096)	(0.073)	(0.084)	(0.097)	(0.150)	(0.134)
controls	x	x	x	x	x	x
N	1,844	1,844	1,844	948	1,844	1,844
within R^2	0.063	0.071	0.032	0.454	0.177	0.134

Source: NEPS SC6 wave 3 and 7, unweighted. *Note*: The sample for the regression in column 4 includes employees with a high probability of automation in 2011; all other columns refer to employees who had a high proportion of routine tasks in their jobs in 2011. Controls include having a temporary contract, hours of work, work experience and having a child in the household. Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

Table 9: Fixed effects regression of job tasks and automation probability on formal, informal and non-formal training with interaction effects between an increase in the complexity of computer use / job change and further training

	Interaction with increasing computer use					**Interaction with job change**				
	(1) routine	(2) analytic	(3) interact.	(4) manual	(5) autom. prob.	(6) routine	(7) analytic	(8) interact.	(9) manual	(10) autom. prob.
non-formal training	-0.042^{**}	0.012	0.004	0.013	0.000	-0.038^{**}	0.002	0.007	0.016	-0.021
	(0.011)	(0.010)	(0.011)	(0.013)	(0.016)	(0.011)	(0.010)	(0.010)	(0.012)	(0.015)
formal training	-0.018	-0.019	0.023	-0.008	-0.053	0.018	0.004	-0.004	-0.035	0.065
	(0.030)	(0.029)	(0.024)	(0.037)	(0.058)	(0.024)	(0.035)	(0.024)	(0.035)	(0.060)
informal training: congress	-0.003	0.004	-0.013	0.029	-0.026	-0.006	0.007	-0.005	0.020	-0.048^{+}
	(0.016)	(0.016)	(0.017)	(0.019)	(0.027)	(0.015)	(0.015)	(0.017)	(0.016)	(0.027)
informal training: lecture	-0.012	-0.001	0.004	-0.009	-0.037	0.000	-0.014	-0.004	-0.007	-0.035
	(0.014)	(0.014)	(0.014)	(0.017)	(0.025)	(0.014)	(0.013)	(0.014)	(0.014)	(0.026)
informal training: media	0.000	0.009	0.007	0.009	-0.009	-0.021	0.009	0.015	0.008	-0.023
	(0.014)	(0.013)	(0.013)	(0.015)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.021)
more complex computer	0.002	0.021	0.027	0.018	0.001	-0.025	0.040^{**}	0.042^{**}	-0.021	-0.044^{+}
use	(0.023)	(0.020)	(0.022)	(0.024)	(0.028)	(0.016)	(0.015)	(0.016)	(0.018)	(0.023)
less complex computer	-0.002	-0.030^{+}	-0.013	0.017	-0.001	0.002	-0.030^{+}	-0.014	0.017	-0.003
use	(0.018)	(0.016)	(0.015)	(0.017)	(0.023)	(0.018)	(0.016)	(0.015)	(0.018)	(0.023)
change of job	-0.045^{+}	-0.023	0.004	-0.009	-0.049	-0.016	-0.070^{*}	-0.002	0.020	-0.049
	(0.024)	(0.021)	(0.021)	(0.018)	(0.032)	(0.032)	(0.027)	(0.028)	(0.028)	(0.039)
change of occupation	-0.010	0.052^{*}	0.056^{*}	-0.023	-0.067^{+}	-0.022	0.054^{*}	0.064^{*}	-0.030	-0.094^{*}
	(0.028)	(0.024)	(0.026)	(0.028)	(0.040)	(0.028)	(0.024)	(0.026)	(0.029)	(0.040)
non-formal training ×	-0.003	0.044	0.016	-0.080^{*}	0.020	-0.020	0.072^{*}	0.001	-0.067^{+}	0.082^{+}
m. compl. comp. / job ch.	(0.033)	(0.032)	(0.032)	(0.038)	(0.045)	(0.032)	(0.029)	(0.031)	(0.038)	(0.043)
formal training ×	0.066	-0.055	-0.129	0.039	0.000	-0.077	-0.088	0.021	0.086	-0.240^{**}
m. compl. comp. / job ch.	(0.047)	(0.083)	(0.080)	(0.054)	(.)	(0.061)	(0.054)	(0.053)	(0.072)	(0.088)
inf. training: congress ×	-0.040	0.058	-0.013	-0.019	0.007	-0.025	0.037	-0.038	0.018	0.090
m. compl. comp. / job ch.	(0.041)	(0.047)	(0.058)	(0.054)	(0.076)	(0.043)	(0.041)	(0.051)	(0.053)	(0.065)
inf. training: lecture ×	0.048	-0.049	-0.016	0.076	0.004	-0.013	0.014	0.020	0.045	-0.053
m. compl. comp. / job ch.	(0.038)	(0.039)	(0.047)	(0.048)	(0.069)	(0.039)	(0.035)	(0.038)	(0.050)	(0.058)
inf. training: media ×	-0.158^{**}	0.029	0.085^{+}	-0.086	-0.231^{**}	-0.013	0.035	0.016	-0.051	-0.098^{+}
m. compl. comp. / job ch.	(0.041)	(0.045)	(0.051)	(0.058)	(0.063)	(0.041)	(0.035)	(0.041)	(0.052)	(0.054)
wave dummy	x	x	x	x	x	x	x	x	x	x
controls	x	x	x	x	x	x	x	x	x	x
N	1,844	1,844	1,844	1,844	948	1,844	1,844	1,844	1,844	948
within R^2	0.191	0.070	0.078	0.044	0.477	0.177	0.081	0.071	0.042	0.472

