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Automation, unemployment, and the role of labor market training[☆]

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ABSTRACT

We provide comprehensive evidence on the consequences of automation risk on the career of unemployed workers and the mitigating role of labor market training. Using almost two decades of administrative data for Austria, we find that a higher risk of automation reduces the job finding probability; a problem which has increased over the past years. This development is associated with increasing re-employment wages and job stability. We also present new aspects of public training in times of technological progress. Provided training counteracts the negative impact of automation on the job finding probability. Its efficiency has declined over the past years, however.

1. Introduction

Over the past years, labor markets in developed countries have undergone substantial changes. Labor-saving technologies such as computer-assisted machines and robots have shifted production toward a more automated process. Industrial robots can now autonomously weld, paint, handle and pack materials. There is evidence that the increasing automation of the workplace has displaced workers from low- and medium-skill occupations, "hollowing out" the middle of the skill distribution (e.g. Autor et al., 2006, 2008; Firpo et al., 2011; Autor and Dorn, 2013).[1] Workers with less specialized skills and abilities are predicted a bleak future (Brynjolfsson and McAfee, 2014). As direct consequences of the risk of increasing automation, a vast majority of individuals are worried about their future and expect diminishing employment prospects and an increase in inequality (Pew Research Center, 2017). Despite the high relevance for decision makers and worries from the population, there still is little evidence on how automation risk affects individual workers and whether current public policies can help.

Our work follows two goals. Our first goal is to study the impact of automation risk on the job finding probability and labor market career of unemployed workers. Unemployed individuals are particularly vulnerable to increasing risk of automation and an

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[1] This "hollowing out", also known as polarization, has been documented not only for the US but also for numerous other developed countries such as Germany (Spitz-Oener, 2006; Dustmann et al., 2009) and the UK (Goos and Manning, 2007). Recently, Goos et al. (2014) showed that it persists in 16 Western European countries. A different strand of the literature suggests increasing import competition, for example, from China, as another important factor. Autor et al. (2016) provide an overview over recent findings in the literature. We do not consider this channel in our work.

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interesting group to study. The risk of automation likely affects the probability of finding new employment but also the ability to form stable matches. Workers who have been negatively affected by increasing automation might have prolonged unemployment spells or choose to leave the labor force altogether. Those individuals who find re-employment might end up in worse matches and less stable employment. It is also possible that increasing automation is hurting only some types of workers while positively affecting those with a valuable set of skills, such as social- and emotional ones; see, for example, the different scenarios considered in Caselli and Manning (2019). Such a development could increase inequality further.

Our second and more important goal is to assess the effectiveness of existing labor market training policies in the context of current technological change. If automation risk adversely affects employment opportunities, what role can public policy play to mitigate these effects? Programs to strengthen workers' skills have received particular attention to counteract the impact of an increasing automation risk. For example, the UK government announced the creation of a nationwide scheme to enhance the skills of workers displaced by automation which has been rolled out since 2020.[2] The SkillsFuture Credit offered by Singapore's government provides subsidies for participating in courses which help individuals to upgrade skills affected by technology and globalization.[3] In most European countries, unemployment training to improve skills already exist and form an integral part of active labor market policies.[4] Given the wide availability and high costs of these programs it is important to know if and how they work in light of recent technological change. This is the first paper explicitly investigating the effectiveness of training policies related to increasing automation risk.

We use almost two decades of high-quality administrative data for Austria covering the whole universe of private sector employees. Our data allows us to obtain precise information about the labor market career of workers. We measure the automation risk of an occupation using the Routine Task Index (RTI) of Autor and Dorn (2013) (see also Autor et al., 1998). This and similar measures have been widely used in the literature, for example, in Goos et al. (2014), Wright (2014), Akerman et al. (2015), and Autor et al. (2019).

The empirical strategy builds on the *Timing-of-Events (ToE)* approach of Abbring and den Berg (2003a). Our model incorporates unobserved and time-invariant workers' skills and abilities, and can allow for quite general selectivity into training, employment opportunities, and unemployment exit states. Under the assumption that unobserved individual heterogeneity is fixed over time, we can account for sorting into occupations with different risks of being automated, depending on workers' unobserved skills. We can also allow for situations where diminishing job opportunities lead workers with less adaptable skills to exit the labor force or to take up lower paying employment.

To identify the training effect, we exploit the timing of events, that is, the information on the timing when a worker receives training and when she leaves unemployment. Intuitively, the distance between these two events, regardless of the unemployment duration before the actual training assignment, identifies the causal effect of training on the exit behavior. Importantly, in our estimation approach we also take both the selective assignment of training and the impact of training on unemployment exit depending on individual unobserved skills into account.

The two key assumptions underlying our estimation approach are that (i) workers do not anticipate the exact start date of unemployment training and (ii) workers' unobserved abilities are time-invariant, similar as in Cortes et al. (2016). To capture any time-varying and occupation-specific search problems, we also include a rich set of individual variables as well as occupational and time fixed effects in our analysis.

We find a significant negative impact of the risk of automation on the job finding probability, with a substantial intensification over the past years for men (but not women). A one standard deviation increase in our Routine Task Index, which is roughly equivalent to the increase in the routine job content between a travel agent and an accounting clerk, decreases the job finding rate by around 8% for men and 15% for women at the beginning of our sample period in the year 2000. For unemployed male workers this effect almost doubles to 16% within 13 years while the impact on women has remained virtually constant.

Our results for post-unemployment outcomes point toward a polarization: Workers in jobs with high automation risk who do find new employment have higher wages and enjoy more job stability. For men, this earnings advantage is even increasing over time. Two possible explanations are consistent with our results. One the one side, occupational switching might explain our findings. Technological progress makes it more difficult for routine workers to find employment. Those workers who find new employment move to higher-paying but less routine intensive jobs (e.g. Cortes, 2016). On the other side, a quality–quantity trade-off where the number of jobs in certain occupations has declined but the remaining ones have become more productive might also play a role (Hershbein and Kahn, 2018). As better matches between firms and workers also have higher comparative advantages in exploiting the benefits of automation, firms become more selective in which workers to hire. This behavior leads to an increase in wages but also a prolonged unemployment duration (Faia et al., 2020). Unfortunately, our data at hand does not allow us to investigate each explanation in more detail. Despite this drawback, our results clearly indicate that recent technological change has the potential to increase inequality even further, not only between groups of workers but also within.

[2] The retraining scheme is currently in its testing phase and is available in six areas across England.

[3] There are also efforts by private companies to help workers learn new skills to shield them from the negative consequences of automation, such as Amazon's Upskilling 2025 program. There is doubt, however, that these private programs are successful without substantial support by local governments (Shipley, 2019).

[4] According to the OECD, training constitutes the second largest active labor market program after out-of-work income and maintenance support in terms of expenditure in most countries. For example, in 2016 around 1.5 billion Euros (0.52% of GDP) were spent on training in Denmark, 1.6 billion Euros in Austria (0.44% of GDP), 6.7 billion Euros in France (0.30% of GDP), and almost 6 billion Euros in Germany (0.19% of GDP). In comparison, only 0.03% of GDP or roughly 6 billion US-Dollars are allocated to training in the US (OECD, 2019).

Skill enhancement through labor market training is successful in counteracting the decreasing re-employment probabilities of workers facing higher risks of automation. These training effects are mostly driven by preferential assignment mechanisms of case workers with shorter waiting times between inflow and the start date of the training for affected workers. The improved job finding rates do not translate into higher wages in general, however. We find that provided training negatively impacts re-employment wages, with exception for workers who are the most affected by increasing automation. Our results suggest that case workers are more concerned with faster re-employment rather than post-unemployment job quality. In addition, they suggest that the effectiveness of training has decreased over time. Adopting the design of programs to recent technological progress could lead to larger benefits for affected workers.

We find interesting differences by subgroups in our analysis. Younger workers as well as highly-educated men affected by automation profit the most from provided training. For younger workers, the results point toward preferential training assignment as likely mechanism for the positive effects. In light of technological change, case workers allocated training slots increasingly toward younger workers. Our results for highly educated men are mostly driven by higher unobserved abilities. These abilities are amplified by assigned training which enforces skill gaps between high and low educated workers further. These results corroborate the claim of an increasing polarization in the labor market.

Our work makes two important contributions to the rapidly growing literature on the individual level impact of automation (Cortes, 2016; Schmillen, 2019; Edin et al., 2018; Bessen et al., 2019; Blien et al., 2021; Dauth et al., 2019; Goos et al., 2021, 2019b).[5] First, we evaluate the potential benefits of skill enhancements through publicly provided training and changes in assignment mechanisms in light of recent technological change. These are important policy parameters which have been so far largely neglected in the empirical literature.[6] Unemployment training programs are well-established tools in active labor market policy in most European countries. Provided training can help individuals whose labor market career is threatened by automation. Training can improve workers' existing skills leading to better re-employment possibilities. Preferred assignment of training to individuals most in need can also lead to a reduction in skill gaps. In our analysis, we do not only investigate the effectiveness of these programs in terms of employment outcomes but also in terms of case worker assignment, as well as wages and tenure in the new job. Re-employment job quality is a key issue and central when tackling increasing inequality in the labor market. Given that some studies forecast the range of job displacements due to digitization to lie between 9% to 50% (Arntz et al., 2017; Frey and Osborne, 2017) and the persistently high share of long-term unemployed in most developed countries, it is crucial to know how automation risk affects unemployed individuals and if current public policies actually work.

Second, we provide a comprehensive picture of how increasing automation risk can affect the job finding probability of unemployed workers and their post-unemployment labor market career. Most existing studies have focused on the risk of automation on individuals' labor market career, separately analyzing the impact on earnings and employment (e.g. Blien et al., 2021; Goos et al., 2021).[7] One problem arising with separately analyzing labor market transitions and earnings is that there is dynamic selection among workers who become employed based on both their observed and unobserved characteristics (Ham and LaLonde, 1996). For example, an individual who leaves unemployment and works in an occupation with lower automation risk may also have higher unobserved abilities. In this case, the positive selection effect of finding new employment may mask the true impact of automation on post-unemployment wages; see also Faia et al. (2020). Disentangling the effects of automation risk from unobserved ability is necessary for a well defined policy debate, however. In our work, we model jointly the job finding probability of unemployed workers and post-unemployment labor market outcomes, allowing for correlation in unobserved abilities between states. By explicitly modeling the interdependence of different outcome and allowing for selectivity, we think we have made an important step toward a better understanding of the labor market impacts of automation.

Moreover, we also contribute to the literature on the determinants of unemployment duration and subsequent job quality. Previous literature on this topic has investigated the effect of human capital depreciation (Acemoglu, 1995; Albrecht et al., 1999; Görlich and de Grip, 2009), search effort (Krueger and Mueller, 2011; Faberman and Kudlyak, 2019), discrimination (Kroft et al., 2013; Eriksson and Rooth, 2014), and the role of individual heterogeneity (Alvarez et al., 2016; Kroft et al., 2016; Abraham et al., 2019). In our work, we look at the impact of increasing automation risk as an important driver of unemployment duration and post-unemployment job quality. We show that technological progress related to automation significantly lowers the job finding probability and affects re-employment outcome, with a strong intensification over time. Thus, it has the potential of increasing inequality and to contribute to the persistence in the high share of long-term unemployed (Krueger et al., 2014; Jaimovich and Siu, 2020). This development should be given considerable care when designing public policies and social benefit systems.

To a certain extent, our work also complements and extends the literature on the evaluation of publicly provided training for unemployed workers (e.g. Lalive et al., 2008; Osikominu, 2013; Richardson and van den Berg, 2013; Hyman, 2018). Compared to existing studies, we look at the effectiveness of provided unemployment training in counteracting the consequences of automation and promoting post-unemployment job quality. Given the high costs of these training programs and a large support for government

[5] There are several papers which investigate the impact of automation and robotization on wages and employment on a more aggregate level as, for example, Autor and Dorn (2013), Graetz and Michaels (2018), Cortes et al. (2017), Acemoglu and Restrepo (2020).

[6] Related is the work by Hyman (2018) and Grigoli et al. (2020). Hyman (2018) evaluates the effectiveness of the Trade Adjustment Assistance program on post-unemployment labor market outcomes for U.S. In a cross country analysis, Grigoli et al. (2020) show that routine workers in countries with higher spending on active labor market policies including placements, benefit administration, employment incentives, and training have a lower likelihood of leaving the labor force.

[7] After the publication of our first working paper version (Schmidpeter and Winter-Ebmer, 2018), Blien et al. (2021) and Goos et al. (2021) also looked at the impact of automation risk on employment and wages.

interventions to limit the influence of robots and automation (Pew Research Center, 2017) a thorough analysis of these programs is warranted.

