Automation, Offshoring, and the Role of Public Policies *

BERNHARD SCHMIDPETER[a] AND RUDOLF WINTER-EBMER[b,c,d,e,f]

[a]Institute for Social and Economic Research, University of Essex
[b]Christian Doppler Laboratory Aging, Health and the Labor Market, JKU Linz
[c]IZA, Institute for the Study of Labor, Bonn
[d]IHS, Institut for Advanced Studies, Vienna
[e]CEPR, Centre for Economic Policy Research, London
[f]CReAM, Centre for Research and Analysis of Migration, London

June 24, 2019

Abstract

We provide comprehensive evidence on the consequences of automation and offshoreability on the labor market career of unemployed workers. Using almost two decades of administrative data for Austria, we find that risk of automation is reducing the job finding probability; a problem which has increased over the past years. We show that this development is associated with increasing re-employment wages and job stability. For workers in occupations at risk of being offshored we find the opposite effect. Our results imply a trade-off between quantity and quality in these jobs. Provided training is in general beneficial for workers in automation-related jobs.

* *Corresponding author*: Rudolf Winter-Ebmer, Johannes Kepler University of Linz, Department of Economics; email: rudolf.winterebmer@jku.at. A previous version was circulated under the title *How do Automation and Offshorability Influence Unemployment Duration and Subsequent Job Quality?*. We would like to thank Matias Cortes, Jeff Smith, seminar participants at IfW Kiel, the Occupations, Skills, and the Labour Market Conference in Mannheim, the ECB Frankfurt, the Meeting of the EALE Ghent, the ESPE in Berlin, and the RES 2018 in Brighton. This research was funded by the Austrian Christian-Doppler Society, the Oesterreichische Nationalbank (Anniversary Fund, project number: 17391), the Linz Institute of Technology (LIT) and the ESRC Centre on Micro-Social Change at ISER (grant RES-518-28-001) .

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. Firms have increasingly used the possibility to shift certain parts of their operations to other firms or abroad in order to save costs and a large share intend to continue doing so in the future (Deloitte, 2016). There is evidence that these developments have 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] In particular, workers with less specialized skills and abilities are predicted a bleak future (Brynjolfsson and McAfee, 2014). As direct consequences of these occupational changes, a vast majority of individuals are worried about the future of work and expect diminishing employment prospects and increasing inequality (Pew Research Center, 2017). Despite the high relevance for decision makers and worries from the population, there is little evidence on how automation and offshoreability affect individual workers and whether public policy can help.

In this paper, we estimate the impact of automation and offshoring on the search behavior and post-unemployment career of unemployed workers using administrative data for Austria. Unemployed individuals are in particular vulnerable to occupational change and an interesting group to study for several reasons:

First, the risks of automation and offshoring are likely to affect both the search behavior of unemployed individuals and their ability to find stable post-unemployment matches. Unemployed individuals who have been negatively affected by such occupational change might have prolonged unemployment spells or choose to leave the labor force all together. Those individuals who find re-employment might end up in worse matches and less stable employment. It is also possible that occupational change benefits only some types of workers while negatively affecting those without special skills; see, for example, the different scenarios considered in Caselli and Manning (2017). Such an outcome would increase inequality in the labor market even further.

Second, if job task content is affecting employment opportunities, what role can public policy play to mitigate these effects? Training and re-training programs to enhance skills of job seekers can potentially be vital policy tools in counteracting the consequences of occupational change. In most European countries, they form an integral part of active labor market policies.[2] It is therefore important to know if and how these programs work. This is the first paper, explicitly investigating the effectiveness of such policies related to automation and offshoreability.

We use almost two decades of high-quality administrative data for Austria covering the whole

[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 this work.

[2] According to the OECD, training constitutes the second larges labor market program after out-of-work income and maintenance support in terms of expenditure. For example, in 2016 around 0.52% of GDP were spent on training in Denmark, 0.44% in Austria, 0.30% in France, and 0.19% in Germany. In comparison, only 0.03% of GDP are allocated to training in the US. (OECD, 2019)

universe of private sector employees. This data allows us to obtain precise information about the labor market career of workers. We measure the automation potential of an occupation using the Routine Task Index (RTI) of Autor and Dorn (2013) (see also Autor et al., 1998) and the risk that a certain occupation will be offshored using the Offshoring Index (OFF) of Blinder and Krueger (2013). These 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. (2018).

To identify the impact of provided unemployment training on the exit behavior and future labor market career of workers we use the *Timing-of-Events (ToE)* approach of Abbring and van den Berg (2003*b*). This allows us to identify training effects under the assumption that workers cannot predict the *exact* start date of the training. We include a rich set of individual variables as well as occupational and time fixed effects to control for occupation-specific search problems. Moreover, we exploit the multiple-spell structure of our data which allows us to account for unobservable ability of workers, similar as in linear-panel data models. Thus, we can allow for quite general selectivity into occupations and employment opportunities.

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 of our Routine Task Index, which is roughly equivalent to the change in the routine job content between a construction worker and a customer service 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 at the end of our observation period, this effect almost doubles to 16% while the impact on women remains constant.

Our results for post-unemployment outcomes point toward a polarization: Those workers in automation-related jobs who do find new employment, have higher wages and to a lesser extent more job stability. For men, this earnings advantage is increasing over time. Taken together, our findings point toward a quality-quantity trade-off where the number of jobs in certain occupations has declined but the remaining ones have become more productive. We provide evidence that this is driven by changes over time benefiting workers with more specialized skills, in line with the findings in Hershbein and Kahn (2018). If the current trends continue, automation has the potential to increase inequality between more and less skilled workers even further in the future.

Labor market training can correct the negative impact of occupational requirements on the job finding rate to a large extent. While training is beneficial to all workers, we find even larger reductions of the unemployment duration due to training for workers in jobs susceptible to automation. These effects are mostly driven by preferential assignment mechanisms of case workers with shorter waiting times between inflow and the start date of the training. Re-employment wages are in general negatively affected by provided training, but to a lesser extend for male workers affected by automation. Our results imply that case workers are more concerned with faster re-employment rather than job quality.

Our results reveal interesting patterns of heterogeneity. In particular, younger workers as well as highly-qualified men affected by occupational change profit the most from unemployment training. Workers with lower levels of education profit the least. These results strengthen our claim of an increasing polarization in the labor market.

Our work primarily contributes to the literature on the individual level impact of occupational change. This literature has mostly focused on the impact of these changes on labor market outcomes without explicitly taking into account public policies (Cortes, 2016; Schmillen, 2018; Hummels et al., 2018; Edin et al., 2018).[3] While exisitng studies are interesting and important, they are silent about the potential benefits of training and re-training programs. In our work, we investigate the impact of automation and offshoreability on search behavior and labor market career of unemployed workers with a strong focus on the possible mitigating role of publicly provided training. Our empirical strategy allows for selectivity into occupations, training, and the chosen exit state which delivers arguably causal estimates. Given that some studies forecast the range of job displacements due to digitalisation 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 and offshoring affect unemployed individuals and if current policies work.

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, 2016), 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 technological change as well as the increasing possibility of offshoring as an additional and important driver of unemployment duration and post-unemployment job quality. We show that in particular technological progress related to automation lowers significantly the job finding probability and affects re-employment outcome, with a strong intensification over time. Thus, it has the potential of increasing inequality even further in the future and to contribute to the persistence in the high share of long-term unemployed (Krueger et al., 2014; Jaimovich and Siu, 2018). This development should be given considerable care when designing public policy and social benefit systems.

Our work 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). Compared to existing studies, we look at the effectiveness of provided unemployment training in counteracting occupational change. We also investigate the (heterogenous) training effect on post-unemployment outcomes which allows us to see how these programs are doing in terms of promoting job quality. Given the high costs of these training programs and a large support for government 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 our data and measures of occupational change as well as some descriptive results. Section 3 discusses our empirical approach. We discuss our results on exit behavior and post-unemployment outcomes in Section 4 while Section 5 explores heterogeneous effects in age and education. Section 6 concludes.

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

2 Data and Measures of Task Requirements

2.1 Data

Our analysis is based on the Austrian Social Security Data (ASSD) and data from the Austrian public labor market administration (AMS). The ASSD is a high-quality administrative data set which comprises the whole universe of Austrian workers employed in the private sector. It contains information until the end of 2016 about daily labor market spells, demographic characteristics, as well as yearly income. A unique person identifier allows us to link individuals to firms. We will use information from the ASSD to obtain the labor market career and individual background of individuals (Zweimüller et al., 2009).

The AMS data contains information about if and when a worker received any training courses during her unemployment spell.[4] In addition, the AMS has recorded the occupation of the last job held by the unemployed worker using the AMS classification system from 2000 onwards. Unfortunately, the AMS does not follow up on the occupation in the new job. Thus, we cannot evaluate the costs or benefits of occupational switching for unemployed individuals in our analysis.[5] To derive the corresponding ISCO-88 codes, we use the cross-walk file provided by the AMS. The unique person identifier allows us to link workers from the AMS file to the ASSD.

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 around one million individuals and more than three million spells. As our estimation procedure, which we will describe in detail in Section 3, is very time consuming, we randomly draw 30,000 males and females respectively from this sample. For each individual-spell combination we obtain pre-unemployment background characteristics such as age, wage earned in last job, tenure in last job as well as the length of the unemployment spell, the post-unemployment destination, and if the individual received training during the current spell.

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

[4] In our data, we observe if the applied labor market policy is categorized as training and schooling but we do not observe the exact course content of the training.