Source: NEPS SC6 wave 3 and 7, unweighted. *Note*: The sample for the regression in column 5 and 10 includes employees with a high probability of automation in 2011; all other columns refer to employees who had a high proportion of routine tasks in their jobs in 2011. Controls include having a temporary contract, hours of work, work experience and having a child in the household. Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

B Figures

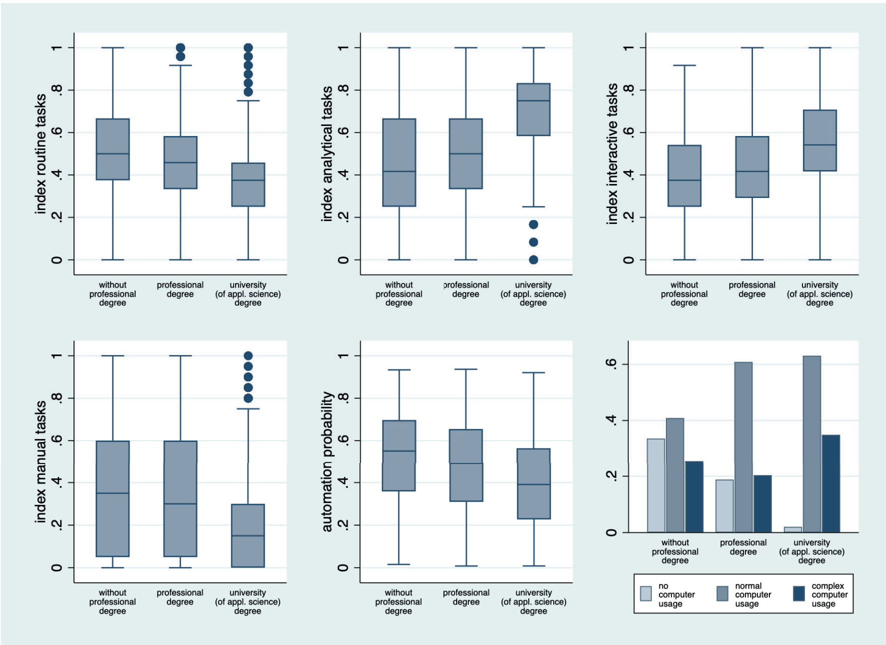

Figure 1: Tasks, automation probability and computer usage by education group

Source: NEPS SC6 waves 3 and 7, unweighted.