The paper proceeds as follows: In Section 2, we describe the institutional setting in Austria. In Section 3 we describe our data and measures of changing occupational requirements. Section 4 discusses our empirical approach. We present our main results in Section 5. In Section 6 we explore heterogeneous effects by age and education. Section 7 concludes.

2. Institutional setting in Austria

The Austrian unemployment benefit system is less generous compared to many other European countries. The exact benefit level and duration is in general determined by age and previous labor market experience. The benefit duration lies between 20 weeks for individuals who were employed for at least one year prior to the unemployment spell and 52 weeks for individuals above 50 years with 9 years of employment out of the past 15 years prior to the unemployment spell. The maximum replacement rate is capped at 60% of net earnings if there are no dependent family members and at 80% otherwise. If an individual has exhausted the maximum benefit duration, she is eligible to apply for means-tested unemployment assistance.

Unemployed individuals are closely monitored by an assigned case worker. In regular intervals, which are normally as short as one week or even less in some cases, the unemployed individual is required to meet with the case worker. During these meetings, case workers check up on the job search effort and refer the unemployed individual to open vacancies deemed suitable. They also provide detailed instructions on the future job search strategy and set new goals. If a job-seeker misses any meeting, fails to comply with the instructions or refuses to take up employment (or training) referred to her by the case worker, she faces punitive sanctions.

Unemployment training to enhance workers' skills is one of the central active labor market policies in Austria. Training courses are offered by the Austrian public labor market administration (AMS). The offered courses are mainly high-intensive full-time courses and include, for example, specialized degree programs in IT and business. The average course duration lies between four to five months, but offered courses can last up to one year and longer. Provided courses are quite expensive and the average cost per course participant is around 3,100 Euros (AMS, 2018). While expenses per course have increased over the past years the AMS has substantially reduced the number of financed course participants. For example, between 2012 and 2018 the number of course participants has dropped by around 15%.

The allocation of training schemes is subject to the discretionary power of the assigned case worker, who checks up on the job search effort of the unemployed and evaluates if participation in a training scheme is beneficial and necessary. Training assignment also depends on the supply of suitable training slots and assignment to available slots occurs in general at very short notice as case workers try to utilize existing training capacities and to fill available slots in order to safe money and keep average course costs low. Unemployed individuals do not have a legal right to participate in training schemes. At the same time, they are required to comply with any training assignment by the case workers. If a job-seeker refuses to take part in training schemes or works actively against the goal of the scheme, she faces punitive sanctions.

Workers who receive unemployment training tend to have slightly stronger labor market attachment. They are also more likely to have medium education level, such as an apprenticeship. Over the past years, there has been an observable change in the assignment procedure of case workers, however. Workers with higher education have been increasingly assigned to training.[8] At the same time, an increasing number of courses offered have been tailored toward the need of higher skilled workers (see, for example, the exposition in Dorr et al., 2019). We explicitly investigate the effectiveness of the changes in assignment priorities later. More detailed descriptive statistics about training assignments can be found in Appendix B.

The administrative AMS training data we use in our analysis contains information about if and when a worker received any training courses during her unemployment spell. While we do not observe the exact course content in the data, from the above discussion it is clear that the purpose of the provided training is to substantively enhance skills and therefore labor market prospects of unemployed workers. Our observed measures can therefore be regarded as a public policy with the aim to increase workers' human capital.

3. Data and descriptive information

3.1. Labor market data

In addition to information on course participation, the AMS has recorded the occupation of the last job held by the unemployed worker using the AMS classification system from 2000 onward. Unfortunately, it does not follow up on the occupation in the new job. Hence, we cannot evaluate the costs or benefits of occupational switching for unemployed individuals in our analysis.[9] While this is certainly a drawback, we provide evidence in the appendix that demand for workers in the middle of the skill distribution has decreased. To derive the corresponding ISCO-88 codes, we use the cross-walk file provided by the AMS.

We can link the AMS data to the Austrian Social Security Data (ASSD), a high-quality administrative data set. The ASSD comprises the whole universe of Austrian workers employed in the private sector. It contains information about daily labor market spells,

[8] The yearly share of individuals who were assigned to training and hold at least the university entrance exam qualification (Matura) increased from 18% in 2000 to 27% in 2013. During the same time period, the share of individuals with an apprenticeship and assigned to training decreased from 59% to 51%.

[9] There is evidence that occupational switching can be beneficial for employed workers (Cortes, 2016).

Table 1
Summary of estimation sample.

	Men	Women
Individuals & Spells		
Individuals	30,000	30,000
Observations	98,051	80,178
Outflow & Training		
Outflow (in %)	99.32	99.53
to New Job (in %)	59.51	52.38
Median Time to New Job (in Days)	81.00	92.00
to Out of Labor Force (in %)	39.82	47.15
Median Time to Out of Labor Force (in Days)	129.00	133.00
Training Received (in %)	19.80	25.64
Median Waiting Time (in Days)	144.00	116.00
Median Time in Training (in Days)	56.00	66.00
Pers. Characteristics		
Age	40.85	40.31
	(9.36)	(8.74)
Non-Austrian (%)	15.61	10.55
	(36.29)	(30.72)
at most Comp. Schooling (%)	22.14	27.72
	(41.52)	(44.76)
Apprenticeship/High-School (%)	59.39	52.32
	(49.11)	(49.95)
Matura/University (%)	18.47	19.96
	(38.81)	(39.97)
Married (%)	42.88	48.66
	(49.49)	(49.98)
Divorce (%)	12.97	18.01
	(33.59)	(38.43)
Others (%)	44.15	33.32
	(49.66)	(47.14)
Last Employment		
RTI in last job	0.00	0.00
	(1.00)	(1.00)
Tenure in Last Job (Days)	409.63	476.19
	(582.81)	(626.37)
Daily Wage in Last Job (Euros)	66.47	45.32
	(33.49)	(29.75)
Displaced from Last Job (%)	30.64	28.54
	(46.10)	(45.16)
Access to Extended Benefits (%)	47.01	50.46
	(49.91)	(50.00)

The table summarizes workers' labor market transitions and descriptive statistics for all variables used in the estimations. The sample includes workers with at least one unemployment spell between 2000 and 2013, randomly drawn from the overall population, see Section 3. Column (1) refers to male workers and Column (2) to female workers. Within each sample, the RTI is standardized to have a mean of zero and a standard deviation of one. An individual is considered Out-of-Labor Force if s/he exits unemployment and does not take up employment within 40 days. Displaced from Last Job refers to individuals who lost their last job due to a plant closure or mass layoff. Access to Extended Benefits denotes the share of spells in our sample where the individual is eligible for benefit duration of more than 20 weeks. Standard deviations are reported in parentheses.

demographic characteristics, as well as yearly income (Zweimüller et al., 2009). A unique person identifier allows us to link individuals to firms. We will use the ASSD to obtain information about the labor market career and background characteristics of individuals.

For our analysis, we choose all individuals who had at least one unemployment spell between the beginning of 2000 and the end of 2013. This selection enables us to follow unemployed workers for at least two years. From this sample, we select all individuals who were between 25 and 60 years old at the start of the unemployment spell. We set the lower age bound to 25 years as younger individuals might choose to return to full-time education. The upper bound is chosen to be around the official early retirement age. We exclude individuals previously employed in agriculture, the mining sector or in the provision of utilities such as energy or waste disposal.

After these adjustments, our data consists of more than one million individuals with more than three million spells in total. As our estimation procedure, which we will describe in detail in Section 4, is very time consuming, we randomly draw 30,000 male and 30,000 female workers from this sample. For each individual-spell combination we obtain pre-unemployment background characteristics such as age, wage earned in the last job, tenure in the last job as well as the length of the unemployment spell, the post-unemployment destination, and whether the individual received any training during the spell.[10]

We then calculate the time between inflow into unemployment and outflow into new employment or out-of-labor force (OLF), whatever comes first. We define an individual to be OLF if she is not registered as unemployed anymore in the ASSD and has not found new employment within 60 days after the unemployment outflow date. We also observe the exact start and end date of a training spell. If an individual received training, we ''stop the clock'' and the time spent in training does not contribute to the unemployment duration. We do this as individuals are likely to stop actively looking for new work during the training activity (as, e.g., Lechner et al., 2011).[11] We provide summary statistics of our sample in Table 1.

On average, male workers have three and female workers two unemployment spells in our data. We observe for almost all individuals an outflow from unemployment, but there are substantial gender differences in the chosen exit state and the outflow time. Around 60% of all men transit from unemployment into new employment with a median job finding time of around 81 days. In contrast, only 52% of all women take up new employment and the median time is 92 days. We also see strong differences in training assignment. The median time until training assignment is 144 days for men and 116 days for women, a difference of almost one month. Women also tend to be assigned to training with slightly longer course duration. Given the strong differences by gender, we will conduct our analysis separately for men and women.

In terms of post-unemployment outcomes, we consider the re-employment wage and tenure in the first job after the unemployment spell. If a new employment spell lasts longer than December 31, 2016, we consider this observation as censored. Concentrating on the first job after the unemployment spell allows us to gauge the impact of occupational change on workers' bargaining power and the immediate market value of their skills.

3.2. Measuring automation risk

Austria has seen similar changes in the job structure and automation risk as most European countries and the US (Goos et al., 2009). In this work, we want to evaluate the consequences of these developments on the labor market outcomes of unemployed workers. To do so, we make use of one-dimensional measures, similar as in Spitz-Oener (2006), Black and Spitz-Oener (2010), Autor and Dorn (2013), and Goos et al. (2014).

We follow a large part of the literature and use the Routine Task Intensity Index (RTI) of Autor and Dorn (2013) to capture the impact of recent technological progress, mapped to our European occupational classification by Goos et al. (2014).[12] The original RTI of Autor and Dorn (2013) is based on the 4th edition of the Dictionary of Occupational Titles published in 1977 (DOT; U.S. Department of Labor, 1977) and uses three task inputs: routine, manual, and abstract tasks.[13] It condenses information on these three task inputs in an occupation o into a one-dimensional measure, which is calculated as follows:

$$RTI_o = ln\left(\frac{T_o^R}{T_o^M T_o^A}\right)$$

where T_o^R, T_o^M, and T_o^A are the routine, manual, and abstract task inputs in occupation o.

The RTI measure is increasing in the importance of routine tasks within an occupation and decreasing in the importance of abstract and manual tasks. Routine tasks follow well defined and described rules which can be easily automated (see also Autor et al., 1998). A higher value of the RTI implies therefore a higher risk that required tasks can be replaced by computer technology.

There are several advantages in using the RTI of Autor and Dorn (2013) as a measure for the risk of automation. First, it has been widely used in recent works investigating the impact of technological progress on individual and aggregate labor market outcomes in different countries (e.g. Goos et al., 2014; Acemoglu and Restrepo, 2020; Faia et al., 2020; Grigoli et al., 2020). The wide use of the RTI enables us to put our estimates in relation with other results presented in the literature and allows us to compare the impacts of technological change on different type of workers.

Second, there is strong evidence that the RTI is highly correlated with other more recent measures of routine intensity and technological progress, such as the Frey and Osborne (2017) measure of computerization probability within an occupation (see, for example, Faia et al., 2020). At the same time, the construction of the RTI is relatively straightforward and is based on easily verifiable inputs. This gives strong support to the external validity of our results and derived policy implications.

Third, the different DOT categories used to construct the RTI are easy to differentiate from each other and other important measures, such as the potential of offshoring a certain task. This is particularly important in our case, as we additionally control for offshoring potential using the Blinder and Krueger (2013) index in our analysis. Other data sets, such as the O*NET and the German

[10] In Appendix A we compare our estimation sample to the total population of unemployed workers in Austria from 2000 to 2013. There is virtually no difference between our randomly drawn estimation sample and the overall population.

[11] For the exit into out of labor force the reasoning is not entirely clear. On the one hand, individuals might be ''locked'' into training and do not consider leaving unemployment. On the other hand, it is also possible that they directly transit from training into non-activity. Here, we also calculate the duration until out of labor force net of the training duration.

[12] In our analysis, we use the index provided in the data supplementary of Goos et al. (2014) which can be found under https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509. They map the US occupation classification system into the two-digit ISCO-88 classification which can be found in our data.

[13] The manual task measure is based on the DOT's assessment of an occupation's requirement for ''eye-foot-hand coordination'', the routine task measure is based on the DOT's occupational classification for "set limits, tolerance and standards" as well as "finger dexterity". The abstract task measure is obtained using the DOT's occupational classification for ''direction control and planning'' and "GED Math".

BIBB-IAB employment survey, provide in some cases only weakly differentiable tasks and many tasks can be assigned to different categories. For example, the O*NET task "Controlling Machines and Processes" can be considered to contribute to both the routine content of a job but also to its offshoring probability; see also the discussion by Acemoglu and Autor (2011).[14] These overlaps make it difficult to give the obtained estimates a clear interpretation, however.