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

likely to stop actively looking for new work during the training activity.[6] We provide summary statistics of our sample in Table 1.

[Table 1]

On average, male individuals are observed around six times and females individuals five times in our data. We observe for almost all individuals in our sample an outflow from unemployment, but there are substantial gender differences in the 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.

2.2 Measuring Changes in Occupational Task Requirements

Austria has seen similar changes in the job structure and occupational task requirements 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 search behavior 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 measure the impact of automation using the Routine Task Intensity Index (RTI) of Autor and Dorn (2013) and mapped to European occupational classification by Goos et al. (2014).[7] The RTI gives an indication, how susceptible certain tasks in a given occupation are to replacement by technology, in particular computers (see also Autor et al., 1998). The index is calculated as follows :

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

where T_o^R, T_o^M, and T_o^A are the routine, manual, and abstract task inputs in an occupation o.[8] The RTI measure is increasing in the importance of routine tasks within an occupation. Routine tasks follow in general prescribed rules which can be easily automated. A higher value of the RTI implies therefore a higher risk that required tasks can be replaced by computer technology.

Solely concentrating on the effect of routine tasks on unemployment duration might miss important points in determining the effects of a changing occupational structure on unemploy-

[6] 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.

[7] 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.

[8] The RTI is based on three task aggregates found in the Dictionary-of-Occupational Title (DOT): 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".

ment duration. While high routine workers are at a higher risk of being replaced by computers, individuals working in occupations which do not need personal interaction or physical presence might also have lower career prospects. These jobs are not bound by any geographic location and can easily be moved to another country (offshored).

To quantify this effect, we will make use of the offshoring measure suggested by Blinder and Krueger (2013). They use the Princeton Data Improvement Initiative to derive three measures that certain tasks can be performed abroad (offshoreability) which are self-reported by households, inferred from household responses, and based on professional coders. The last measure is preferred by Blinder and Krueger (2013) and we use it in our analysis calling it Offshorability Index (OFF) hereafter. The OFF determines the risk that tasks required by an occupation, and therefore employment, might be "offshored" to a different country.[9] Jobs at lower risk of being offshored require in general more face-to-face interaction and physical presence. Thus, it is likely that OFF does not only measure offshoreability but also the impact of location-flexible working arrangements in our analysis.

Notice that OFF measures a different dimension of changing task requirements compared to the RTI. OFF captures the risk for tasks or jobs to be replaced where the geographic location does not matter for fulfilling the job requirements. Thus, a low OFF does not necessarily imply a low RTI. For example, occupations with rather low routine task content are call-center agent and taxi driver. Conducting the tasks required to work in the first occupation are not restricted to certain geographic areas and therefore they can be easily offshored, unlike a taxi driver who is bound to a specific location. The correlation of both indices in our sample is with 0.46 indeed quite low. Both indices are time invariant, so that we have a consistent definition of automation and offshoring over time.

In order to facilitate the interpretation of the results and to be able to compare both measures, we standardize the indices to have a mean of zero and a standard deviation of one in our samples. In Appendix A, we provide further details on the occupations used in our analysis and the relation between RTI and OFF within occupations.

2.3 Descriptive Information

In this section, we present some descriptive results. The goal is to show the relationship between our measures of occupational change 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 both the RTI and OFF. 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 distributions.

Occupations which can be found at the lower part of the RTI distribution include, for example, Science Professionals and Corporate Managers. Occupations which fall in the lower part of the OFF distribution include Personal and Protective Service Workers and Drivers. Examples of occupations which can be found at the upper part are Office and Service Clerks

[9] While the measure of Blinder and Krueger (2013) depends on a survey conducted in the US, Goos et al. (2014) show that it is actually highly correlated to offshoring decisions of companies in Europe. As it is the case with the RTI, we make use of the mapped index provided by Goos et al. (2014)

in the case of the RTI, and Science Professionals and Machine Operators in the case of the OFF. The example of Science Professionals, who can be found at both the bottom and the top of our two measures, highlights the importance of concentrating on more than one measure of a changing work environment. This is also mentioned by Cortes et al. (2017) who show that within a neoclassical model advances in automation technology on its own is not able to generate the changes in occupational shares and employment propensities observed in the data.

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

[Figure 1]

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 for both our RTI and OFF during the first six months of the unemployment spell. This finding provides evidence that our measures of occupational change do indeed affect the probability of finding a new job, especially in the short run. With ongoing duration of the unemployment spell, skill requirements in the previous job seem to matter less and it is more likely that stigma effects play a dominant role (e.g. Kroft et al., 2013; Eriksson and Rooth, 2014).

Second, one can see pronounced gender differences in the importance of occupational requirements. Men formerly employed in occupations with lower OFF index have a slightly higher transition rate into employment than men who worked in low routine jobs. For women, we observe that both categories of our RTI are associated with a higher re-employment hazard compared to a lower OFF index. One likely reason for these observed differences is gender-specific sorting into occupations (e.g. Black and Spitz-Oener, 2010).

The pattern documented in Figure 1 might be the direct consequence of fewer employment possibilities caused by occupational change. To investigate this further, we also look at vacancy postings and calculate the average growth of the share of vacancies between 2011 and 2014. Unfortunately, the available information is provided at the 1-digit level so that only a rough comparison to our indices is possible.[10] Table 2 contains the yearly share of vacancies posted and the average annual growth rate.

[Table 2]

Groups associated with both a high RTI and OFF index, such as office clerks, have expe-

[10]The data was obtained from Statistik Austria which provide only average yearly figures of vacancy postings and only at a 1-digit level. Statistics for open vacancies can be found here http://www.statistik.at/web_de/statistiken/menschen_und_gesellschaft/arbeitsmarkt/offene_stellen/index.html where we used the document "Offene Stellen lt. Offene-Stellen-Erhebung nach ausgewählten Merkmalen, Jahresdurchschnitt 2011 bis 2016".

rienced a lower growth in the share of open positions over time. In contrast, management or professional occupations have seen a rise in the relative share of vacancies posted. The vacancy postings provide suggestive evidence that our measures are related to job opportunities. They also show that, despite the well documented fall in the employment share in certain occupations, there is no evidence that these types of jobs disappear completely.[11]

A possible implication of this finding is that, although employment possibilities decrease, workers who are able to re-enter employment might have better post-unemployment labor market outcomes. For example, it is possible that these occupations have experienced considerable within-occupational changes in task requirements and demand now fewer but highly skilled and more productive workers (Hershbein and Kahn, 2018). We will shed more light on this in our empirical analysis.

We find less clear evidence that our measures are related to training assignment. The results are shown at the lower panel in Figure 1. Men formerly employed in high RTI occupations tend to have a slightly higher probability of receiving training than those who worked in high OFF occupations at the beginning of the unemployment spell, but case workers seem to be in general more concerned with the threat of automation than offshorability. For women, we observe the opposite. Those who were employed in occupations with higher-risk of being outsourced or offshored are, in general, more likely to receive training than other workers.

The results from our preliminary analysis show that occupational task requirements seem to be important in determining the transition from unemployment to employment but there is less clear evidence whether decision makers are aware of the consequences. The simple analysis presented here has, however, obvious shortcomings. 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.

3 Econometric Framework

3.1 Modeling Treatment Assignment and Exit Behavior

Obtaining causal estimates of occupational change and unemployment training on workers' exit behavior is a difficult task. Assignment to training during the unemployment spell is related to numerous factors and it certainly is related to the previous job content. The job search behavior of an individual is likely to be affected by the expected career prospects, in turn influenced by unobserved ability, occupational change, and received training. In general, one can expect the training assignment probability and the likelihood of leaving unemployment to be correlated.

In our work, we make use of the *Timing of Events* approach proposed by Abbring and van den Berg (2003*b*) and jointly estimate the duration until exit and the duration until the first training spell by means of a continuous-time multivariate duration model. Our method exploits the access to multiple-spell data which facilitates identification and allows for quite general forms of selectivity. Abbring and van den Berg (2003*b*) show that the effect of unemployment

[11] Autor (2015) points out that medium-skilled jobs require nowadays a mixture of tasks. For example, the task requirements for a modern office clerk comprises of doing the paper work but also organizing and planning. Hence, it is unlikely that these occupations completely "die out".

training can be identified without any parametric assumption or exclusion restriction.[12] The approach has been widely used in the program and training evaluation literature for different countries, see, for example, van den Berg et al. (2004), Lalive et al. (2005), and Osikominu (2013). An additional advantage of the method is the possibility to model the training effect in a flexible way (see also Richardson and van den Berg, 2013).

Given the recent discussion in the literature on the impact of occupations and changing task requirements on workers (e.g. Cortes et al., 2017), 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 investigate in detail how our RTI and OFF can affect the selective career decisions of unemployed workers.

In our empirical specification, we allow the impact of RTI and OFF 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 and OFF_τ. While we could model the temporal impact of RTI and OFF on our hazards in more general ways, the computation of more flexible models is very time intensive. For example, allowing the effects of our indices to change flexible by year would introduce additional 70 parameters in our simple model containing already 138 parameters. We show in Appendix B that our linear time trend model captures changes in the impact of RTI and OFF over time pretty well. The results from this analysis will help us to understand how occupational changes have intensified over the past years.