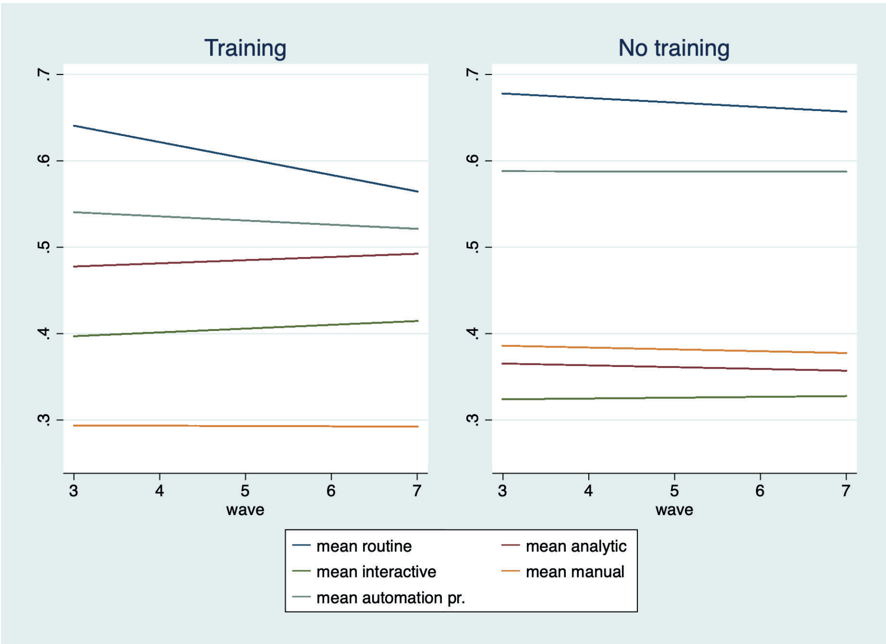

Figure 2: Task change of routine intense workers between 2011/2012 and 2015/2016

Source: NEPS SC6 waves 3 and 7, unweighted.

C Further results

Table 10: Fixed effects regression of job tasks and automation probability on formal, informal and non-formal training with interaction effects between having a university degree and further training

	(1) routine	(2) analytic	(3) interactive	(4) manual	(5) autom. prob.
non-formal training	−0.036**	0.018+	0.003	−0.001	−0.012
	(0.011)	(0.010)	(0.011)	(0.013)	(0.017)
formal training	−0.005	−0.028	0.010	−0.042	−0.004
	(0.027)	(0.033)	(0.028)	(0.038)	(0.063)
informal training: congress	−0.016	0.021	−0.019	0.009	−0.026
	(0.018)	(0.019)	(0.022)	(0.022)	(0.033)
informal learning: lecture	−0.004	−0.005	0.026	0.008	−0.049+
	(0.016)	(0.015)	(0.017)	(0.020)	(0.027)
informal learning: media	−0.030+	0.029*	0.014	0.012	−0.038
	(0.016)	(0.014)	(0.016)	(0.018)	(0.023)
more complex computer use	−0.025	0.045**	0.039*	−0.027	−0.037
	(0.016)	(0.015)	(0.016)	(0.019)	(0.023)
less complex computer use	0.000	−0.029+	−0.015	0.018	0.005
	(0.018)	(0.016)	(0.015)	(0.017)	(0.023)
change of job	−0.039+	−0.022	0.003	−0.010	−0.031
	(0.023)	(0.021)	(0.021)	(0.018)	(0.032)
change of occupation	−0.021	0.052*	0.061*	−0.031	−0.091*
	(0.028)	(0.025)	(0.026)	(0.029)	(0.040)
non-formal training	−0.037	0.009	0.026	0.014	0.055+
× uni. degree	(0.027)	(0.031)	(0.024)	(0.025)	(0.029)
formal training	−0.015	−0.026	−0.016	0.123+	−0.192
× uni. degree	(0.069)	(0.060)	(0.049)	(0.064)	(0.127)
informal learning: congress	0.018	−0.006	0.036	0.049	−0.035
× uni. degree	(0.032)	(0.034)	(0.037)	(0.035)	(0.061)
informal learning: lecture	0.010	−0.006	−0.093**	−0.033	0.027
× uni. degree	(0.030)	(0.031)	(0.032)	(0.034)	(0.059)
informal learning: media	0.029	−0.071*	0.010	−0.047	−0.030
× uni. degree	(0.030)	(0.033)	(0.028)	(0.032)	(0.049)
wave dummy	x	x	x	x	x
controls	x	x	x	x	x
N	1,844	1,844	1,844	1,844	948
within R^2	0.176	0.071	0.078	0.040	0.460