To facilitate the interpretation of our results, we standardize the RTI to have a mean of zero and a standard deviation of one. In Appendix A, we provide further details on the occupations used in our analysis.[15]

3.3. Descriptive information

In this section, we present some descriptive results about the relationship between automation risk and both the allocation into training and the likelihood of finding new employment. We do so by first dividing our sample according to an individual's position in the distribution of the RTI. We then concentrate on those individuals who worked before the unemployment spell in occupations which fall into either the bottom third part or the upper third part of the distribution. Occupations which can be found at the lower part of the RTI distribution include, for example, Science Professionals and Corporate Managers. Examples of occupations which can be found at the upper part are office and service clerks.

We calculate the smoothed daily likelihood of transiting into new employment and entering training during the unemployment spell using the method of Müller and Wang (1994). The results of this exercise are depicted in Fig. 1 separately for men and women. The upper part of the figure shows the transition probability into new employment. The lower part depicts the empirical estimates for the transition rates into training.

Looking at the transition rates from unemployment to employment at the upper part of the figure, two features become apparent. First, for both men and women, transition rates into re-employment are substantially higher at lower values of our RTI during the first six months of the unemployment spell. This finding provides evidence that our measure of automation risk, indeed, affects the probability of finding a new job. With ongoing duration of the unemployment spell, automation risk in the previous job seems to matter less and it is more likely that stigma effects play a more dominant role (e.g. Kroft et al., 2013; Eriksson and Rooth, 2014). Second, one can see pronounced gender differences. In general, men have a higher re-employment probability than women, regardless of the risk of automation. This may be caused by gender differences in job search behavior or the availability of job offers.

The pattern documented in Fig. 1 might be the direct consequence of fewer employment possibilities caused by technological progress. In Appendix B we provided suggestive evidence that the observed pattern is related to job opportunities using aggregated data on vacancy postings.

We also find evidence that automation risk is related to training assignment. The corresponding assignment hazards are shown at the lower panel in Fig. 1. In general, assignment varies considerably over the duration of the unemployment spell. Men formerly employed in high RTI occupations (top tertile) have a higher probability of receiving training as compared to those in the lower tertile. Differences in assignments are even larger for women. For both men and women, these differences due to automation risk remain visible into the late phase of the unemployment spell.

The results from our preliminary analysis show that automation risk seems to be important in determining the transition from unemployment to employment. We also find evidence that decision makers are aware of these consequences. The simple analysis presented here has obvious shortcomings, however. We have abstracted from important elements such as worker sorting or selective training assignment. Taking these factors into account is important to guide a well-defined policy debate.

4. Econometric framework

The job search behavior of an individual and therefore the probability of finding employment is likely affected by the expected career prospects, which is, in turn, influenced by unobserved ability, automation, and received training. We make use of the *Timing of Events* approach proposed by Abbring and den Berg (2003a) to model this interdependence. We proceed by first discussing the underlying assumptions we make in our model on selectivity and anticipation. Then, we describe our model and estimation approach in more detail.

[14] One concern might be that since our measure of the RTI is based on the DOT published in 1977 it does not necessarily reflect the current risk of automation. We also tested the robustness of our results using an alternative measure of routine input based on the O*NET data in 2000 and following Acemoglu and Autor (2011). The results are qualitatively similar to those reported here. Given our discussion and the clear advantage of using the RTI, we prefer to use it as the main measure.

[15] We also include the offshoring measure of Blinder and Krueger (2013) in our analysis. See our previous working paper version Schmidpeter and Winter-Ebmer (2018) for a more detailed discussion on this measure.

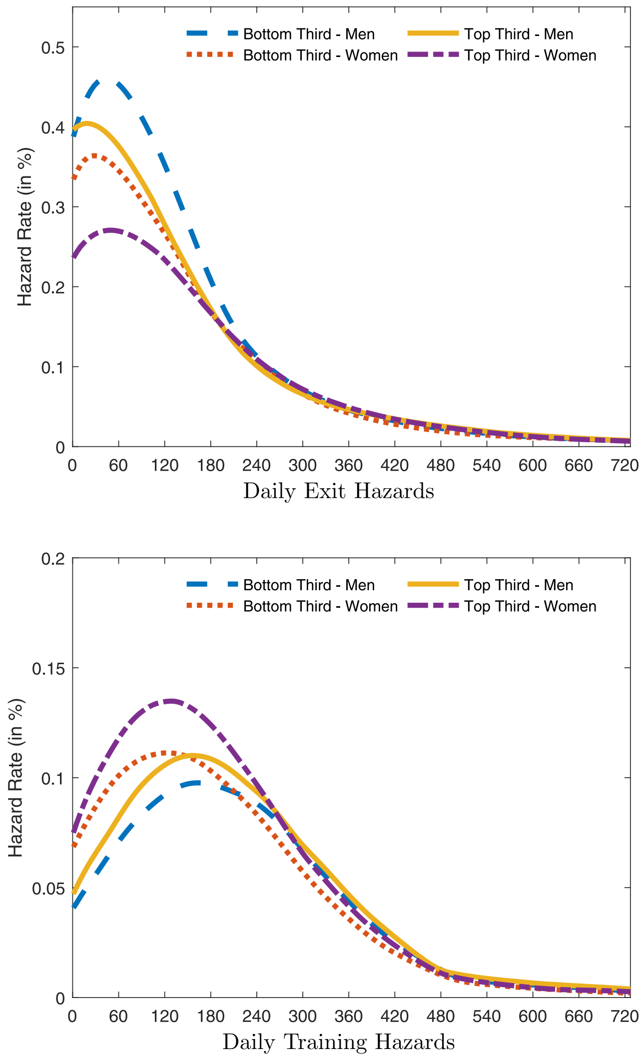


Fig. 1. Empirical transition rates.
This figure presents smoothed daily transition rates into employment (upper panel) and into training (lower panel) estimated separately for the upper and lower third of the RTI distribution. The RTI index is based on Autor and Dorn (2013) and were mapped to European classification as in Goos et al. (2014). Hazards were smoothed using the method of Müller and Wang (1994).

4.1. Identification assumptions

The key parameter in our model is the effect of training on the exit from unemployment in light of recent technological change. We jointly estimate the duration until exiting unemployment and the duration until the start of training by means of a continuous-time multivariate duration model, which we describe in more detail in the next section. Jointly modeling the training assignment process and the unemployment exit process enables us to account for possible selection into training by allowing for correlation in the unobserved individual heterogeneity between the processes (see Abbring and den Berg, 2003a). To identify the training effect, we then exploit the information on the timing of training assignment and the timing on the unemployment exit.

Informally, we can identify the training effect on unemployment exit in the *Timing of Events* model by splitting the data into two parts: (i) a competing risk part for the duration until an individual either finds new employment, receives training or leaves the labor market, whatever outcome comes first, and (ii) the remaining duration from the time of receiving training until exit to new employment or out of labor force. The training effect can be identified from Part (ii), where the timing of consecutive events is exploited. The *Timing of Events* approach has been widely used in the program and training evaluation literature for different countries — typically in a single-spell environment only, see, for example, Van den Berg et al. (2004), Lalive et al. (2005), and Osikominu (2013).

However, we are not only interested in the general effect of training but also if training can be effective in light of recent technological progress. One concern in identifying heterogeneous training effects might be that unobserved individual heterogeneity, such as productivity and motivation, is correlated with selection into occupations, our RTI, and the effectiveness of training. Therefore, solely exploiting the timing of events to identify our effect of interest might not be sufficient in our setting.

To account for possible selectivity into occupations we exploit the access to multiple-spell data and assume that individual unobserved heterogeneity is fixed over time (see also the discussion in Richardson and van den Berg, 2013).[16] By assuming that individual unobserved heterogeneity is fixed over time we can allow for correlation of unobserved individual traits, such as productivity, motivation, and ability, with our RTI measure (and all other control variables) and the effectiveness of assigned training, similar as in linear panel data models (Abbring and Van den Berg, 2003b; Abbring and den Berg, 2003a). Therefore, workers with different (but constant) unobserved abilities can sort themselves into different occupations in our model. We can also allow for situations where case workers base their training assignment on unobserved individual heterogeneity, such as productivity. Then, exploiting the timing of events similarly as described above but within our panel data framework allows us to identify the training effect depending on technological progress.

Assuming time-fixed unobserved heterogeneity implies that we need to rule out any unobserved dynamic effects, such as learning about one's own abilities over time when, for example, choosing an occupation. We also need to rule out that training assignment by the case worker is based on time-varying but unobserved worker characteristics. In addition, our model does not allow for dynamic effects where individual outcomes or treatment assignments between spells are related through factors *other* than our covariates and time-fixed unobserved heterogeneity. Imposing time-invariant heterogeneity therefore requires that we account for important time-varying factors between spells which affect individuals' labor market outcomes and possible training assignments.

To account for a wide range of selection possibilities, we include a rich set of personal and pre-unemployment job characteristics, such as reason for job loss, pre-unemployment tenure and wages, in our model. For example, pre-unemployment wages and tenure capture personal circumstances which, besides fixed individual productivity, are taken into account by the case workers when deciding whom to assign to training. Being affected by a plant closure might be an important determinant for switching occupations (e.g. Gathmann and Schöneberg, 2010, for a more general discussion).

Even when including our rich set of personal and pre-unemployment job characteristics, one might still be concerned that unobserved heterogeneity is changing over time, for example, when individuals learn about their own abilities. Previous research has shown, however, that learning does not seem to play an important role when considering occupational wage premia once comparative advantage is taken into account (Gibbons et al., 2005). We are therefore confident that by allowing for time-invariant unobserved heterogeneity and including a rich set of personal and employment characteristics we can capture important changes in individuals labor market outcomes and training assignment processes over time sufficiently well. We provide more details on changes in individuals' job and personal characteristics between spells in Appendix B.

While our model allows for general selectivity under the assumption that individual unobserved heterogeneity is time invariant, key to the identification of the training effect is also the so-called no-anticipation assumption. This requires that future program participants do not foresee the assigned start date of the course and do not react on it. The no-anticipation assumption does not require that training has to be assigned completely at random. Participants can hold believes about the probability of when to enter a training course and might know when they are at a high risk, as long as they do not act on their believes before the actual start date of the course. In other words, unemployment training is only allowed to have an effect on the exit hazard from the actual participation date onward.

The no-anticipation assumption would be violated if prospective participants did reject job offers or lower their search intensity shortly before a (believed) training assignment. Unemployed workers are, however, closely monitored by their case worker. They risk losing their benefits for a prolonged time period if they do not apply for jobs or do not accept any position referred to by the case worker. In addition, assignment of training schemes is subject to the discretionary power of the case worker. A job-seeker has no legal entitlement to participate in training schemes. Case workers evaluate if participation in a training scheme is necessary and beneficial during meetings with the job-seeker. On the other hand, if an individual is assigned to a training measure, participation is compulsory. Refusing to do so or deliberately foiling the goal of the assigned measure will lead to a reduction in benefits.

The no-anticipation assumption would also be violated if case workers communicated the training assignment well before the actual start date to the job-seeker and she reacted on this new set of information. In this case, the total treatment would be comprised of an actual training effect and a notification effect (Crépon et al., 2018).[17] As discussed in Section 2, allocation of training is organized in the short-term and depends on the supply of eligible training slots. A high utilization of the available capacities is the preferred target.

As further support for the no-anticipation assumption, we find considerable variation in the timing of training starts during the unemployment spell. This can be seen from the assignment hazards plotted in Fig. 1. We also find only modest differences in key observed characteristics between participants and non-participants (Tables B.1 and B.2 in Appendix B). It is therefore highly unlikely that an individual can anticipate future training assignment.[18]

[16] If we were only interested in the overall training effect access to single-spell data would be sufficient to identify the impact of training on unemployment exit. This is as by jointly modeling the time until training and the time until unemployment exit we can allow for correlation between these processes on unobservable characteristics and therefore account for selectivity in the training assignment process.

[17] If unemployed workers do not value unemployment training, the possibility of receiving sanctions for not starting a training program may lead to a positive "threat effect" of notification on the exit rate (e.g. Black et al., 2003).

[18] In addition, if the time between anticipation and actual assignment is short relative to the overall duration, then the introduced bias is likely negligible; see Richardson and van den Berg (2013).

4.2. Modeling treatment assignment and exit behavior

We assume that the exit and treatment transition rates have a mixed proportional hazard specification.[19] We consider both the exit into a new job (NJ) and the transition into Out-of-Labor Force (OLF) in our analysis. This allows us to explicitly evaluate the impact of automation risk on withdrawals from the labor force.

In our empirical specification, we allow the impact of RTI to (linearly) change over time by interacting our indices with a linear time trend τ and using 2000 as base year. We denote these time-interacted variables by RTI_τ. This interaction effect will help us to understand how technological progress has intensified over the past years.[20] We show in Appendix E that our linear time trend model captures changes in the impact of RTI over time very well.