We assume that the exit and treatment transition rates have a mixed proportional hazard specification. For a realized spell with duration T until exit and duration D until the first labor market policy, the exit rate for $e \in \{NJ, OLF\}$ is defined as

$$\begin{aligned}\theta_e(T|RTI, OFF, x, \nu_e, D) = \lambda_e(T) exp\,(x'\beta_E + \gamma^{RTI}_{2000,e} RTI_{2000} + \gamma^{RTI}_{\tau,e} RTI_\tau + \\ \gamma^{OFF}_{2000,e} OFF_{2000} + \gamma^{OFF}_{\tau,e} OFF_\tau + \\ \delta_e(RTI, OFF)\mathbb{1}(T > D) + \nu_e)\end{aligned} \tag{1}$$

In our exit hazard, $\lambda_e(T)$ represents a fully flexible baseline hazard, displaying individual duration dependence. ν_e captures the unobserved heterogeneity on the exit rate and the vector x includes observable individual characteristics. Importantly, we also include occupational dummies defined on a 1-digit level here which capture any occupational specific effects possibly correlated with RTI and OFF.

In Equation (1), we are particularly interested in the coefficients γ^{RTI}_{2000} and γ^{BK}_{2000} which give the effect of our Routine and Offshoreability Index on the hazards in the base year 2000, and γ^{RTI}_{τ} and γ^{BK}_{τ} which give estimates of how occupational change affects the exit hazards over time. Notice that 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 $\delta(RTI, OFF)$ captures the shift in the exit hazard due to provided training. We allow $\delta(RTI, OFF)$ to depend on our measures of occupational change. More precisely, in

[12] We do not discuss the technical requirements here and refer to Abbring and van den Berg (2003*b*) for a detailed discussion.

our analysis we model $\delta(RTI, OFF)$ as[13]

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

This allows us to evaluate whether workers at the risk of automation and offshoring receive more effective unemployment training and whether/how this has changed over time.

Key to the identification of $\delta(RTI, OFF)$ in Equation (1) is the so-called no-anticipation assumption. This assumption requires that future program participants do not foresee the exact assigned start date of the course. Therefore, unemployment training is only allowed to have an effect on the exit hazard from the actual participation date onward. The no-anticipation assumption does not imply that training has to be assigned completely at random. Participants can hold believes about the probability of getting a training course and might know when they are at a high risk, as long as they do not act on their believes.

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, training assignment is usually managed by the case worker and there is no right of participation.

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, training would be comprised of an actual effect of training and a notification effect (Crépon et al., 2018). Given the short-term organization of Austrian training courses, this seems unlikely in our case.

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

$$\begin{aligned}\theta_P(D|RTI, OFF, x, \nu_P) = \lambda_P(D) exp \big(x'\beta_P + \gamma^{RTI}_{2000,P} RTI_{2000} + \gamma^{RTI}_{\tau,P} RTI_\tau + \\ \gamma^{OFF}_{2000,P} OFF_{2000} + \gamma^{OFF}_{\tau,P} OFF_\tau + \nu_P\big)\end{aligned} \tag{3}$$

Here ν_P captures unobserved heterogeneity on the treatment hazard and the vector x includes observable individual characteristics as well as time and occupation dummies. In particular, the assignment decision of the case worker may depend on both RTI and OFF as well as on our linear time trends. The estimated parameters give us an indication how aware case workers are of the impact of automation and offshoreability on workers' labor market careers and whether the 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 ν_e and ν_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

[13] See also the discussion in Abbring and van den Berg (2003*b*) and Richardson and van den Berg (2013).

the following way

$$p_m = P(\nu_{NJ} = \nu_{NJ}^m, \nu_{OLF} = \nu_{OLF}^m, \nu_P = \nu_P^m) = \frac{exp(\alpha_m)}{\sum_{m=1}^{M} exp(\alpha_m)} \tag{4}$$

Parameterizing the probabilities in this way avoids constrained maximization. In practice, we set the maximum numbers of estimated mass points M to five in order to save on computational time, but our results are not sensitive to the exact number of mass points chosen.[14]

We model individual duration dependence in a flexible way via a piecewise constant function $\lambda_j(T) = \exp(\sum_{k=1}^{10} \lambda_{j,k} \mathbb{1}_k(T))$ 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 purpose 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

$$\begin{aligned}\mathscr{L} = \sum_{i=1}^{N} \log \Bigg\{ \sum_{m=1}^{M} p_m \prod_{j=1}^{J_i} \prod_{e=1}^{E} \theta_e(T_{ije}|x_{ije}, \nu_e^m, D_{ij})^{\Delta_{ij,e}} \exp\left(- \int_0^{T_{ije}} \theta_e(T_{ije}|x_i, \nu_e^m, D_{ij}) \right) \\ \theta_P(D_{ij}|x_{ij}, \nu_P^m)^{\Delta_{ij,P}} \exp\left(- \int_0^{D_{ij}} \theta_P(D_{ij}|x_{ij}, \nu_P^m) \right) \Bigg\}\end{aligned} \tag{5}$$

where E is the total number of exit states considered and $\Delta_{i,e}$ and $\Delta_{i,P}$ are censoring dummies.

Notice that our log-likelihood function imposes that an individual has the same heterogeneity term across unemployment spells (see also van der Klaauw and van Ours, 2013). This allows us to exploit the panel structure of the data, similar as in linear panel data models. Applying this restriction has the advantage that the chosen exit state as well as our measures RTI and OFF (and all other control variables) are allowed to be correlated with the unobserved heterogeneity of workers in a very general way (Abbring and Van den Berg, 2003*a*; Abbring and van den Berg, 2003*b*). We can therefore allow for situations where workers with different (but constant) unobserved abilities sort themselves into different occupations. Likewise, we can also allow for situations where unobserved ability influences the chosen exit destination.

Our approach rules out unobserved dynamic effects, such as learning about one's own abilities over time when choosing an occupation. Previous research has shown, however, that learning does not seem to play an important role when considering occupation wage premia once comparative advantage is taken into account (Gibbons et al., 2005). Our model also rules out situations where individual outcomes or treatment assignments between spells are related

[14] In certain circumstances it might be possible that an estimated heterogeneity parameter takes a large negative value which makes it impossible to invert the Hessian matrix and obtain standard errors. In such a case, we fix the heterogeneity parameter and leave it as a constant in the estimation. 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. (2007*a*) and Gaure et al. (2007*b*) for more details on the optimization approach.

through factors other than our covariates and unobserved heterogeneity. For example, we cannot allow for situations where individuals are less likely assigned to training in the future if they received any training during previous unemployment spells *regardless* of their ability or personal characteristics. This situation is very unlikely as case workers decide training assignments depending on personal circumstances and ability of a worker rather than on their (unconditional) assignment history. Notice that our model does not rule out situations where future assignment decisions of case workers are related to the motivation of workers, as this will be captured by our unobserved heterogeneity.

3.2 Modeling Post-Unemployment Outcomes

We are also interested in how our measures of occupational change and training affects re-employment job-quality, such as wages and job stability.[15] Considering post-unemployment outcomes introduces additional problems into our analysis. Taking up new employment or not is endogenous and we need to account for this additional type of selectivity. For example, the job finding probability of a worker may be correlated with her re-employment wages. We take this into account in our analysis by estimating post-unemployment outcomes simultaneously with training assignment and search behavior, and allow for correlation among unobservables across different states.

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.[16] We model the wage hazard *after* exiting the unemployment spell θ_ω similar as in Equation (1):

$$\begin{aligned}\theta_\omega(W|RTI, OFF, x, \nu_\omega, D, T_{NJ}) = \lambda_\omega(W) exp\big(x'\beta_\omega + \gamma^{RTI}_{2000,\omega} RTI + \gamma^{RTI}_{\tau,\omega} RTI_\tau + \\ \gamma^{OFF}_{2000,\omega} OFF + \gamma^{OFF}_{\tau,\omega} OFF_\tau + \\ \delta_\omega(RTI, OFF)\mathbb{1}(T_{NJ} > D) + \nu_\omega\big)\end{aligned} \tag{6}$$

where $\delta_\omega(RTI, OFF)$ and $\lambda_\omega(W)$ are similarly defined as before. We choose the interval points in the baseline hazard $\lambda_\omega(W)$ to occur at every 10th percentile of the observed wage distribution.

As we observe an individual's re-employment wage only if she found new employment, we face a double censoring problem. Denote by $\Delta_{ij,\omega}$ the censoring indicator which takes a value of one if the re-employment wage lies below the 99th percentile and by $S_\omega(W|x, \nu_\omega, D, T_{NJ})$ 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. Then, the contribution of adding re-employment wages as additional state to an individual's likelihood is

$$\mathscr{L}^{\omega}_{ij} = \Big[\theta_\omega\left(W|x, \nu_\omega, D, T_{NJ}\right)^{\Delta_{ij,\omega}} S_\omega\left(W|x, \nu_\omega, D, T_{NJ}\right)\Big]^{\Delta_{ij,NJ}} \tag{7}$$

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

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

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

$$\mathscr{L}_{ij}^{PE} = \Big[\theta_{PE}\left(T_{PE}|x, \nu_{PE}, D, T_{NJ}\right)^{\Delta_{ij,PE}} S_{PE}\left(T_{PE}|x, \nu_{PE}, D, T_{NJ}\right)\Big]^{\Delta_{ij,NJ}} \tag{8}$$

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' 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 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 in this case, we will change the sign when reporting our estimates on the wage hazard. Thus, in our case a reported positive coefficient when considering this outcome can still be interpreted as having a positive effect on workers' post-unemployment wages.