Source: NEPS SC6 wave 3 and 7, unweighted. *Note*: The sample for the regression in column 5 includes employees with a high probability of automation in 2011; all other columns refer to employees who had a high proportion of routine tasks in their jobs in 2011. Controls include having a temporary contract, hours of work, work experience and having a child in the household. Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

Table 11: Fixed effects regression of job tasks and automation probability on formal, informal and non-formal training with further controls

	(1) routine	(2) analytic	(3) interactive	(4) manual	(5) autom. prob.
non-formal training	-0.026^{*}	0.020	0.016	0.005	-0.016
	(0.013)	(0.012)	(0.012)	(0.014)	(0.019)
num. non-formal training	-0.005^{+}	0.000	-0.003	-0.001	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
formal training	-0.013	-0.027	0.005	0.006	-0.052
	(0.026)	(0.028)	(0.024)	(0.032)	(0.060)
informal training: congress	-0.012	0.014	-0.014	0.024	-0.032
	(0.015)	(0.015)	(0.017)	(0.017)	(0.027)
informal training: lecture	-0.003	-0.008	0.002	0.006	-0.044^{+}
	(0.014)	(0.013)	(0.014)	(0.016)	(0.024)
informal training: media	-0.024^{+}	0.013	0.017	-0.001	-0.043^{*}
	(0.013)	(0.013)	(0.013)	(0.015)	(0.021)
more complex computer use	-0.025	0.045^{**}	0.042^{**}	-0.028	-0.040^{+}
	(0.016)	(0.016)	(0.015)	(0.019)	(0.023)
less complex computer use	0.000	-0.031^{*}	-0.014	0.017	0.000
	(0.018)	(0.016)	(0.015)	(0.017)	(0.024)
change of job	-0.039	-0.022	0.001	-0.006	-0.039
	(0.024)	(0.021)	(0.022)	(0.018)	(0.032)
change of occupation	-0.024	0.055^{*}	0.063^{*}	-0.031	-0.078^{+}
	(0.028)	(0.025)	(0.026)	(0.029)	(0.040)
promotion	0.006	-0.011	0.004	-0.036	0.013
	(0.018)	(0.018)	(0.019)	(0.023)	(0.033)
health satisfaction	0.001	-0.003	-0.001	-0.007^{+}	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
wave 7	0.036	-0.029	-0.206^{**}	-0.103	-0.015
	(0.077)	(0.096)	(0.073)	(0.084)	(0.097)
controls	x	x	x	x	x
N	1,844	1,844	1,844	1,844	948

Source: NEPS SC6 wave 3 and 7, unweighted. *Note*: The sample for the regression in column 5 includes employees with a high probability of automation in 2011; all other columns refer to employees who had a high proportion of routine tasks in their jobs in 2011. Controls include having a temporary contract, hours of work, work experience and having a child in the household. Robust standard errors in parentheses. Significance Level: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.