For an individual i who was previously employed in occupation o and who has a realized spell with duration T_i until exit and duration D_i until the first labor market policy, we define the exit rate for $e \in \{NJ, OLF\}$ as

$$\theta_e(T_i|RTI_o, x_i, v_e, D_i) = \lambda_e(T_i) exp\left(x_i'\beta_E + \gamma^{RTI}_{2000,e} RTI_{o,2000} + \gamma^{RTI}_{\tau,e} RTI_{o,\tau} + \delta_e(RTI)\mathbb{1}(T_i > D_i) + v_e \right) \tag{1}$$

In Eq. (1), $\lambda_e(T_i)$ represents a fully flexible baseline hazard, displaying individual duration dependence. The vector v_e captures the impact of time-fixed unobserved worker heterogeneity on the exit rate, such as an individual's ability or work ethic. The vector x_i includes observable individual and previous employment characteristics, as presented in Table 1. We also include a full set of year and occupational dummies defined on a 1-digit level in our estimation. The year dummies capture general macroeconomic shocks. The inclusion of 1-digit occupation dummies in our estimation accounts for any general occupation-specific traits possibly correlated with our RTI. We therefore follow a conservative strategy when estimating the impact of automation on workers. Notice that even when including occupational group dummies, our RTI exhibits large variation across occupations within a major occupational group. For example, in the major group "Clerks", our RTI for Office Clerks is 2.54 while it is 1.50 for Customer Service Clerks.

The coefficient γ^{RTI}_{2000} gives the effect of automation risk on the exit hazards in the base year 2000, and γ^{RTI}_{τ} reflects how the automation risk has affected the exit hazards over time. Given our parameters and using the year 2000 as base year, we can calculate the total impact of our RTI on the exit hazard in year τ by $\gamma^{RTI}_{2000} + (\tau - 2000) \cdot \gamma^{RTI}_{\tau}$.

The parameter $\delta(RTI)$ captures the shift in the exit hazard due to provided training. We allow $\delta(RTI)$ to depend on the automation risk.[21] More precisely, in our analysis we model $\delta(RTI)$ as (see also the discussion in Abbring and den Berg, 2003a; and Richardson and van den Berg, 2013)

$$\delta_e(RTI) = \delta_e + \delta^{RTI}_{2000,e} RTI_o + \delta^{RTI}_{\tau,e} RTI_{o,\tau} \tag{2}$$

This allows us to evaluate whether workers at the risk of automation receive more effective unemployment training and whether/how this has changed over time. The estimates of $\delta(RTI)$ are the key parameters of interest in our analysis.

Similar to our exit hazards, we model the arrival rate of labor market training (treatment hazard) as

$$\theta_P(D_i|RTI_o, x_i, v_P) = \lambda_P(D_i) exp\left(x_i'\beta_P + \gamma^{RTI}_{2000,P} RTI_{o,2000} + \gamma^{RTI}_{\tau,P} RTI_{o,\tau} + v_P \right) \tag{3}$$

Here v_P captures unobserved heterogeneity in the treatment assignment and the vector x_i includes observable individual characteristics and time as well as occupation dummies. The assignment decision of the case worker may depend on RTI as well as on our linear time trend. The estimated parameters give us an indication of how aware case workers are of the risk of automation on workers' labor market careers and whether their focus has changed over time.

In our model we allow for selectivity and do not impose any restrictions on the correlation of the unobserved components v_e and v_P. Hence, selection into treatment can affect the exit transitions and vice versa. We assume that the distribution of heterogeneity to be a priori unknown and approximate it by means of a discrete distribution as suggested by Heckman and Singer (1984). The associated probability for having M possible mass points is parametrized in the following way

$$p_m = P(v_{NJ} = v^m_{NJ}, v_{OLF} = v^m_{OLF}, v_P = v^m_P) = \frac{exp(\alpha_m)}{\sum_{m=1}^{M} exp(\alpha_m)} \tag{4}$$

Parameterizing the probabilities in this way avoids constrained maximization. In practice, we set the maximum numbers of estimated mass points M to five, but our results are not sensitive to the exact number of mass points chosen.[22] In certain circumstances an estimated heterogeneity parameter converges to a large negative value. This happens, for example, if we do not observe a transition into employment for some individuals and a "defective risk" is present in the data. A large heterogeneity parameter introduces

[19] In a multi-spell setting assuming a mixed proportional hazard model is not crucial for identification; see Abbring and den Berg (2003a).

[20] While we could model the temporal impact of RTI on our hazards in more general ways, the computation of more flexible models is very time intensive.

[21] We also let the training effect depend on the Blinder and Krueger (2013) measure of offshoreability. We do not find any strong evidence for heterogenous training effects with respect to this measure; see Schmidpeter and Winter-Ebmer (2018).

[22] We find that the estimated coefficients in our models remain fairly stable after adding the fourth mass point. Therefore, we think that choosing five mass points is a reasonable compromise between too few and too many mass points (Lombardi et al., 2019). In Appendix C we show results for alternative numbers of mass points.

numerical problems in our estimation and makes it impossible to invert the Hessian matrix and to obtain standard errors. In such a case, we mark and fix the problematic parameter and treat it as a constant in any further estimation.[23]

We model individual duration dependence in a flexible way via a piecewise constant function $\lambda_j(T_i) = \exp(\sum_{k=1}^{10} \lambda_{j,k} \mathbb{1}_k(T_i))$ for $j = \{NJ, OLF, P\}$. In total we distinguish ten time intervals, where we keep the intervals small at the beginning of the unemployment duration to capture changes in the benefit regime. For estimation purposes we normalize the first parameter to 0 for each considered hazard.

We estimate the parameters by means of maximum likelihood. Having N individuals in total with individual i having in total J_i spells, and observing the time to exit T_{ij} (or censoring) and the time to unemployment training D_{ij} (or censoring) for each of these spells, the log-likelihood function for our empirical model is

$$\mathscr{L} = \sum_{i=1}^{N} \log \left\{ \sum_{m=1}^{M} p_m \prod_{j=1}^{J_i} \prod_{e=1}^{E} \theta_e(T_{ije}|RTI_{oje}, x_{ije}, v_e^m, D_{ij})^{\Delta_{ij,e}} S_e(T_{ije}|x_{ij}, v_e^m, D_{ij}) \right.$$
$$\left. \theta_P(D_{ij}|RTI_{oj}, x_{ij}, v_P^m)^{\Delta_{ij,P}} S_P(D_{ij}|x_{ij}, v_P^m) \right\} \tag{5}$$

where E is the total number of exit states considered, $\Delta_{i,e}$ and $\Delta_{i,P}$ are censoring dummies, and $S(\cdot)$ is the survival function. Notice that our log-likelihood function indeed imposes that an individual has the same heterogeneity term across unemployment spells (see also van der Klaauw and van Ours, 2013).

4.3. Modeling post-unemployment outcomes

We are also interested in how automation risk and skill enhancement through training affects re-employment job-quality, such as wages and job stability.[24] Considering post-unemployment outcomes introduce additional problems into our analysis. Whether to take up new employment is likely endogenous. Workers who find a new job, most likely differ both in terms of observable and unobservable characteristics. The differences in observable characteristics can be controlled for by the inclusion of covariates. To take into account selectivity on unobserved characteristics, we simultaneously model the selection process into training and later into employment (out-of-labor force) and post-unemployment outcomes, allowing for correlation among individual heterogeneity terms across the different states (Ham and LaLonde, 1996).

When modeling the effect on re-employment wages W, we make use of the approach proposed by Donald et al. (2000) (see also Cockx and Picchio (2013) for an extension). Donald et al. (2000) show that the cumulative distribution function of wages can be modeled using hazard functions, similar as in duration analysis.[25] We model the wage hazard θ_ω for individual i *after* exiting the unemployment spell similar as in Eq. (1):

$$\theta_\omega(W_i|RTI_o, x_i, v_\omega, D_i, T_{i,NJ}) = \lambda_\omega(W_i) exp\left(x_i'\beta_\omega + \gamma_{2000,\omega}^{RTI} RTI_{o,2000} + \gamma_{\tau,\omega}^{RTI} RTI_{o,\tau} + \right.$$
$$\left. \delta_\omega(RTI)\mathbb{1}(T_{i,NJ} > D_i) + v_\omega \right) \tag{6}$$

where $\lambda_\omega(W_i)$ are baseline hazards, defined similarly as before, and v_ω reflects unobserved heterogeneity. We choose the knots in the baseline hazard to occur at every 10th percentile of the observed wage distribution. $\delta_\omega(RTI)$ summarizes the impact of provided training on post-unemployment wages. As before, the effect is allowed to differ by the automation risk an individual faces.

As we only observe an individual's re-employment wage if she found a new job, we face a double censoring problem. Denote by $\Delta_{ij,\omega}$ an indicator which takes a value of one if the re-employment wage lies below the 99th percentile and by $S_\omega(W_{ij}|RTI_{oj}x_{ij}, v_\omega, D_{ij}, T_{ij,NJ})$ the survival function. Remember that $\Delta_{ij,NJ}$ is the censoring indicator taking a value of one if we observe an outflow into new employment for the jth unemployment spell of individual i. Then, the contribution of adding re-employment wages as additional state to an individual's likelihood is

$$\mathscr{L}_{ij}^{\omega} = \left[\theta_\omega \left(W_{ij}|RTI_{oj}, x_{ij}, v_\omega, D_{ij}, T_{ij,NJ} \right)^{\Delta_{ij,\omega}} S_\omega \left(W_{ij}|RTI_{oj}, x_{ij}, v_\omega, D_{ij}, T_{ij,NJ} \right) \right]^{\Delta_{ij,NJ}} \tag{7}$$

We model the job stability hazard in a similar way. Denote by $\Delta_{ij,PE}$ an indicator which takes a value of one if the new employment was terminated before the end of our observation period and let $S_{PE}(T_{ij,PE}|RTI_{oj}x_{ij}, v_{PE}, D_{ij}, T_{ij,NJ})$ be the survival function. An individual's contribution to the likelihood when adding re-employment job stability as an additional state is given by

$$\mathscr{L}_{ij}^{PE} = \left[\theta_{PE} \left(T_{ij,PE}|RTI_{oj}, x_{ij}, v_{PE}, D_{ij}, T_{ij,NJ} \right)^{\Delta_{ij,PE}} S_{PE} \left(T_{ij,PE}|RTI_{oj}, x_{ij}, v_{PE}, D_{ij}, T_{ij,NJ} \right) \right]^{\Delta_{ij,NJ}} \tag{8}$$

Before discussing our results, we want to highlight that in terms of our post-unemployment outcomes usually negative coefficients are interpreted as having a positive impact on workers' future labor market career. This is straightforward to see when considering job stability, but it might be more complicated when using wages as outcome. The wage hazard is the instantaneous probability of having a re-employment wage W conditional on receiving at least W. It has therefore a similar interpretation as any hazard when

[23] We do so for estimated heterogeneity points below -20. Furthermore, in the optimization process we account for possible degenerate distributions; see also Gaure et al. (2007a,b) for more details on the optimization approach.

[24] Related to our setting, Arni et al. (2013) look at how sanctions and warnings affect subsequent employment stability and wages in Switzerland.

[25] The estimator requires censoring, so we follow Donald et al. (2000) and assume that wages above the 99th percentile are censored.

Table 2
Effect of automation risk on exit behavior and re-employment wages.

	(1) Male	(2)	(3)	(4)	(5) Female	(6)	(7)	(8)
	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Treatment hazard θ_{Training}	Wages θ_{ω}	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Treatment hazard θ_{Training}	Wages θ_{ω}
Panel a: Automation Risk								
γ^{RTI}	−0.088***	−0.018	0.190***	0.195***	−0.168***	−0.045	0.232***	0.076***
	(0.033)	(0.036)	(0.047)	(0.029)	(0.031)	(0.031)	(0.042)	(0.028)
γ_{τ}^{RTI}x 10	−0.051***	−0.045**	−0.058**	0.055***	0.015	−0.036*	−0.093***	0.010
	(0.015)	(0.019)	(0.023)	(0.014)	(0.020)	(0.021)	(0.025)	(0.019)
Panel b: Training								
δ	0.596***	0.268***		−0.214***	0.767***	0.368***		−0.132***
	(0.016)	(0.018)		(0.015)	(0.017)	(0.016)		(0.017)
δ_{2000}^{RTI}	0.046*	−0.026		0.081***	0.012	−0.013		−0.004
	(0.028)	(0.030)		(0.029)	(0.030)	(0.031)		(0.029)
δ_{τ}^{RTI}x 10	−0.024	0.031		−0.100***	−0.005	0.030		0.005
	(0.035)	(0.038)		(0.038)	(0.039)	(0.042)		(0.040)
Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobs. Heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blinder & Krueger Offshoring Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time & Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−124,861.10				−128,052.86			

This table summarizes the estimation results of RTI on the re-employment hazard θ_{NJ}, wage hazard θ_{ω}, and Out-of-Labor Force (OLF) hazard. The sample comprises 98,051 (men) and 80,178 (women) observations respectively. All models include linear trends in RTI using the year 2000 as baseline. In addition, individual characteristics, time dummies, occupational dummies defined one a 1-digit level, and the Blinder and Krueger (2013) Measure of Offshoreability are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function. The number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 4. To estimate the effect on the distribution of re-employment wages the top 99th percentile of the wage distribution was censored (Donald et al., 2000). During estimation, one mass point in both the Men and Women Sample converged to a large negative number. They were marked and treated as constants during further estimation. Standard errors are reported in parentheses.

considering spell length as an outcome. One can show that under the MPH assumption imposed, the sign of the impact on the wage distribution is the opposite to the sign estimated on the coefficient of interest (Cockx and Picchio, 2013). To ease interpretation, we will change the sign when reporting our estimates on the wage hazard. Thus, positive coefficient when considering wages can be interpreted as having a positive effect on workers' post-unemployment wages.