4 Main Estimation Results

Table 3 presents the estimation results from our flexible model allowing for heterogenous training effects and linear trends when including post-unemployment wages as additional outcome. Table 4 contains a similar set of estimates but considering job stability as an additional outcome. The left part of the table presents our results for men and the right part for women. For brevity, we only show the coefficients on our variables of interest but all estimates contain individual level control variables as well as year and occupational dummies. In each Table, Panel a shows the results for our measures of occupational requirements and Panel b the estimated training effects on the log-hazard rates.

As one can see from the results presented in the Tables, the estimates on the training and exit hazards are virtual identical regardless of considering wages or job stability as post-unemployment outcome. This gives us confidence in our identification strategy. Given this similarity, we discuss the training assignment and exit process only for our model with post-unemployment wages as additional outcome.

[Tables 3 & 4]

4.1 Automation, Offshoring and Exit Behavior

Our estimates for the impact of automation and offshoring on the duration until re-employment are given in Columns (1) and (5) of Table 3 for men and women respectively. To facilitate interpretation of our time trends, we plot the impact of a one standard deviation increase of RTI and OFF on the job finding hazard over time together with a 95% confidence intervals in Figure 2.

Our results show that for men, the risk of automation significantly lowers the job finding probability in all time periods. A one standard deviation increase in our RTI index decreases the re-employment probability by 8% in 2000 and by 16% in 2014, implying a considerable drop in the job finding rate over time.[17] This conclusion is also supported by a more flexible model with time dummies presented in Appendix B.

To give a more specific example, consider an unemployed cashier and an unemployed welder. The difference in the RTI between those two occupations is around one standard deviation. Our estimates imply that the job finding probability of an unemployed cashier is 9 percentage points (pp) lower in the year 2000 compared to the welder. Within 10 years, this difference has substantially increased to 12 pp.[18]

The impact of automation on female workers is slightly stronger at the beginning of our sample period, but it remains virtually constant thereafter. A one standard deviation increase in our RTI index decreases the re-employment probability by 15% in 2000 and by 14% in 2014.

In contrast to our findings for the risk of automation, we find a positive impact of offshoreability on re-employment for men over time. An increase of OFF by one standard deviation had virtually no impact on the job finding probability in 2000 for men, but has increased it significantly to around 7% by the end of our sample period. A similar increase in OFF reduced the re-employment likelihood for women by around 10% in 2000, but only by 4% in 2014. In line with the findings of Goos et al. (2014), we find that the risk of automation has a greater impact on the labor market career of unemployed workers compared to the risk of offshoring.

Columns (2) and (6) of Table 3 report the impact of occupational change on the likelihood of leaving the labor market. We find that a higher risk of automation is associated with a slightly lower likelihood of leaving the labor force for both men and women. Part of the effect might be driven that automation 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. In terms of offshoreability, we find the opposite effect, although our estimates are not statistically significant.

4.2 Automation, Offshoring and Training Assignment

Given that the risk of automation significantly reduces the re-employment probability for both men and women, it is interesting to see if case workers have been aware of these developments.

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

[18] Cashiers have a RTI of 1.28 and welders a RTI of 0.27. This implies that the employment probability shifts in the year 2000 by $exp(-0.088 \cdot 1.28) - 1$ and in the year τ by $exp(-0.088 \cdot 1.28 - 0.005 \cdot (\tau - 2000) \cdot 1.28) - 1$ for the cashier as compared to a person with average characteristics.

In this section, we briefly discuss the impact of our measures on the training assignment process.

Columns (4) of Table 3 show the impact of RTI and OFF on the assignment likelihood for male works. One can see that case workers were intentionally or unintentionally aware of the potential negative consequences of automation. We estimate that a one standard deviation increase of our RTI has a positive significant impact on the log-training hazard of 0.19. Our trend estimates γ_τ, reported in the next line, show, however, that there has been a shift in the focus over the past years. Although workers who used to be employed in occupations at high risk of automation are still more likely to receive training, this *positive discrimination* is getting smaller over time. Our estimates imply that a one standard deviation increase of our RTI decreases the log-training hazard every year by around 0.006. This implies, for example, that the probability of receiving training for an unemployed cashier – continuing our example from above – decreases within 10 years by around 10 pp while it is only 1.7 pp lower for welders over the same time period.

Our results for women, reported in Column (8) of the table, are very similar. Like for men, we find that female workers who are more affected by automation are more likely to be assigned to training but there is a substantial shift away from this process over time. Our trend estimates are even slightly larger compared to men.

The impact of offshoring on the assignment process is less pronounces and mostly negative. Male workers affected by offshoreability receive less likely training with a slight intensification over time. Our estimates are, however, only marginally significant. For women, we do not find any evidende that case workers base their decision on this measure.

These results are quite interesting. Case workers tend to factor the disadvantage of automation into account when assigning training programs. 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 measures are more effective in placing individuals in high-quality work. We will explore this further below.

4.3 Effects of Labor Market Training on Exit Behavior

We find that labor market training has a highly significant and positive effect on the re-employment probability, as can be seen in Panel b of Table 3. Received 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 unemployment training leads to a significant increase of the likelihood of transiting into out of labor force, but to a much lower extent.

For men, we find evidence that training effectiveness differs by the degree of automation and offshoreabilty in the previous job. A one standard deviation increase in our RTI increased the impact of training on the job finding probability by an additional and significant 8 pp in 2000, but its effectiveness has decreased since then. We find the opposite effect for training associated to our OFF measure. At the beginning of our sample period, provided training had actually a (not significantly) lower effect for workers in occupation with high offshoring potential, but effectiveness of training has increased since then significantly. We do not find any results for women. Our estimates are very small and not statistically significant for this group.

These differential effects of automation or offshoring do not, however, capture the full effect of training on the unemployment duration of workers. To calculate the full effect of labor market policy, we need to consider two different effects. First, there is the direct effect of training related to our measures of occupational change analyzed in this section. Second, there is an indirect effect of training, operating through the difference in the assignment process of case workers discussed in the previous section. As we have shown, this process depends significantly on the previous job content. Thus high/low RTI and OFF workers have different expected waiting times until training assignment. Receiving training earlier or later will amplify general and heterogenous training effects. To quantify these two effects, we use our estimates from Table 3 to simulate the total effectiveness of training.

We first calculate for each year y of our sample the expected duration until training assignment $S_{y,j}^{Index}$, using either our RTI or OFF and setting it to 0 ($j = low$) or 1 ($j = high$), which corresponds to a one-standard-deviation change in the index. We then use the expected duration until training assignment in a second step when calculating the expected duration until new employment NJ_j^{Index}. When calculating the durations, we use the estimates reported in Table 3 and set all other covariates to their sample average as observed in the year 2000. This constitutes our baseline of the total effectiveness of labor market training.[19]

To gauge whether changes in the assignment process or changes in direct training effects are driving this time trend, we conduct similar set of calculations but fix now the respective parameters to our values for the year 2000. In other words, we do not allow for any changing impact of either RTI or OFF on the training and exit hazards over time.

Given our durations obtained under these different scenarios, we calculate the relative benefits of unemployment training in year y as

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

where $Index$ is either RTI or OFF and $j = \{high, low\}$.

Equation (9) expresses the relative benefits of provided unemployment 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. Thus, 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 different 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

[19] 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 Index I, and $j = \{low, high\}$ the expected duration until re-employment as $\sum_{i=1}^{5} p_i \left(\int_0^{tu} S(z | x = \bar{x}_{2000}, I = j, \nu_{NJ}^i, D = s) dz + tu \cdot P(t \geq tu) \right)$, 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.

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 in effectiveness due to changing priorities of case workers.

Figure 3 presents the results from this exercise, separately for automation and offshoring for both genders. The solid-dotted line presents our baseline for workers with RTI and OFF set to the low level, our baseline estimates. On average, training reduces unemployment duration by around 15 % for both men and women, which is quite sizable.

In comparison, the solid line shows the benefits of training if we set RTI or OFF to a high level and thus allow for different training assignment as well as changing training effects over time. The dashed and dotted line show the results for high values of our indices if either training assignment or training programs had had a similar impact as in 2000. Similarly, the dotted-dashed line presents the relative benefits of unemployment training if both the assignment process and training programs had the same effect throughout the sample period as in the year 2000.

From our results, it is clear, that both men and women with higher values of RTI profit substantially more from training as compared to workers with lower values of RTI. At the beginning of our observation period, assigned training reduced the unemployment duration for men for high values of RTI by 19.5% (relative to 15% at baseline), whereas training reduces the unemployment duration of women by 21% (relative to 15% at baseline).

These advantages of high-RTI workers have decreased over time. For men, the decreasing benefits are almost equally driven by the changing assignment focus and the less effective training programs. If both components had stayed on the same level as in 2000, provided training could have reduced unemployment duration by up to 3 pp more than under the current regime. For women, we find that almost the entire decline in training effectiveness is due to changing assignment priorities. Had case workers based their assignment decision on the same characteristics as in the year 2000, provided training could be up to 4 pp more effective nowadays. This difference is quite large when compared to our baseline estimates.

In contrast, training programs related to offshoring for men bring no additional advantage. Workers in jobs with higher offshoring potential have benefited less from training compared to those with lower values of our OFF, over most of our sample period. Its effectiveness has, however, improved over time. This development is almost exclusively driven by better training efficiency. In contrast, women in jobs with higher offshoring potential have benefited slightly more from labor market training. As before, we find a substantial fall in the effectiveness of these training programs over time, which is driven by the changes in priorities of case workers.

Overall, unemployment training can compensate the negative impact of occupational change on the unemployment duration to a large extent and bring workers back to the labor market. Its effectiveness has, however, decreased over time. In the next chapter we will explore the quality of the jobs unemployed workers transit into.