5. Main results

Table 2 summarizes our main results, Columns (1) to (4) for men and Columns (5) to (8) for women. In the table, Panel a contains the results for the effects of automation risk on the log-hazard rates. Panel b presents the estimated training effects. We only show the coefficients on our variables of interest RTI in the tables, but all estimates contain individual level control variables as well as year and occupational dummies.[26]

Table 3 contains the same set of estimates as reported in Table 2 with the exception that we consider job stability instead of post-unemployment wages as an additional outcome in Columns (4) and (8). Comparison of our two models when only altering post-unemployment outcomes also helps us to gauge if any instabilities during the estimation procedure may affect our results.

As one can see from the tables, the estimates for the training hazard (θ_P), the exit hazards into new employment (θ_{NJ}), and the out-of-labor-force hazard (θ_{OLF}) are virtually identical regardless of considering wages or job stability as post-unemployment outcome. The similarity in our main estimates when altering post-unemployment information is comforting and gives reassurance about the stability of our results. For brevity's sake, in the discussion, we concentrate on the model including post-unemployment wages as additional outcome.

The discussion proceeds in four steps. First, we discuss the impact of automation risk on the job finding probabilities of individuals. Second, we discuss the relation between automation risk and training assignment. Third, we present the effects of skill enhancement through training on workers' exit behavior. It turns out that training can counteract the negative impact of automation risk on workers' job finding rate. We also find that there has been a shift in assignment priorities which has disadvantaged the most vulnerable workers. Fourth, we discuss the impact of automation risk on post-unemployment wages and its implications for increasing inequality.

[26] In the main part of our paper, we concentrate on all unemployed workers, regardless of the reason for the inflow. We report estimates from a sample of workers from plant closures as additional robustness check in Appendix D. All conclusions made in the main part remain also valid using this sub-sample.

Table 3
Effect of automation on exit behavior and re-employment job stability.

	(1) Male	(2)	(3)	(4)	(5) Female	(6)	(7)	(8)
	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Treatment hazard $\theta_{Training}$	Job Stability hazard θ_{PE}	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Treatment hazard $\theta_{Training}$	Job Stability hazard θ_{PE}
Panel a: Automation Risk								
γ^{RTI}	−0.097***	−0.025	0.205***	−0.197***	−0.157***	−0.046	0.228***	−0.215***
	(0.033)	(0.036)	(0.047)	(0.027)	(0.032)	(0.030)	(0.042)	(0.029)
γ_{τ}^{RTI} x 10	−0.052***	−0.046**	−0.059**	0.014	0.011	−0.036*	−0.090***	0.015
	(0.015)	(0.019)	(0.023)	(0.014)	(0.020)	(0.021)	(0.025)	(0.021)
Panel b: Training								
δ	0.596***	0.284***		0.010	0.751***	0.369***		0.101***
	(0.016)	(0.018)		(0.015)	(0.018)	(0.017)		(0.016)
δ_{2000}^{RTI}	0.047*	−0.034		−0.013	−0.005	−0.015		0.012
	(0.028)	(0.030)		(0.027)	(0.030)	(0.031)		(0.030)
δ_{τ}^{RTI} x 10	−0.035	0.042		0.015	0.007	0.030		−0.022
	(0.036)	(0.039)		(0.037)	(0.040)	(0.041)		(0.042)
Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobs. Heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blinder & Krueger Offshoring Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time & Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−159,843.39				−155,192.38			

This table summarizes the estimation results of RTI on the re-employment hazard θ_{NJ}, wage hazard θ_{ω}, and Out-of-Labor Force (OLF) hazard. The sample comprises 98,051 (men) and 80,178 (women) observations respectively. All models include linear trends in RTI using the year 2000 as baseline. In addition, individual characteristics, time dummies, occupational dummies defined one a 1-digit level, and the Blinder and Krueger (2013) Measure of Offshoreability are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function. The number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 4. To estimate the effect on the distribution of re-employment tenure, all spells without an observed outflow by the end of 2016 are censored. During estimation, one mass point in the Men Sample converged to a large negative number. It was marked and treated as a constant during further estimation. Standard errors are reported in parentheses.

5.1. Effect of automation risk on exit behavior

Impact on Re-Employment Probabilities: Our estimates for the risk of automation on the job finding rate are reported in Columns (1) and (5) of Table 2 for men and women respectively. To facilitate interpretation of our time trends, we also plot the effect of a one standard deviation increase of RTI on the job finding hazard over time together with a 95% confidence interval in Fig. 2.

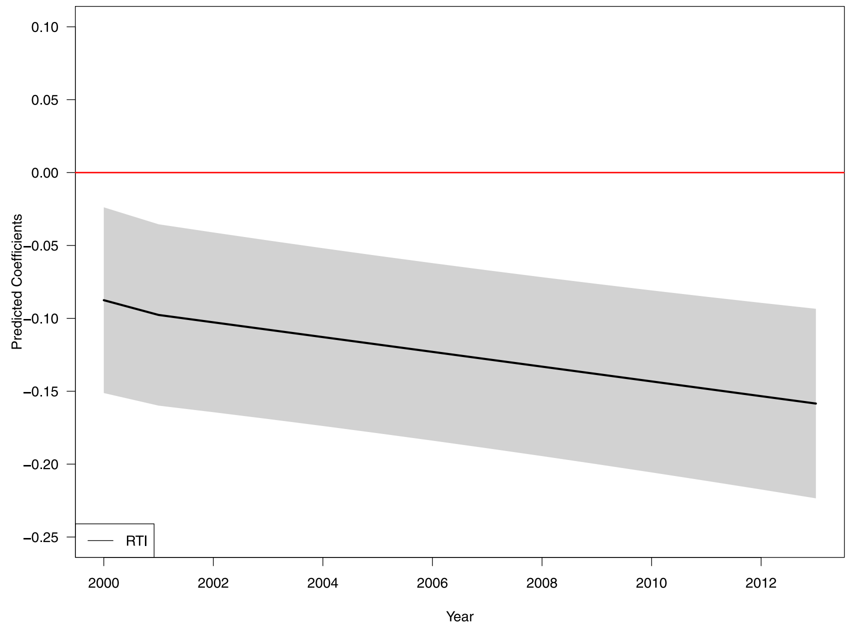
Our results show that the risk of automation significantly lowers the job finding probability for men. A one standard deviation increase in the RTI decreased the re-employment probability by 8% in 2000.[27] These negative effects of automation have since then amplified. In 2014, a similar increase in the RTI reduces the job finding rate by 16%, implying a considerable drop over time. We come to similar conclusions when using a more flexible model where we interact our measures with yearly time dummies; see Appendix E.

To give our results more context, consider two workers: an unemployed office clerk and an unemployed service clerk. Assume that both workers have similar observed and unobserved characteristics and therefore only differ in their occupational choice. The difference in the standardized RTI between those two occupations is roughly 1. In the year 2000, the risk of automation reduces the job finding probability by around 12% for the service clerk and by around 20% for the office clerk, implying a gap of roughly 8 percentage points (pp). This lower job finding probability corresponds to an increase in the unemployment duration by around 6 weeks in our example. Within 10 years, the gap in the job finding probabilities caused by automation has substantially widened to 11 pp, an increase by more than 35% and corresponding to roughly one additional month of unemployment.[28] Notice that this gap is solely due to differences in the automation risk in the occupations and not to differences in other worker characteristics.

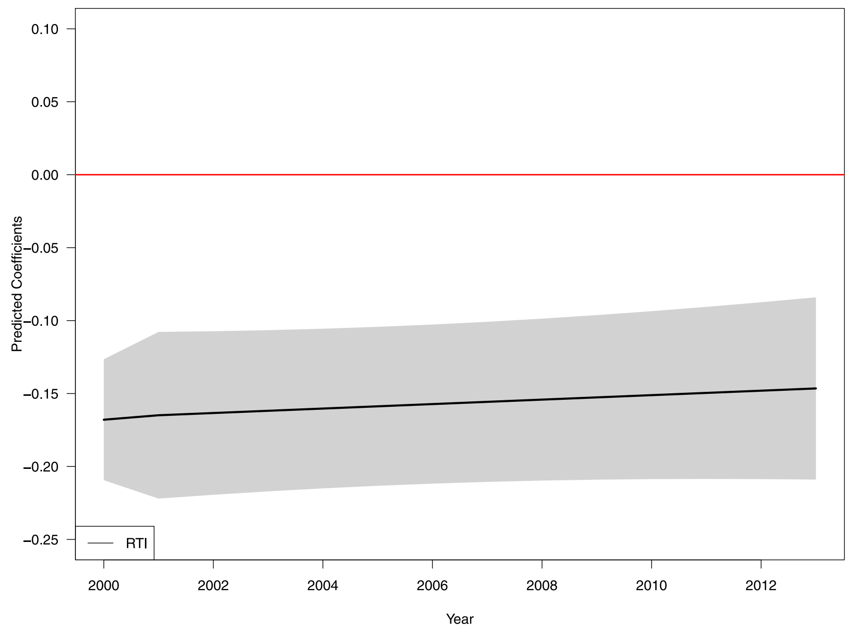
The impact of the risk of automation on female workers is slightly stronger at the beginning of our sample period compared to men, as can be seen in Column (5) in Table 2. Unlike our results for men we do not find a strong intensification over time, however. A one standard deviation increase in our RTI index decreases the re-employment probability by 15% in 2000 and remains virtually constant thereafter. As women are more likely to be found in occupations less affected by increasing automation compared to men

[27] Remember, we normalized the standard deviation of our indices to 1.

[28] Office clerks have a RTI of 2.54 and service clerks a RTI of 1.50. This implies that the employment probability shifts in the year 2000 by $exp(-0.088 \cdot 2.54) - 1 = -0.20$ and in the year τ by $exp(-0.088 \cdot 2.54 - 0.005 \cdot (\tau - 2000) \cdot 2.54) - 1 = -0.30$ for the office clerk as compared to an individual with average characteristics. We describe how we simulate the expected unemployment duration in the next but one section.



a. Men



b. Women

Fig. 2. Impact of automation risk on re-employment hazard over time.
The figures depict the estimates of the coefficient on the RTI for the linear time trend model together with 95% Confidence Intervals for the Re-Employment Hazard as reported in Table 2.

(see Table A.3), these results also show that, on average, technological progress has a relatively positive effect on the job search process of unemployed women compared to unemployed men; see also Black and Spitz-Oener (2010), and Cortes et al. (2020).

Impact on Leaving the Labor Force: Columns (2) and (6) in Table 2 summarize the impacts of automation risk on the likelihood of leaving the labor force. For both, men and women we find that a higher risk of automation is associated with a lower probability of leaving the labor force, in particular in later years. Part of this effect might be driven by the fact that automation risk is associated with higher re-employment wages, as we will show later. Thus, individuals might be more inclined to stay in the labor market and hoping to climb the wage ladder when finding re-employment.

5.2. Effect of automation risk on training assignment

Given that the risk of automation significantly reduces the re-employment probability for both men and women, it is interesting to evaluate if case workers have been aware of these developments. In this section, we briefly discuss the impact of our measures on the training assignment process. Columns (3) and (7) in Table 2 summarize the results for men and women respectively.

Case workers try to compensate for the potential negative consequences of the risk of automation — particularly at the beginning of our observation period. A one standard deviation increase of our RTI increases the likelihood of receiving training by 20% for men and 26% for women. Our trend estimates γ_τ, reported in the next line, show that there has been a shift in the focus over the past years, however. Although workers at high risk of automation still are more likely to receive training, this *positive discrimination* has become smaller over time. A one standard deviation increase in the RTI decreases the training assignment likelihood by around 1 pp for women and 0.6 pp for men each year. To continue our example from the previous section, this implies, that the probability of receiving training for an unemployed male office clerk decreases from 62% in 2000 to 40% within 10 years. This reduction is relatively large and corresponds to a 35% fall compared to our baseline estimates in the year 2000.

Our results for the training assignment process are quite interesting. Case workers tend to factor the disadvantage of automation-prone occupations into account when making their decisions. The reduced attention toward these workers is surprising though, given the current public debate about the consequences of automation and digitization on workers. In this light, one would have expected the opposite to be true. One reason for this development might be that case workers have a lower propensity of assigning unemployment training but the assigned training might be more effective in bringing individuals back to work. The discussion in Section 2 point toward a shift in assignment strategies in the direction of fewer but more expensive courses. We discuss this issue further in the next sections below.

5.3. Effects of labor market training on exit behavior

Columns (1) & (2) as well as (5) & (6) in Panel b in Table 2 summarize our estimates on the impact of provided training on exit behavior for male and female workers. We find that skill enhancement through labor market training has, in general, a highly significant and positive effect on the re-employment probability, as can be seen from the estimates for δ. Training shifts the likelihood of finding new employment for males by around 75% and even more so for female workers. These results are very similar to training effects found for other countries (e.g. Richardson and van den Berg, 2013). We also find that labor market training leads to an increase of the likelihood of transiting out of labor force, but to a much lesser extent. One explanation for this finding might be that workers who receive training become overly optimistic about their job prospects and adjust their wage expectations upwards, leading to an expiration of benefit eligibility and transition out of the official unemployment register.[29]

Is training able to compensate workers for the problems related to automation risk? For men, training effectiveness differs by the degree of automation: A one standard deviation increase in our RTI increases the impact of training on the job finding probability by an additional and significant 8 pp in 2000 or around 11% when compared to our baseline.[30] The effectiveness has decreased since then, although our trend estimates are not significant on any conventional level. We do not find similar results for women. The point estimates are very small and not statistically significant.

These differential effects of automation do not capture the full impact of training on the total unemployment duration of workers, however. To obtain a comprehensive picture on how skill enhancement is affecting the job finding probabilities one needs to consider two channels. First, there is the direct effect of training related to our measure of automation risk, as discussed in this section. Second, there is also an indirect effect of training, operating through the difference in the assignment process of case workers, as discussed in the previous section. As we have shown, this process depends as well on automation risk. Thus workers with different RTI have different expected waiting times until training assignment. Receiving training at all or earlier during the unemployment spell will, thus, amplify general and specific (automation-risk related) training effects. To quantify these two channels, we use our estimates from Table 2 to simulate the total effectiveness of training.

We first calculate for each year y of our sample the expected duration until training assignment $S^{RTI}_{y,j}$, using our RTI and then setting it to 0 ($j = low$) or 1 ($j = high$). The difference between these two states corresponds to a one-standard-deviation change in our measure. We then use the expected duration until training assignment in a second step when calculating the expected duration until new employment $NJ^{RTI}_{y,j}$. For all calculations, we use the estimates reported in Table 2 and set all other covariates to their sample average as observed in the year 2000. This constitutes our baseline estimates of the total effectiveness of labor market training.[31]

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29 Related to this point, Mueller et al. (2021) show that job-seekers' biased beliefs substantially influence their likelihood of leaving unemployment and that in particular long-term unemployed are overly optimistic.

30 The figures are based on the results presented in Table 2. Using these estimates and all else equal, an increase of the RTI by one standard deviation compared to the mean increases the job finding probability by around $exp(.596 + 0.046) - exp(.596) = 0.08$.

31 In practice, using our parameter estimates and average of our covariates in 2000 $\bar{x}_{2000}$ we calculate for each of our sample years y, our RTI, and $j = \{low, high\}$ the expected duration until re-employment as $\sum_{i=1}^{5} p_i \left(\int_0^{tu} S(z|x = \bar{x}_{2000}, I = j, v^i_{NJ}, D = s)dz + tu \cdot P(t \geq tu) \right)$, where $S(\cdot)$ is the conditional survival rate, s the simulated duration until training assignment, and $P(t \geq tu)$ the conditional probability of surviving after time tu. The upper limit tu is chosen to be 10 years.

To gauge whether changes in the assignment process or changes in direct training effects are driving our time trend, we conduct a similar set of calculations but fix now our estimates for RTI to the value in the year 2000 when simulating the duration until training (the assignment process) or the duration until exit (changes in training effectiveness). Given the duration obtained under these two scenarios, we calculate the relative benefits of labor market training in year y as

$$\Delta_y^{Training} = \left(\frac{E[NJ_{y,j}^{RTI} | Index = j, D_y = S_{y,j}^{RTI}, x = \bar{x}_{2000}]}{E[NJ_{y,j}^{RTI} | Index = j, D_y = \infty, x = \bar{x}_{2000}]} - 1 \right) \cdot 100 \tag{9}$$

where j is set to either high or low.

Eq. (9) expresses the relative benefits of labor market training as the percentage change in the duration until re-employment by comparing the obtained duration with the simulated training assignment to the one if no training had been assigned. Notice that a negative number is associated with a beneficial impact of training on the re-employment duration.

A similar interpretation holds when comparing the results under our two scenarios. If $\Delta_y^{Training}$ is lower when holding the indirect effect of training assignment fixed at 2000 levels compared to our baseline, then the difference can be interpreted as the loss in effectiveness of the direct effect of training. Likewise, if $\Delta_y^{Training}$ is lower when holding the direct effect of training fix compared to our baseline, then the difference can be interpreted as the loss due to changing priorities of case workers.

Fig. 3 presents the results from this exercise. The solid line presents our baseline for workers with RTI set to the low level, our baseline estimates. For persons with low automation risk, training reduces unemployment duration by around 15% for both men and women, which is quite sizable.[32]

In comparison, the dashed line shows the benefits of training if we set RTI to a high level and thus allowing the different training assignment as well as changing training effects over time. From our results, it is clear, that both men and women with higher values of RTI profit substantially more from training compared to workers with lower values of RTI. At the beginning of our observation period, training reduced the unemployment duration for men with high values of RTI by almost 20% (relative to 15% at baseline), whereas training reduces the unemployment duration of women by around 21% (relative to 15% at baseline).

These advantages decrease over time, however. Had the provision of training be based on the same characteristics as in the year 2000, provided training could be 2 to 3 pp more effective nowadays for workers affected by automation, as shown by the dashed–dotted lines in Fig. 3. These differences are quite sizable when compared to our baseline estimates and are significantly different to the current state of training.[33]

For men, we find evidence that the decreasing benefits are almost equally driven by the changing assignment focus of case workers and less effective training programs. This can be seen from the (almost) similar impact on the unemployment duration if we hold either training assignment (long dashed–dotted line) or training effectiveness (dashed–dotted line) fixed at their 2000 level. For women, we find evidence that almost the entire decline in training effectiveness is due to changing assignment priorities (dashed–dotted line). Unlike our counterfactual when fixing both training assignment and effectiveness, neither of these effects in isolation are statistically distinguishable from our baseline effects, however.

5.4. Automation risk and post-unemployment outcomes

In this section, we discuss the impact of automation risk on post-unemployment outcomes. We follow a similar structure as above and first discuss the impact of automation risk on post unemployment outcomes. Then, we present our heterogeneous training effects. The results of automation risk on re-employment wages are summarized in Columns (4) and (8) in Table 2 for men and women respectively.

5.4.1. Re-employment wages

Impact of Automation Risk on Re-Employment Wages: The results presented in Column (4) of the table show that male workers who are more affected by automation risk and who find new employment have in general higher re-employment wages.[34] We also find a strong amplification of this development over time. Interestingly, these results are opposite to the impact of automation risk on re-employment probabilities.

Our results for women reported in Column (8) of the table point toward a similar development. The estimates are, in general, somewhat smaller and, unlike those for men, do not change over time. The differences compared to our results for men might be (partly) explained by women in Austria working more part-time and therefore benefiting less from any labor market development.

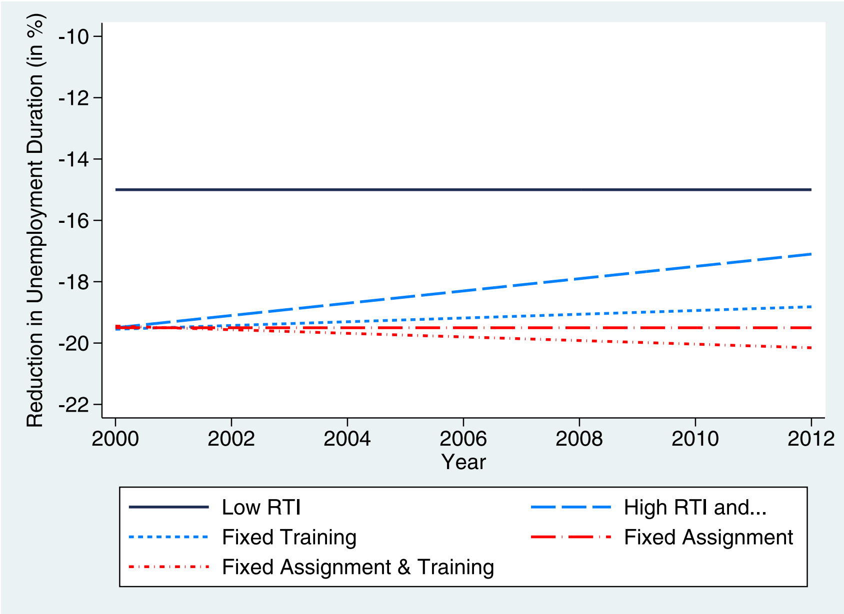
The estimated trade-off points toward different possible explanations for our results. First, workers displaced from high RTI occupations are, on the one hand, less likely to find new employment. On the other, hand, those workers who do find new employment might tend to switch to lower RTI but higher paying occupations. Therefore, they also benefit more from wage growth and job stability, similarly as in Cortes (2016).

Second, while “routine” jobs have seen a decline in employment opportunities, they have also experienced changes in the task requirements, ultimately leading to fewer but more productive jobs (Hershbein and Kahn, 2018; Gregory et al., 2019). If automation

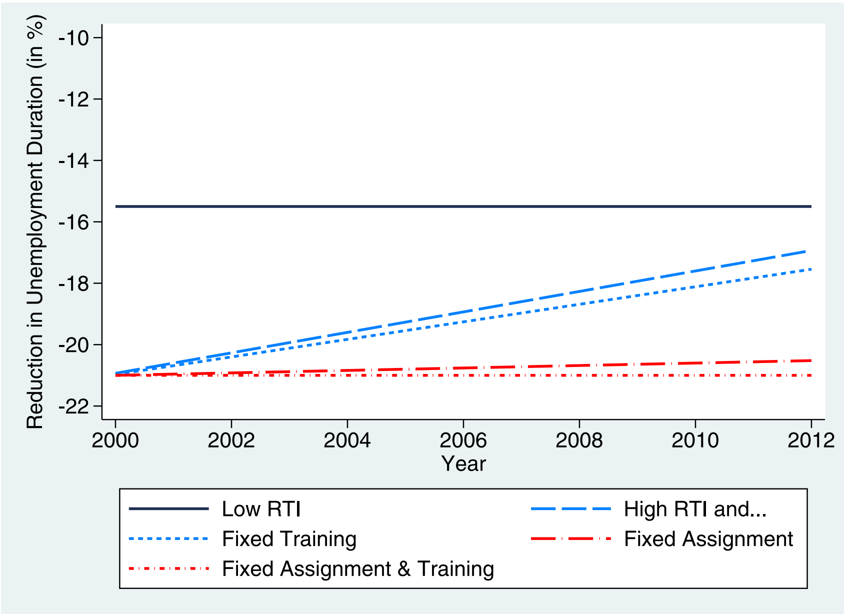
[32] Notice that there are small changes in the effectiveness of training over time. As described in Section 4, this is as δ does not only depend on the RTI but also the offshoring index of Blinder and Krueger (2013).

[33] In Appendix E we provide the corresponding standard errors for our effects and also show results for intermediate values of RTI.

[34] Remember that for readability, a positive coefficient on the wage hazard implies higher re-employment wages.