4.4 Occupational Change and Post-Unemployment Outcomes

4.4.1 Re-Employment Wages

The impact of our measures on re-emplolyment wages can be found in columns (3) and (7) in Table 3 for men and women respectively. Male workers who are more affected by automation and who find new employment have in general higher re-employment wages.[20] We find a strong amplification of this development over time. Our results for women are somewhat smaller and we do not find evidence that it is changing over time.

Taken together with our findings from the previous sections, our results for automation point toward a trade-off between the quality and quantity of available jobs. Workers who were previously employed in "routine" jobs have seen a decline in employment opportunities. At the same time, they also have likely experienced changes in the task requirements leading to fewer but more productive jobs (Hershbein and Kahn, 2018; Gregory et al., 2019).[21]

We see a similar trade off when we look at the impact of offshoreability. For men, previously working in an occupation at higher risk of offshoring has increasing the re-employment probability. At the same time, we also estimate a negative impact on re-employment wage. For women, offshoring reduces the employment rate, but increases post-unemployment wages.

In general, our results for women imply that their post-unemployment wage is less affected by occupational changes compared to men. These differences might be (partly) explained by women in Austria working more likely part-time than men and therefore benefit less from any within-occupational upskilling.

We have seen that training can be effective in lowering unemployment duration for workers strongly affected by occupational change. In this light, it is interesting to see what are the effects of training on subsequent wages. Columns (3) and (7) in Panel b of Table 3 show that there is a trade off in the effectiveness of training with respect to re-employment probabilities and wages for both men and women. Provided training increases the likelihood of transiting into new employment, but reduces the wages for those who found a new job. This implies that case workers are more concerned in bringing unemployed workers back to work and less with post-unemployment job quality.

There are, however, slight differences by previous job content. Male workers with higher RTI were significantly less impacted by the negative effect of training on re-employment wages at the beginning of our sample period. This effect strongly decreases over time. Our results indicate the opposite for our measure of offshoreabilty. Workers with unemployment training in occupations at risk of being offshored had lower wages at the beginning, but have seen an improvement since then. These results mirror those discussed for the effect of training on exit behavior. As before, we do not find any heterogeneous training effects for women.

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

[21] An alternative explanation is put forward by Modestino et al. (2016) who argue that during the great recession employers behaved opportunistically by demanding higher skills.

4.4.2 Job Stability

We also look at tenure in the first job after leaving unemployment as another form of employment quality. The results are presented in Table 4. The impact of our measures of occupational change on the treatment and exit hazards are very similar as when using post-unemployment wages as additional outcome and we do not discuss them in detail here.

Interestingly, we find that male workers affected by automation do not only have higher re-employment wages but also enjoy better job stability. A one standard deviation increase in our RTI decreases the separation probability by around 18%, which is highly significant. This effect has remained remarkably stable over time. In contrast, a one standard deviation increase of our OFF increases the job separation probability by around 6%.

The estimates for women, reported in Column (7) of Table 4 are similar. A one standard deviation increase in our RTI decreases the separation probability from the current employer by 19%, while a one standard deviation increase of our OFF increases the separation probability by around 4%. We do not find any evidence that this trend has changed over time.

We find small but negative effects of labor market training on post-unemployment job stability. Women who received training have lower post-unemployment job duration and an increased separation rate by around 11%. Likewise, male workers who received training have a slightly elevated and marginally significant likelihood of leaving the new employer. We do not find any noticeable heterogeneous effects.

Our findings imply that automation can create better paying and more stable jobs, but only for those workers who are able to find new employment. Falling job finding probabilities – together with the quality of these jobs – lead to an increase in polarisation in the labor market. Unlike automation, jobs susceptible to offshoring are characterized by shorter post-unemployment jobs and lower wages. The developments documented in our work have the possibility to increase inequality even further in the future.

5 Heterogenous Effects

Occupational changes might in particular affect older and less educated workers. Older workers might be more reluctant to adjust to new occupational requirements than younger ones reducing their search behavior and increasing the likelihood of leaving the labor force. Education may also be an important factor which influences the impact of occupational change on re-employment and wages. New technology can complement more skilled workers while it might substitute for workers without specialized skills.

Table 5 shows the estimation results for different age groups where we split the sample by the median age of the workers. For brevity, we only show the results on our re-employment hazard and wages, but all models include out-of-labor force as an additional state, as well as the training assignment process. Given our previous discussion and to give an indication of the total effect of provided training, we present its impact on the unemployment duration graphically in Figures 4 for our age groups.

[Table 5 & Figure 4]

Younger unemployed workers were more affected by the risk of automation than older ones at the beginning of our sample period. While the effect remained largely constant for the younger age group, we find an increasing and significantly negative impact of automation on the re-employment probability of older workers over time. For both age groups, we find that those workers who find new employment tend to have higher wages. Interestingly, our estimates also show that the improvement is stronger for younger workers. This shows that automation has the potential to increase inequality especially among this group (e.g. Muro et al., 2019) but also that older male workers are increasingly affected by changing occupational requirements.

Mostly older male worker are affected by offshoring with lower job finding probabilities and re-employment wages. We do not find that the risk of offshoring affects the re-employment likelihood of younger workers, but it leads to substantially lower re-employment wages.

Older female workers are significantly more affected by automation than younger ones. Our estimates for the older age group is almost twice as large compared to those for the younger group. In contrast to our results for male workers, we do not find any evidence that this impact is changing over time. We also find that for both age groups wages are positively affected by automation. In terms of offshoring, we find a significant negative impact on younger female workers only.

Figure 4 shows the relative impact of assigned training. Panel a and b. show the benefits for men for high and low values of the RTI and OFF.[22] Panel c and d. does the same for women. Looking at the graphs, one major result emerges: there is a large difference between older and younger workers in the total effectiveness of labor market training on the unemployment duration. These differences are quite substantial, in particular for workers affected by occupational change, and amount to up to 10 pp. While automation has a larger impact on the job finding rates of younger workers, public policies can help to soften its impact. As before, we also find that this positive impact on the job finding rate is associated with lower re-employment wages.

Table 6 presents the results for different education groups. We consider individuals who have finished at least an university entrance exam to be highly educated while those with at most apprenticeship and/or intermediate school as low educated. Figure 5, which follows the same structure as Figure 4, presents the total effect of training on the unemployment duration.

[Table 6 & Figure 5]

We see strong differences in the impact of occupational change on the labor market career of unemployed workers by education. Highly educated male workers are not much affected by these developments, as can be seen in Columns (1) and (2) of the Table. We find some small negative effects of offhsoring on re-employment wages over time. For highly educated women, the results presented in Column (5) and (6) show that offshoring has a strong negative effect on

[22] As before, we set the difference between high and low values to one which corresponds to an increase of one standard deviation

the job finding probability, but compared to men we do not find any effect on re-employment wages.

Our findings for lower educated persons stand in stark contrast. For men, a one standard deviation increase in our RTI decreased the job finding probability by 12% in 2000. The impact has severely intensified since then and a similar change in the RTI has decreased the job finding probability by 20% by the end of our sample period. We find similar negative effects for women but no evidence that these have changed over time, as one can see from the results in Column (7) of the table. Both estimates are highly significant and 30% to almost 50% higher compared to our overall estimates shown in Table 3. We also find that the quantity-quality trade-off in terms of jobs is entirely driven by this education group.[23]

For lower educated men, we find a similar trade-off as before in terms of offshoring. Over time a higher risk of offshoring is associated with a higher job finding probability but lower re-employment wages. For women, we find comparable effects but employment opportunities have marginally improved over time.

Figure 5 shows the relative impact of assigned training for our different education groups. Highly educated male workers benefit in general more from provided unemployment training compared to lower skilled ones regardless of the impact of occupational change. Within skill-groups, we find that those more affected by occupational change benefit in general more from training, with exception of offshoreability and lower eduated workers. Our results are very similar for women. In general, our results imply that provided public policies, while helpful in general, can increase inequality between skill groups further.

6 Conclusion

There has been an increasing interest from both scholars and policy makers in the effect of automation and offshoring on workers. While there is a large amount of studies on aggregate impacts of occupational changes on employment, evidence on individual-level consequences is scant. In this work, we use almost two decades of administrative data for Austria and look at the consequences of automation and offshoreability on the exit behavior and future labor market career of unemployed workers. This is also the first paper to study systematically the effectiveness of labor market training in this setting.

For both men and women, automation is reducing job finding rates of unemployed workers significantly; for men this disadvantage is also increasing over time. We find a trade off between quantity and quality of employment. Those who find a new job tend to have higher re-employment wages and more stable jobs. We provide evidence that these effects have intensified over the past years and that in particular workers with lower educational attainment and fewer special skills are affected. These results suggest that occupations have undergone considerable within-changes with a move towards routine-labor saving technology and higher demand for

[23] When dividing the lower education group into those who have an apprenticeship/high-school degree and those with only compulsory schooling, we find a similar employment-wage trade-off for the former group while we only find negative employment effects for the latter group. This supports the hypothesis that special skills become more important, in particular for lower educated workers.

highly-skilled workers.

We find a similar but reversed quality-quantity trade off when looking at the impact of offshoreability. For men, a higher risk of offshoring is associated with increasing job finding probabilities over time. This comes at the cost of lower re-employment wages and job stability, implying that these jobs are in general of lower quality.