Men



Women

Fig. 3. Relative benefits of provided unemployment training.
The figure shows the benefits of providing unemployment training over our sample period for high and low values of our RTI. The sample comprises 98,051 (men) and 80,178 (women) observations respectively. The simulation takes into account that high and low RTI workers have different baseline unemployment durations and different assignment probabilities. The relative benefits of provided training are calculated using Eq. (9) and the expected durations are calculated using the estimates from Table 2 setting all other covariates to their average in 2000. The solid line represents the relative benefits of training setting RTI to 0 (low). The dashed lines show the relative benefits of training setting RTI to 1 (high). The short dash-dotted lines show the relative benefits setting RTI to high and keeping both training assignment and effectiveness fixed at 2000 levels. Setting RTI to 1, the long dashed–dotted lines show the results if training assignment had a similar impact as in 2000. Similarly, the dotted lines show the results if training programs had a similar impact as in 2000.

complements productive worker–firm matches, firms might therefore become more selective in hiring workers which increases post-unemployment wages but also unemployment duration (see also Faia et al., 2020). Using vacancy posting data from the AMS, we find suggestive evidence that the share of vacancies requiring cognitive or social skills has indeed increased faster for routine occupations than non-routine ones.[35]

Our results are consistent with both a story of occupational switching and also a story of occupational upskilling. Unfortunately, the data does not allow us to fully investigate any of the two given explanations further. Despite this drawback, our results clearly indicate that recent technological change has reduced the job finding probability for affected workers but also increased re-employment wages.

An alternative explanation for our findings might be that our effects are explained by possible selection into unemployment and therefore a selected sample. Workers in occupations with lower risk of automation might have lower unemployment risk in general. Those workers who transit from low routine jobs into unemployment are of lower productivity than those unemployed workers who previously held a job at higher risk of automation. Lower productivity could therefore explain the lower re-employment wages for workers previously employed in low RTI occupations.

As we only observe pre-unemployment occupations for unemployed individuals, we cannot investigate potential differences in the transition into unemployment. Notice, however, that in our estimation approach we take workers' unobserved productivity into account. Any remaining bias must therefore rely on temporal changes in productivity, which seems unlikely in our setting. As additional robustness check, we provide estimates for a sample of workers who were involuntary displaced from their previous job due to plant closures or mass lay-offs in Appendix D. For this sample, selection into unemployment should arguably be less of a concern. The estimation results concentrating on involuntary displaced workers are very much in line with those obtained using the overall sample of unemployed workers. Therefore, it is unlikely that selection into unemployment can entirely explain our estimated trade-off.

Impact of Training on Re-Employment Wages: Our results for the benefits of training are mixed when considering its impact on re-employment wages, as summarized in Panel b in Table 2. Provided training lowers re-employment wages significantly for both men and women in general. At the same time, we also found that it increases the likelihood of finding new employment.

One the one side, our results might imply that case workers are more concerned with bringing unemployed individuals back to work and less by post-unemployment job quality, as measured by starting wages in the new firm. These differences in case workers' priorities can potentially explain the estimated trade-off.

On the other side, this trade-off might also be explained by case workers prioritizing unemployed individuals with lower productivity when assigning training. These low productive workers benefit in general less from training and have therefore lower re-employment wages. This productivity difference would then be partially reflected in our estimates. While we cannot rule out this explanation entirely, notice that we account for possible unobserved differences in workers' productivity in our estimation approach. We jointly estimate training assignment and post-unemployment outcome which should account for any selective decision made by the case workers. Under the additional assumption that workers' productivity is fixed over time, our estimates capture the impact of training on re-employment wages net of any workers' unobservables, such as productivity.

We find differences in the impact of training on re-employment wages by automation risk. Particularly, men working in occupations more at risk of automation profited in terms of relatively higher wages. Workers in highly automatable jobs, such as office clerks, even saw a slight increase in wages as a result of training. This effect has decreased over time, however. We do not find a similar pattern for unemployed women.

These results are related to the findings of Hyman (2018) for the U.S. Using an instrumental variable strategy, he finds that workers who were displaced as a result of increasing import competition (or offshoring) initially benefit from re-training. These benefits decay over time, however, and annual incomes between trained and non-trained workers converge after 10 years. Hyman (2018) traces this decay back to short-run demanded skills becoming rapidly obsolete. Our results imply that increased human capital through unemployment training is in general less rewarded in Austria.

5.4.2. Job stability

We briefly summarize the impact of automation risk on tenure in the first job after unemployment in this section. The results are summarized in Table 3. As the impact of the RTI on the treatment and exit hazards are very similar as when using post-unemployment wages as additional outcome we do not discuss them here.

Impact of Automation Risk on Job Stability: Workers affected by automation not only have higher re-employment wages but also enjoy better job stability in the new job, as can be seen from Columns (4) and (8) in Table 3. A one standard deviation increase in our RTI decreases the separation probability from the first post-unemployment employer by around 18%, which is also highly significant. For women, our estimates are even more pronounced. A one standard deviation increase in the RTI decreases the separation rate by around 22%. Unlike our results for wages, these effects on job tenure have remained remarkably stable over time.

As for wages, the positive effect on post-unemployment job stability might be driven by firms' selectivity when hiring workers affected by automation risk. If firms find suitable workers with whom to form a productive match the relationship is long lasting.

[35] For example concentrating Office Clerks (ISCO-Code 41), Customer Service Clerks (ISCO-Code 42), Personal and Protective Service Workers (ISCO-Code 51), and Sales Workers (ISCO Code 52) occupations, we find that demand for cognitive skills has increased more than four-fold and demand for social skills more than eight fold in clerical occupations from 2000 to 2014. In comparison, the increase in the demand for cognitive skills in the Personal Service and Sales Workers occupations is only roughly half the size.

Table 4
Effect of automation risk on exit behavior & re-employment wages for different age groups.

	(1) Men	(2)	(3)	(4)	(5) Women	(6)	(7)	(8)
	Older Workers $Age > 41$		Younger Workers $Age \leq 41$		Older Workers $Age > 40$		Younger Workers $Age \leq 40$	
	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}
Panel a: Automation Risk								
γ^{RTI}_{2000}	0.005	0.185***	−0.124***	0.199***	−0.235***	0.098**	−0.100***	0.070*
	(0.055)	(0.046)	(0.041)	(0.037)	(0.051)	(0.044)	(0.039)	(0.036)
γ^{RTI}_{τ}x 10	−0.081***	0.043*	−0.009	0.075***	0.041	0.013	−0.017	0.024
	(0.025)	(0.022)	(0.021)	(0.020)	(0.033)	(0.031)	(0.028)	(0.026)
Panel b: Training								
δ	0.614***	−0.207***	0.585***	−0.196***	0.807***	−0.105***	0.755***	−0.165***
	(0.026)	(0.022)	(0.023)	(0.020)	(0.027)	(0.026)	(0.023)	(0.021)
δ^{RTI}_{2000}	0.015	−0.037	0.058	0.138***	0.067	−0.066**	−0.020	0.036
	(0.045)	(0.048)	(0.036)	(0.037)	(0.050)	(0.047)	(0.038)	(0.038)
δ^{RTI}_{τ}x 10	0.049	0.023	−0.093*	−0.188***	−0.063	0.055	0.032	−0.044
	(0.054)	(0.058)	(0.048)	(0.052)	(0.061)	(0.062)	(0.054)	(0.056)
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobs. Heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blinder & Krueger Offshoring Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time & Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−66,295.81		−57,788.25		−63,353.99		−63,856.50	

This table summarizes the estimation results of RTI on the re-employment hazard θ_{NJ} and wage hazard θ_{ω} using the age sub-sample. The results for Out-of-Labor Force are not reported for brevity. The sample is split by the median age with an age below 41 years (40 years) referring to young men (women) and an age above 41 years (40 years) referring to old men (women). The Young Worker sample comprises 52,232 (men) and 41,704 (women) observations. The Old Worker sample comprises 45,819 (men) and 38,474 (women) observations. All models include linear trends in RTI using the year 2000 as baseline. In addition, individual characteristics, time dummies, occupational dummies defined one a 1-digit level, and the Blinder and Krueger (2013) Measure of Offshoreability are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function. The number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 4. To estimate the effect on the distribution of re-employment wages the top 99th percentile of the wage distribution was censored (Donald et al., 2000). During estimation two mass points in the Old Workers Sample for men and women as well as one mass point in the Young Workers Sample for women converged to a large negative number. They were marked and treated as a constant during further estimation.

Thus, next to increasing wage inequality, increasing job stability is another source of how automation can contribute to increasing inequality in the labor market.

Impact of Training on Job Stability: Panel b in Table 3 summarizes our estimates on the impact of training on post-unemployment job stability. We find small and insignificant effects of provided training on the tenure at the new employer for men. For women, training is increasing the separation probability from the new employer by around 10%, mirroring our results on the impact of training on post-unemployment wages. For both men and women, we do not find any evidence that training effects differ by previous job content.

6. Heterogenous effects

We now turn to the analysis of heterogeneous effects focusing on two potentially important determinants of adjustments to technological progress: education and age. Increasing automation risk might in particular affect older and less educated workers. Older individuals might be more reluctant to adjust to new work requirements than younger ones. This can reduce their job finding probability and increase the likelihood of leaving the labor force. Education may also be an important factor which influences the impact of automation risk on re-employment and wages. New technology can complement higher educated individuals while it might substitute for workers without specialized skills. Given the change in assignment priorities as discussed above, higher-educated workers might also disproportionally benefit from unemployment training.

For brevity, our discussion in this section proceeds only in three steps.[36] First, we discuss the impact of automation risk on the job finding probability. Second, we present the effect of skill enhancement through training on individual exit behavior without explicitly discussing the training assignment mechanisms. Third, we discuss the impact of automation risk on post-unemployment wages. The results are summarized in Table 4 for different age groups and in Table 5 by educational attainment.

[36] As before, all models include out-of-labor force as an additional state as well as the training assignment process.

Table 5
Effect of automation risk on exit behavior & re-employment wages for different education levels.

	(1) Men	(2)	(3)	(4)	(5) Women	(6)	(7)	(8)
	High Education		Low Education		High Education		Low Education	
	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}	Employment hazard θ_{NJ}	Wages θ_{ω}
Panel a: Automation Risk								
γ_{2000}^{RTI}	−0.001	0.073	−0.129***	0.258***	0.042	−0.012	−0.226***	0.071**
	(0.064)	(0.059)	(0.039)	(0.034)	(0.067)	(0.061)	(0.035)	(0.032)
γ_{τ}^{RTI} x 10	−0.015	0.056*	−0.067***	0.052***	0.014	0.040	0.009	−0.016
	(0.033)	(0.033)	(0.018)	(0.016)	(0.034)	(0.033)	(0.025)	(0.025)
Panel b: Training								
δ	0.585***	−0.259***	0.567***	−0.206***	0.693***	−0.154***	0.791***	−0.123***
	(0.037)	(0.033)	(0.019)	(0.017)	(0.037)	(0.036)	(0.019)	(0.018)
δ_{2000}^{RTI}	0.019	0.122*	0.061*	0.065**	−0.002	0.019	0.008	−0.004
	(0.058)	(0.064)	(0.032)	(0.033)	(0.051)	(0.054)	(0.036)	(0.037)
δ_{τ}^{RTI} x 10	−0.005	−0.144*	−0.044	−0.080*	−0.020	0.022	0.012	−0.029
	(0.070)	(0.080)	(0.042)	(0.045)	(0.065)	(0.068)	(0.049)	(0.052)
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unobs. Heterogeneity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blinder & Krueger Offshoring Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time & Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−25,496.70		−98,586.95		−26,292.35		−101,446.18	

This table summarizes the estimation results of RTI on the re-employment hazard θ_{NJ} and wage hazard θ_{ω} using the education sub-sample. The results for Out-of-Labor Force are not reported for brevity. The sample is split by educational attainment with having at least Matura referring to higher education and having at most an apprenticeship referring to lower education. The High Education sample comprises 18,112 (men) and 16,005 (women) observations. The Low Education sample comprises 79,939 (men) and 64,173 (women) observations. All models include linear trends in RTI using the year 2000 as baseline. In addition, individual characteristics, time dummies, occupational dummies defined one a 1-digit level, and the Blinder and Krueger (2013) Measure of Offshoreability are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function. The number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 4. To estimate the effect on the distribution of re-employment wages the top 99th percentile of the wage distribution was censored (Donald et al., 2000) During estimation one mass points in both the High Education Sample and the Low Education Sample for women converged to a large negative number. They were marked and treated as constants during further estimation. Standard errors are reported in parentheses.

6.1. Heterogenous effect of automation risk and exit behavior

Exit Behavior for Different Age Groups: Columns (1) & (3) as well as (5) & (7) in Table 4 summarize the results: We distinguish between older and younger workers, splitting the samples by the median age. The median age is 41 years for males and 40 years for females.