For women, we estimate comparable effects of automation on the job finding probability but a considerably lower impact on re-employment wages. In addition, we do not find evidence that the impact of automation has changed since the beginning of the 2000s for this group, likely as a large share of women are working part-time and thus are less affected by any within occupational changes. Taken together, our results support the notion of gender-specific impacts of automation.

We show that provided unemployment training can be effective in counteracting the negative employment effects of occupational changes. In particular, younger workers and those with higher education profit most from these measures while older workers and those with less specialized skills 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.

While we show that active labor market policies can be one way to master the employment challenges imposed by automation and digitization, our results also highlight the danger of increasing inequality. Unemployed workers who have the special skills to adopt to new situations face better labor market outcomes with higher wages and job stability. Those workers who lack the special skills have prolonged unemployment spell and end up in worse matches.

References

Abbring, J. H. and Van den Berg, G. J. (2003*a*), 'The Identifiability of the Mixed Proportional Hazards Competing Risks Model', *Journal of the Royal Statistical Society. Series B* **65**(3), 701–710.

Abbring, J. H. and van den Berg, G. J. (2003*b*), 'The Nonparametric Identification of Treatment Effects in Duration Models', *Econometrica* **71**(5), 1491–1517.

Abraham, K. G., Haltiwanger, J., Sandusky, K. and Spletzer, J. R. (2019), 'The Consequences of Long-Term Unemployment: Evidence from Linked Survey and Administrative Data', *ILR Review* **72**(2), 266–299.

Acemoglu, D. (1995), 'Public Policy in a Model of Long-Term Unemployment', *Economica* **62**(246), 161–178.

Acemoglu, D. and Restrepo, P. (2018), 'Robots and Jobs: Evidence from the U.S. Labor Market', *mimeo* .

Akerman, A., Gaarder, I. and Mogstad, M. (2015), 'The Skill Complementarity of Broadband Internet', *The Quarterly Journal of Economics* **130**(4), 1781–1824.

Albrecht, J. W., Edin, P., Sundström, M. and Vroman, S. B. (1999), 'Career Interuptions and Subsequent Earnings: Reexamination Using Swedish Data', *Journal of Human Resources* **34**(2), 294–311.

Alvarez, F. E., Borovičková, K. and Shimer, R. (2016), 'Decomposing Duration Dependence in a Stopping Time Model', *NBER Working Papers No. 22188* .

Arni, P., Lalive, R. and van Ours, J. C. (2013), 'How Effective are Unemployment Benefit Sanctions? Looking Beyond Unemployment Exit', *Journal of Applied Econometrics* **28**(7), 1153–1178.

Arntz, M., Gregory, T. and Zierahn, U. (2017), 'Revisiting the risk of automation', *Economic Letters* **159**, 157–160.

Autor, D. (2015), 'Why Are There Still So Many Jobs Left? The History and Future of Workplace Automation', *Journal of Economic Perspectives* **29(3)**, 3–30.

Autor, D., Dorn, D. and Hanson, G. (2018), 'When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men', *forthcoming American Economic Review: Insights* .

Autor, D. H. and Dorn, D. (2013), 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market', *American Economic Review* **103(5)**, 1553–1597.

Autor, D. H., Dorn, D. and Hanson, G. H. (2016), 'The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade', *Annual Review of Economics* **8**, 205–240.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2006), 'The Polarization of the U.S. Labor Market', *The American Economic Review* **96(2)**, 189–194.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2008), 'Trends in U.S. Wage Inequality: Revising the Revisionists', *Review of Economics and Statistics* **90**(2), 300–323.

Autor, D. H., Katz, L. F. and Krueger, A. B. (1998), 'Computing Inequality: Have Computer Changed the Labor Market', *Quarterly Journal of Economics* **113**(4), 1169–1213.

Black, S. E. and Spitz-Oener, A. (2010), 'Explaining Women's Success: Technological Change and the Skill Content of Women's Work', *The Review of Economics and Statistics* **92(1)**, 187–194.

Blinder, A. S. and Krueger, A. B. (2013), 'Alternative Measures of Offshorability: A Survey Approach', *Journal of Labor Economics* **31**(2), S97–S128.

Brynjolfsson, E. and McAfee, A. (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, Vol. a, New York: W.W. Norten & Company.

Caselli, F. and Manning, A. (2017), 'Robot Arithmetic: Can New Technology Harm All Workers or the Average Worker', *forthocoming American Economic Review: Insights* .

Cockx, B. and Picchio, M. (2013), 'Scarring Effects of Remaining Unemployed for Lon-Term Unemployed School Leavers', *Journal of the Royal Statistical Society: Series A* **176**(4), 951–980.

Cortes, G. M. (2016), 'Where have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data', *Journal of Labor Economics* **34**(1), 63–105.

Cortes, G. M., Jamovich, N. and Siu, H. E. (2017), 'Disappearing Routine Jobs: Who, How, and Why', *Journal of Monetary Economics* **91**, 69–87.

Crépon, B., Ferrarci, M., Jolivet, G. and van den Berg, G. J. (2018), 'Information Shocks and the Empirical Evaluation of Training Programs During Unemployment Spells', *Journal of Applied Econometrics* **33**(4), 594–616.

Deloitte (2016), '2016 global outsourcing survey', https://www2.deloitte.com/content/dam/Deloitte/fi/Documents/technology/2016%20GOS%20Exec%20Summary_Nordic.pdf. accessed 20-March-2019.

Donald, S. G., Green, D. A. and Paarsch, H. J. (2000), 'Differences in Wage Distributions Between Canada and the United States: An Application of a Flexible Estimator of Distribution Functions in the Presence of Covariates', *Review of Economic Studies* **67**(4), 609–633.

Dustmann, C., Ludsteck, J. and Schönberg, U. (2009), 'Revisiting the German Wage Structure', *The Quarterly Journal of Economics* **124(2)**, 843–881.

Edin, P.-A., Evans, T., Graetz, G., Sofia, H. and Michaels, G. (2018), Individual consequences of occupational decline. mimeo Uppsala University.

Eriksson, S. and Rooth, D.-O. (2014), 'Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence from a Field Experiment', *American Economic Review* **104**(3), 1014–1039.

Faberman, R. J. and Kudlyak, M. (2016), 'The Intensity of Job Search and Duration', *forthcoming American Economic Journal: Macroeconomics* .

Firpo, S., Fortin, N. M. and Lemieux, T. (2011), 'Occupational Tasks and the Change in the Wage Structure', *IZA Discussion Paper No. 5542* .

Frey, C. B. and Osborne, M. A. (2017), 'The future of employment: How susceptible are jobs to computerisation?', *Technological Forecasting and Social Change* **114**, 254–280.

Gaure, S., Roed, K. and Zhang, T. (2007*a*), 'Details of Estimation - Elaborating on Time and Causality', *mimeo* .

Gaure, S., Roed, K. and Zhang, T. (2007*b*), 'Time and Causality: A Monte Carlo Assessment of the Timing-of-Events Approach', *Journal of Econometrics* **141**(2), 1159–1195.

Gibbons, R., Katz, L. F., Lemieux, T. and Parent, D. (2005), 'Comparative Advantage, Learning, and Sectoral Wage Determination', *Journal of Labor Economics* **23**(4), 681–723.

Goos, M. and Manning, A. (2007), 'Lousy and Lovely Jobs: The Rising Polarization of Work in Britain', *The Review of Economic and Statistics* **89(1)**, 118–133.

Goos, M., Manning, A. and Salomons, A. (2009), 'Job Polarization in Europe', *American Economic Review: Papers and Proceedings* **99(2)**, 58–63.

Goos, M., Manning, A. and Salomons, A. (2014), 'Explaining Job Polarization: Routine-Biased Technological Change and Offshoring', *American Economic Review* **104(8)**, 2509–2526.

Görlich, D. and de Grip, A. (2009), 'Human Capital Depreciation During Hometime', *Oxford Economic Papers* **61**(1), i98–i121.

Graetz, G. and Michaels, G. (2018), 'Robots at Work', *Review of Economics and Statistics* **100**(5), 753–768.

Gregory, T., Salomons, A. and Zierahn, U. (2019), 'Racing With or Against the Machine? Evidence from Europe', *IZA Discussion Paper 12063* .

Heckman, J. J. and Singer, B. (1984), 'A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data', *Econometrica* **52**(2), 271–320.

Hershbein, B. and Kahn, L. B. (2018), 'Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings', *American Economic Review* **108**(7), 1737–1772.

Hummels, D., Munch, J. R. and Xiang, C. (2018), 'Offshoring and Labor Markets', *Journal of Economic Literature* **56**(3), 981–1028.

Jaimovich, N. and Siu, H. E. (2018), 'The Trend is the Cycle: Job Polarization and Jobless Recoveries', *forthcoming Review of Economics and Statistics* .

Kroft, K., Lange, F. and Notowidigo, M. J. (2013), 'Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment', *Quarterly Journal of Economics* **128**(3), 1123–1167.

Kroft, K., Lange, F., Notowidigo, M. J. and Katz, L. F. (2016), 'Long-Term Unemployment and the Great Recession: The Role of Composition, Duration Dependence, and Non-Participation', *Journal of Labor Economics* **34**(S1), S7–S54.

Krueger, A., Cramer, J. and Cho, D. (2014), 'Are the Long-Term Unemployed on the Margins of the Labor Market', *Brookings Papers on Economic Activity* **Spring**, 229–280.

Krueger, A. and Mueller, A. (2011), 'Job Search, Emotional Well-Being and Job Finding in a Period of Mass Unemployment: Evidence from High-frequency Longitudinal Data', *Brookings Paper on Ecnomic Activity* **Spring**, 1–57.