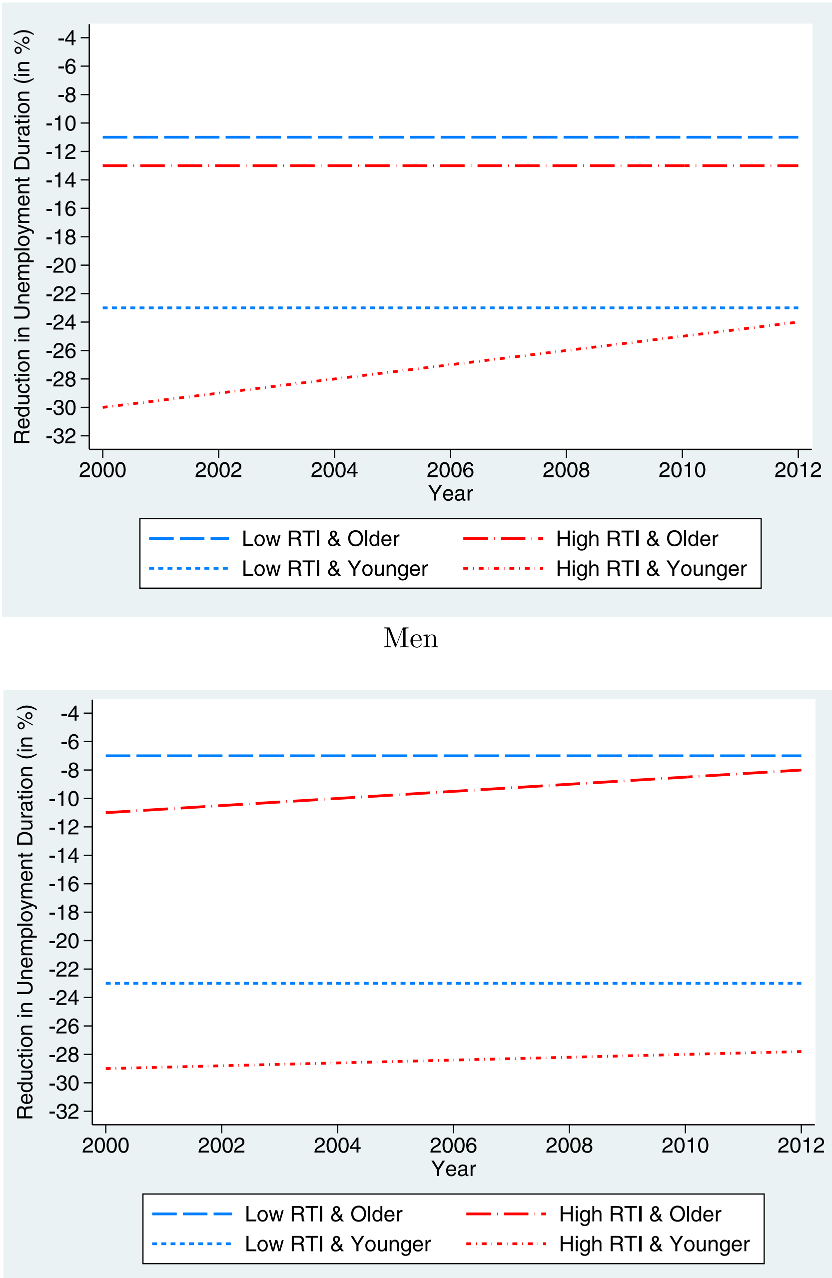
Three interesting features become apparent from our estimation results. First, there has been an increasing intensification of automation risk on the job finding rate for older male workers. While our estimates on the impact of automation risk on the re-employment probability is small and insignificant at the beginning of the sample period, it strongly increases over time. The estimated coefficient of −0.008 is around 60% higher compared to our baseline estimates; see Table 2.

Second, we find a constant impact of automation risk on the job finding probabilities of younger workers with a small sign of intensification over time. While younger workers are more affected by automation risk than older ones in general, our estimates imply a convergence over time. The relative deterioration of job prospects for older workers implies that this age group increasingly has more difficulties to adapt to technological progress.

Third, we find that older women are, in general, much stronger affected by automation risk than older men. As before, we do not find strong evidence for a changing impact of automation risk on the employment probabilities over time, neither for older nor for younger unemployed women. Overall, our results show that automation has the potential to increase inequality among different age groups (e.g. Muro et al., 2019).

Exit Behavior for Different Education Groups: Columns (1) & (3) as well as (5) & (7) in Table 5 summarize the estimation results for two different education groups. We define a worker to have high education if she holds at least a university entrance exam (Matura)

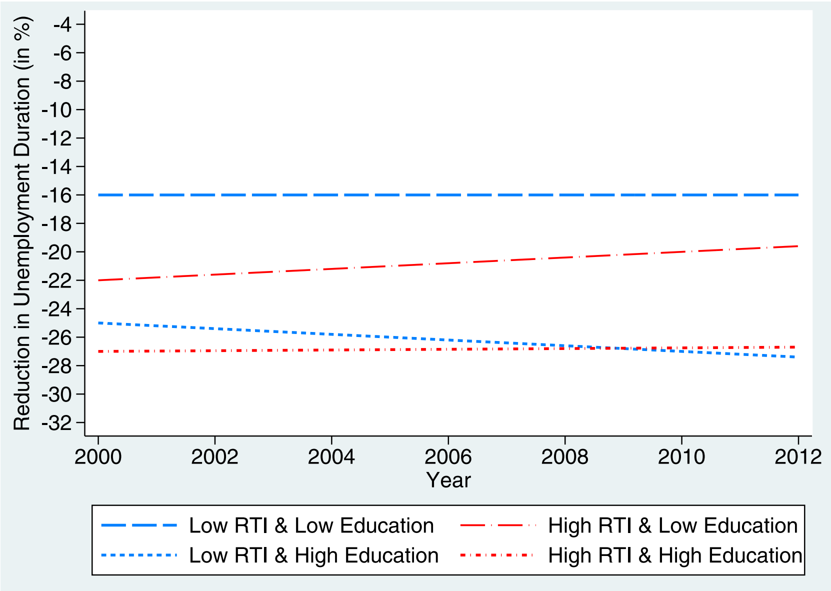
There is a very strong gradient by education. The labor market outcomes of lower educated men and women are more affected by automation risk. In contrast, automation risk does not influence the job finding probability for highly-educated individuals.



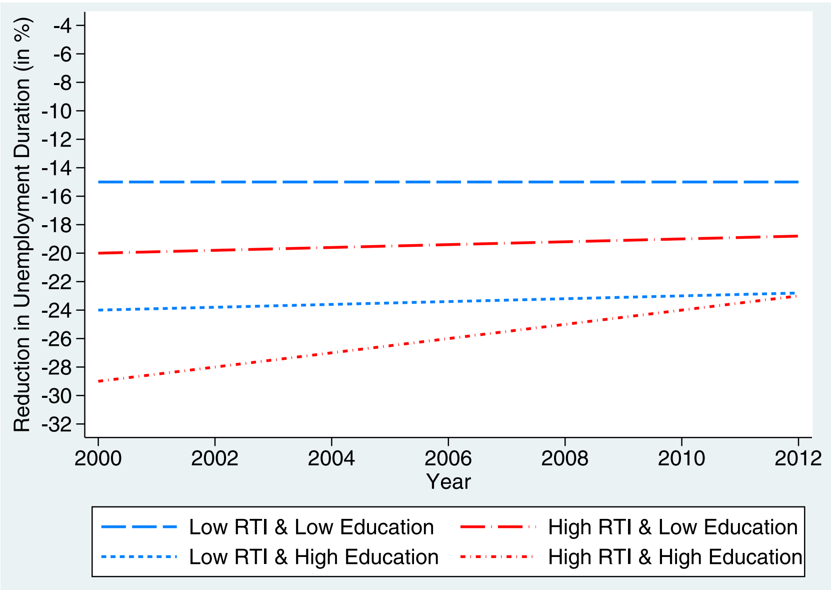
Men

Women

Fig. 4. Relative benefits of provided unemployment training over time by different age groups.
The plots show the relative benefits of providing unemployment training when increasing RTI by one standard deviation. The sample is split by the median age with an age below 41 years (40 years) referring to young men (women) and an age above 41 years (40 years) referring to old men (women). The Young Worker sample comprises 52,232 (men) and 41,704 (women) observations. The Old Worker sample comprises 45,819 (men) and 38,474 (women) observations. The simulation takes into account that high and low RTI workers have different baseline unemployment durations and different assignment probabilities. The relative benefits of provided training are calculated using Eq. (9) and the expected durations are calculated using the estimates from Table 4 setting all other covariates to their average in 2000. The dashed and long dashed–dotted lines represents the relative benefits of training setting RTI to 0 (low) for older and younger workers respectively. The short dashed and dotted lines represents the relative benefits of training setting RTI to 1 (high) for older and younger workers respectively.



Men



Women

Fig. 5. Relative benefits of provided unemployment training over time by different education groups.
The plots show the relative benefits of providing unemployment training when increasing RTI by one standard deviation. The sample is split by educational attainment with having at least Matura referring to higher education and having at most apprenticeship referring to lower education. The High Education sample comprises $18,112$ (men) and $16,005$ (women) observations. The Low Education sample comprises $79,939$ (men) and $64,173$ (women) observations. The simulation takes into account that high and low RTI workers have different baseline unemployment durations and different assignment probabilities. The relative benefits of provided training are calculated using Eq. (9) and the expected durations are calculated using the estimates from Table 5 setting all other covariates to their average in 2000. The dashed and long dashed–dotted lines represents the relative benefits of training setting RTI to 0 (low) for lower and higher education respectively. The short dashed and dotted lines represents the relative benefits of training setting RTI to 1 (high) for lower and higher education respectively.

6.2. Heterogenous effects of labor market training on exit behavior

Impact of Training for Different Age Groups: As before, we present the impact of training graphically in Fig. 4. The upper graph shows the results for men and the lower graph for women. In each graph, we distinguish between high and low RTI, where the difference corresponds to an increase of one standard deviation in the index.

Looking at the graphs, one major result emerges: Training is more effective for younger workers than older ones, regardless of the automation risk. The difference is quite substantial and amounts to up to 10 pp for men. While automation has a larger impact on the job finding rates of younger workers, public policies can help to soften its impact. In all four cases in the graph, training is more beneficial in high RTI cases as compared to low RTI cases. While beneficial, the effectiveness of training has decreased over time for younger men.

Impact of Training for Different Education Groups: Fig. 5, which follows the same structure as Fig. 4, presents the effect of training on the unemployment duration by educational groups.

With regard to automation risk, individuals with lower educational attainment profit the most from training. The increase is between 4 to 6 pp for men with a high RTI compared to men with low RTI. The effect for women is very similar (4–5 pp). In contrast, we do not find that training has a differential impact by automation risk for high-educated men. There is a small advantage for high-educated women, however. At the beginning of the period, those in high RTI jobs fare somewhat better after training than those with low RTI jobs.

6.2.1. *Heterogenous effect of automation risk on re-employment wages*

Re-Employment Wages for Different Age Groups: Columns (2) & (4) as well as (6) & (8) in Table 4 summarize the results for re-employment wages for our two age groups. For both young and old male workers, we find a similar trade-off as before. On the one side, there are decreasing re-employment probabilities associated with increasing automation risk. On the other side, higher automation risk is also related to higher re-employment wages. Young men are more affected by this trade-off, with a strong intensification over time.

We also find that training negatively impacts re-employment wages regardless of age. Only for young and high RTI training is able to compensate the negative impact, but this effect fades over time.

Re-Employment Wages for Different Education Groups: Only low-educated workers experience a significant employment-wage trade-off (see Table 5), which is particularly strong for men.

Men at high risk of automation (both with high or low education) profit from training — in particular at the beginning of the observations period. We do not observe the same development for women.

7. Conclusion

Changes in the labor market due to automation and digitalization are among the most-discussed policy issues. While there is a large amount of studies on the aggregate impact of automation or robots on the number of jobs, evidence on individual-level consequences – and on policy options – is still scant. In this work, we use almost two decades of administrative data for Austria and look at the consequences of automation risk on the job finding probability and future labor market career of unemployed workers. This is also the first paper to study systematically the effectiveness of skill enhancement through provided labor market training in this setting.

For both men and women, a higher risk of automation reduces the job finding rates of unemployed workers significantly. For men, this effect has strongly intensified over time. We find a trade-off between quantity and quality of employment: workers who find a new job tend to have higher re-employment wages and more stable jobs. We show that these effects have intensified over the past years and that, workers with lower educational attainment and lower ability to cope with technological change are particularly affected.

Provided unemployment training can be effective in counteracting the negative employment effects of automation risk. In particular, younger workers and those with higher levels of education profit most from these measures. Older workers and those with lower educational attainment do less so. Interestingly, we also find that training reduces re-employment wages implying that these programs are more effective in bringing workers faster back to work than improving job quality. Overall, refining training and adopting programs to recent technological progress could lead to larger benefits for affected workers.

While we show that active labor market policies can be one successful strategy to overcome the challenges imposed by automation and digitalization, our results also highlight the danger of increasing inequality. Unemployed workers who have the skills to adopt to new situations face better labor market outcomes with higher wages and job stability. Those workers who lack the ability to cope with technological change have prolonged unemployment duration and end up in worse matches.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2021.103808.

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