Lalive, R., Van Ours, J. C. and Zweimüller, J. (2008), 'The Impact of Active Labour Market Programmes on the Duration of Unemployment in Switzerland', *Economic Journal* **118**(525), 235–257.

Lalive, R., Zweimüller, J. and van Ours, J. C. (2005), 'The Effect of Benefit Sanctions on the Duration of Unemployment', *Journal of the European Economic Association* **3**(6), 1386–1417.

Modestino, A., Shoag, D. and Ballance, J. (2016), Upskilling: Do Employers Demand Greater Skill when Workers are Plentiful?, Technical report, Northeastern University.

Müller, H.-G. and Wang, J.-L. (1994), 'Hazard Rate Estimation Under Random Censoring with Varying Kernels and Bandwidth', *Biometrics* **50(1)**, 61–76.

Muro, M., Maxim, R. and Whiton, J. (2019), 'Automation and Artificial Intelligence - How Machines are Affecting People and Places', *Brookings Institute Report January 2019* .

OECD (2019), 'Oecd stats', https://stats.oecd.org/Index.aspx?QueryId=8540. accessed 30-March-2019.

Osikominu, A. (2013), 'Quick Job Entry or Long-Term Human Capital Development? The Dynamic Effect of Alternative Training Schemes', *Review of Economic Studies* **80**(1), 313–342.

Pew Research Center (2017), 'Automation and Everyday Life', *Report - October* .

Richardson, K. and van den Berg, G. (2013), 'Duration Dependence versus Unobserved Heterogeneity in Treatment Effects: Swedish Labor Market Training and the Transition Rate to Employment', *Journal of Applied Econometrics* **28**(2), 325–351.

Schmillen, A. (2018), 'Vocational education, occupational choice and unemployment over the professional career', *forthcoming Empirical Economics* .

Spitz-Oener, A. (2006), 'Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure', *Journal of Labor Economics* **24(2)**, 235–270.

van den Berg, G., van der Klaauw, B. and van Ours, J. C. (2004), 'Punitive Sanctions and the Transition Rate from Welfare to Work', *Journal of Labor Economics* **22**(1), 211–241.

van der Klaauw, B. and van Ours, J. C. (2013), 'Carrot and Stick: How Re-Employment Bonuses and Benefit Sanctions Affect the Exit Rates from Welfare', *Journal of Applied Econometrics* **28**(2), 275–296.

Wright, G. C. (2014), 'Revisiting the Employment Impact of Offshoring', *European Economic Review* **66**, 63–83.

Zweimüller, J., Winter-Ebmer, R., Lalive, R., Kuhn, A., Wuellrich, J.-P., Ruf, O. and Büchi, S. (2009), 'Austrian Social Security Database', *NRN Working Paper No. 0903 April* .

7 Tables

Table 1: Summary of Estimation Sample

	Men	Women
Individuals & No. of Spells		
Individuals	30,000	30,000
Average No. of Spells	6.08	4.84
Total Observations	98,051	80,178
Outflow & Training		
Outflow (in %)	99.32	99.53
to Employment (in %)	59.51	52.38
Median Time until Employment (Days)	81.00	92.00
to Out of Labor Force (in %)	39.82	47.15
Median Time until Out-of-Labor Force (Days)	129.00	133.00
Training Received (in %)	19.80	25.64
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)
Divorced (%)	12.97	18.01
	(33.59)	(38.43)
Others (%)	44.15	33.32
	(49.66)	(47.14)
Last Employment		
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)

Median time until new job or out of labor force is conditional on exiting unemployment. Out of Labor Force refers to the state when an individual exits unemployment and does not take up employment within 60 days. Matura refers to the final entrance exam for the university in Austria. Others refers to person who are either single or cohabitating with a partner. Displaced from Last Job refers to individuals who lost their last job due to plant closure or mass lay-off. Access to Extended Benefits denotes the share of spells in our sample where the individual is eligible for at least 20 weeks of unemployment benefits. Standard deviations are reported in parentheses.

Table 2: Share of Total Vacancies Posted by Major ISCO Group

	Years				Ann. Growth Rate
	2011	2012	2013	2014	$\Delta^{2011-2014}_{Average}$
Managers (1)	2.17%	2.31%	2.92%	2.72%	8.67%
Professionals (2)	11.67%	12.54%	11.21%	11.84%	0.82%
Technicians (3)	17.50%	18.44%	18.59%	18.24%	1.43%
Clerical Support Workers (4)	6.11%	6.77%	6.61%	4.96%	−5.51 %
Service and Sales Workers (5)	29.85%	25.07%	31.34%	29.92%	1.48%
Craft & related Trades Workers (7)	16.28%	19.31%	14.44%	14.08%	−3.03 %
Plant & Machine Operators, and Assemblers (8)	6.92%	5.33%	4.45%	5.12%	−8.14 %
Elementary Occupations (9)	7.87%	8.36%	8.14%	7.04%	−3.31 %

The table presents the share of average yearly vacancies posted for each major ISCO group as provided by Statistik Austria (http://www.statistik.at/web_de/statistiken/menschen_und_gesellschaft/arbeitsmarkt/offene_stellen/index.html). $\Delta^{2011-2014}_{Average}$ is the average annual growth rate between 2011 and 2014 in the share of vacancies posted of the respective ISCO group. Note that the %-Shares do not add up to one as Skilled Agricultural, Forestry and Fishery Workers as well as unknown occupations are excluded from the table.

Table 3: Impact of Occupational Changes on Exit Behavior and Re-Employment Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male				Female			
	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Wages hazard θ_{ω}	Treatment hazard $\theta_{\mathrm{Training}}$	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Wages hazard θ_{ω}	Treatment hazard $\theta_{\mathrm{Training}}$
Panel a: Occupational Requirements								
γ^{RTI}	-0.088^{***}	-0.018	0.195^{***}	0.190^{***}	-0.168^{***}	-0.045	0.076^{***}	0.232^{***}
	(0.033)	(0.036)	(0.029)	(0.047)	(0.031)	(0.031)	(0.028)	(0.042)
γ_{τ}^{RTI}x 10	-0.051^{***}	-0.045^{**}	0.055^{***}	-0.058^{**}	0.015	-0.036^{*}	0.010	-0.093^{***}
	(0.015)	(0.019)	(0.014)	(0.023)	(0.020)	(0.021)	(0.019)	(0.025)
γ_{2000}^{OFF}	-0.003	0.030	-0.172^{***}	-0.057^{*}	-0.102^{***}	-0.006	0.040^{**}	0.018
	(0.031)	(0.021)	(0.024)	(0.019)	(0.030)	(0.021)	(0.022)	(0.020)
γ_{τ}^{OFF}x 10	0.052^{***}	0.018	-0.015	-0.011	0.046^{**}	0.026	-0.013	-0.029
	(0.015)	(0.018)	(0.015)	(0.024)	(0.021)	(0.020)	(0.021)	(0.026)
Panel b: Training								
δ	0.596^{***}	0.268^{***}	-0.214^{***}		0.767^{***}	0.368^{***}	-0.132^{***}	
	(0.016)	(0.018)	(0.015)		(0.017)	(0.017)	(0.016)	
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)	
δ_{2000}^{OFF}	-0.047	0.001	-0.056^{*}		0.007	-0.017	-0.018	
	(0.029)	(0.031)	(0.029)		(0.030)	(0.030)	(0.029)	
δ_{τ}^{OFF}x 10	0.069^{*}	-0.028	0.092^{**}		0.014	0.036	-0.017	
	(0.037)	(0.040)	(0.039)		(0.041)	(0.041)	(0.041)	
Linear Trends	Yes				Yes			
Unobs. Heterogeneity	Yes				Yes			
Individual Control Variables	Yes				Yes			
Time & Occupation Dummies	Yes				Yes			
Log-Likelihood	-124,861.10				-128,052.86			

OLF refers to Out-of-Labor Force. The model includes a linear trend in RTI and OFF using the year 2000 as baseline. In addition to the reported variables, control variables for individual characteristics, time dummies, and occupational dummies defined one a 1-digit level are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function and the number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 3. 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 fixed and included as constants in the estimation. In total, 211 parameters were estimated. Standard errors are reported in parentheses.

Table 4: Impact of Occupational Changes on Exit Behavior and Re-Employment Job Stabilty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male				Female			
	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Job Stability hazard θ_{PE}	Treatment hazard $\theta_{\mathrm{Training}}$	Employment hazard θ_{NJ}	OLF hazard θ_{OLF}	Job Stability hazard θ_{PE}	Treatment hazard $\theta_{\mathrm{Training}}$
Panel a: Occupational Requirements								
γ^{RTI}	-0.097^{***}	-0.025	-0.197^{***}	0.205^{***}	-0.157^{***}	-0.046	-0.215^{***}	0.228^{***}
	(0.033)	(0.036)	(0.027)	(0.047)	(0.032)	(0.030)	(0.029)	(0.042)
γ_{τ}^{RTI}x 10	-0.052^{***}	-0.046^{**}	0.014	-0.059^{**}	0.011	-0.036^{*}	0.015	-0.090^{***}
	(0.015)	(0.019)	(0.014)	(0.023)	(0.020)	(0.021)	(0.021)	(0.025)
γ_{2000}^{OFF}	-0.002	0.039^{*}	0.062^{***}	-0.069^{**}	-0.094^{***}	-0.015	0.041^{**}	0.018
	(0.022)	(0.024)	(0.018)	(0.031)	(0.023)	(0.022)	(0.022)	(0.030)
γ_{τ}^{OFF}x 10	0.054^{***}	0.019	0.010	-0.007	0.046^{**}	0.024	-0.031	-0.034
	(0.016)	(0.018)	(0.015)	(0.024)	(0.021)	(0.020)	(0.021)	(0.026)
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)	
δ_{2000}^{OFF}	-0.048	0.008	0.046^{*}		0.002	-0.011	0.035	
	(0.029)	(0.031)	(0.028)		(0.031)	(0.030)	(0.030)	
δ_{τ}^{OFF}x 10	0.075^{**}	-0.029	-0.039		0.022	0.037	0.006	
	(0.037)	(0.040)	(0.037)		(0.042)	(0.041)	(0.044)	
Linear Trends	Yes				Yes			
Unobs. Heterogeneity	Yes				Yes			
Individual Control Variables	Yes				Yes			
Time & Occupation Dummies	Yes				Yes			
Log-Likelihood	-159,843.39				-155,192.38			

OLF refers to Out-of-Labor Force.The model includes a linear trend in RTI and OFF using the year 2000 as baseline. In addition to the reported variables, control variables for individual characteristics, time dummies, and occupational dummies defined one a 1-digit level are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function and the number of mass points for the distribution of unobserved heterogeneity was set to five; see Section 3. To estimate the effect on the distribution of re-employment tenure, all spells without an outflow at the end of the sample period ares censored. During estimation, one mass point in the Men Sample converged to a large negative number. It was fixed and included as constants in the estimation. In total, 211 parameters were estimated. Standard errors are reported in parentheses.

Table 5: Heterogenous Impacts of Occupational Changes on Exit Behavior & Re-Employment Wages by Age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				Women			
	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: Occupational Requirements								
γ_{2000}^{RTI}	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_{τ}^{RTI}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)
γ_{2000}^{OFF}	-0.078^{**}	-0.185^{***}	0.019	-0.161^{***}	-0.056	0.027	-0.162^{***}	0.042^{*}
	(0.037)	(0.032)	(0.027)	(0.024)	(0.035)	(0.032)	(0.027)	(0.026)
γ_{τ}^{OFF}x 10	0.083^{***}	-0.014	0.026	-0.016	0.017	-0.010	0.099^{***}	-0.003
	(0.025)	(0.023)	(0.021)	(0.019)	(0.032)	(0.030)	(0.030)	(0.029)
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_{2000}^{RTI}	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_{τ}^{RTI}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)
δ_{2000}^{OFF}	-0.010	0.022	-0.060	-0.101^{***}	0.005	0.014	0.005	-0.042
	(0.046)	(0.052)	(0.039)	(0.039)	(0.051)	(0.045)	(0.039)	(0.038)
δ_{τ}^{OFF}x 10	0.007	0.013	0.107^{**}	0.137^{**}	0.027	-0.029	-0.002	-0.010
	(0.056)	(0.062)	(0.050)	(0.054)	(0.062)	(0.060)	(0.058)	(0.058)
Linear Trend	Yes		Yes		Yes		Yes	
Unobs. Heterogeneity	Yes		Yes		Yes		Yes	
Individual Control Variables	Yes		Yes		Yes		Yes	
Time & Occupation Dummies	Yes		Yes		Yes		Yes	
Log-Likelihood	-66,295.81		-57,788.25		-63,353.99		-63,856.50	

The table shows the estimates for the re-employment hazard θ_{NJ} and wage hazard θ_ω only, but all models also include Out-of-Labor force as an additional exit state. The model includes a linear trend in RTI and OFF using the year 2000 as baseline. In addition to the reported variables, control variables for individual characteristics, time dummies, and occupational dummies defined one a 1-digit level are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function and the number of mass points for the distribution of unobserved heterogeneity was set to five. 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). The distinction between older and younger workers was obtained by using the median of the age distribution. 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 fixed and included as constants in the estimation; see Section 3. In total, 211 parameters were estimated. Standard errors are reported in parentheses.

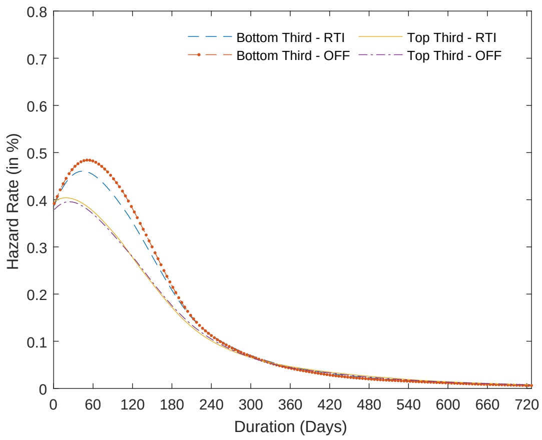
Table 6: Heterogenous Impacts of Occupational Changes on Exit Behavior & Re-Employment Wages by Education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				Women			
	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: Occupational Requirements								
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)
γ_{2000}^{OFF}	-0.030	0.009	0.021	-0.223^{***}	-0.179^{***}	-0.024	-0.075^{***}	0.061^{***}
	(0.044)	(0.042)	(0.025)	(0.023)	(0.049)	(0.045)	(0.024)	(0.023)
γ_{τ}^{OFF}x 10	0.011	-0.098^{***}	0.061^{***}	-0.009	0.048	-0.012	0.042^{*}	0.012
	(0.038)	(0.036)	(0.018)	(0.017)	(0.049)	(0.046)	(0.024)	(0.024)
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)
δ_{2000}^{OFF}	0.045	-0.108	-0.078^{**}	-0.049	0.096	0.063	-0.004	-0.029
	(0.074)	(0.071)	(0.033)	(0.032)	(0.076)	(0.078)	(0.034)	(0.032)
δ_{τ}^{OFF}x 10	0.000	0.196^{**}	0.095^{**}	0.060	-0.076	-0.089	0.021	0.005
	(0.085)	(0.087)	(0.042)	(0.045)	(0.090)	(0.092)	(0.047)	(0.048)
Linear Trend	Yes		Yes		Yes		Yes	
Unobs. Heterogeneity	Yes		Yes		Yes		Yes	
Individual Control Variables	Yes		Yes		Yes		Yes	
Time & Occupation Dummies	Yes		Yes		Yes		Yes	
Log-Likelihood	-25,496.70		-98,586.95		-26,292.35		-101,446.18	

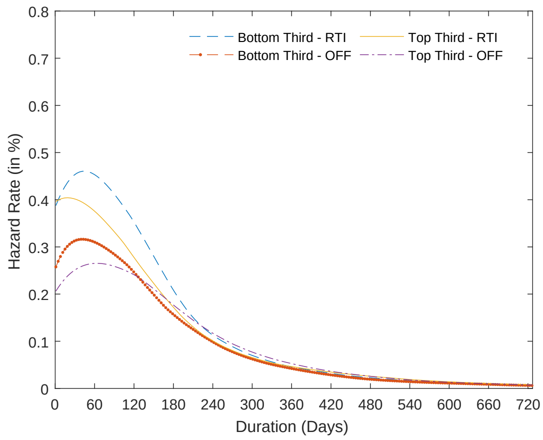
The table shows the estimates for the re-employment hazard θ_{NJ} and wage hazard θ_{ω} only but all models include Out-of-Labor force as an additional exit state. The model includes a linear trend in RTI and OFF using the year 2000 as baseline. In addition to the reported variables, control variables for individual characteristics, time dummies, and occupational dummies defined one a 1-digit level are included in the estimation. Duration dependence is modeled using a flexible piece-wise constant function and the number of mass points for the distribution of unobserved heterogeneity was set to five. 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). High education refers to having at least Matura (University Entrance Exam). 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 fixed and included as constants in the estimation; see Section 3. In total, 211 parameters were estimated. Standard errors are reported in parentheses.

8 Figures

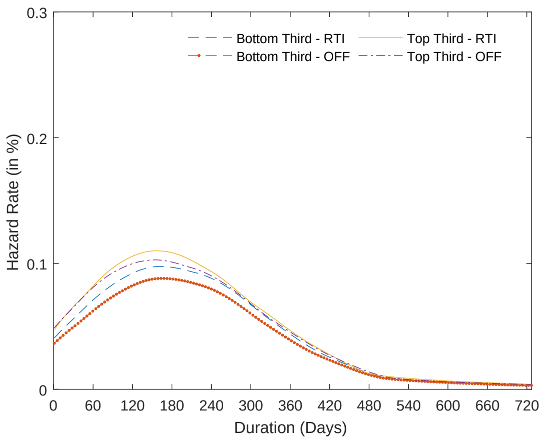
Figure 1: Empirical Transition Rates



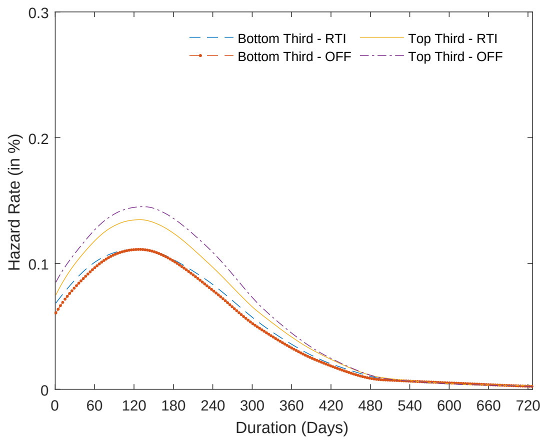
a. Exit Hazards Men



b. Exit Hazards Women



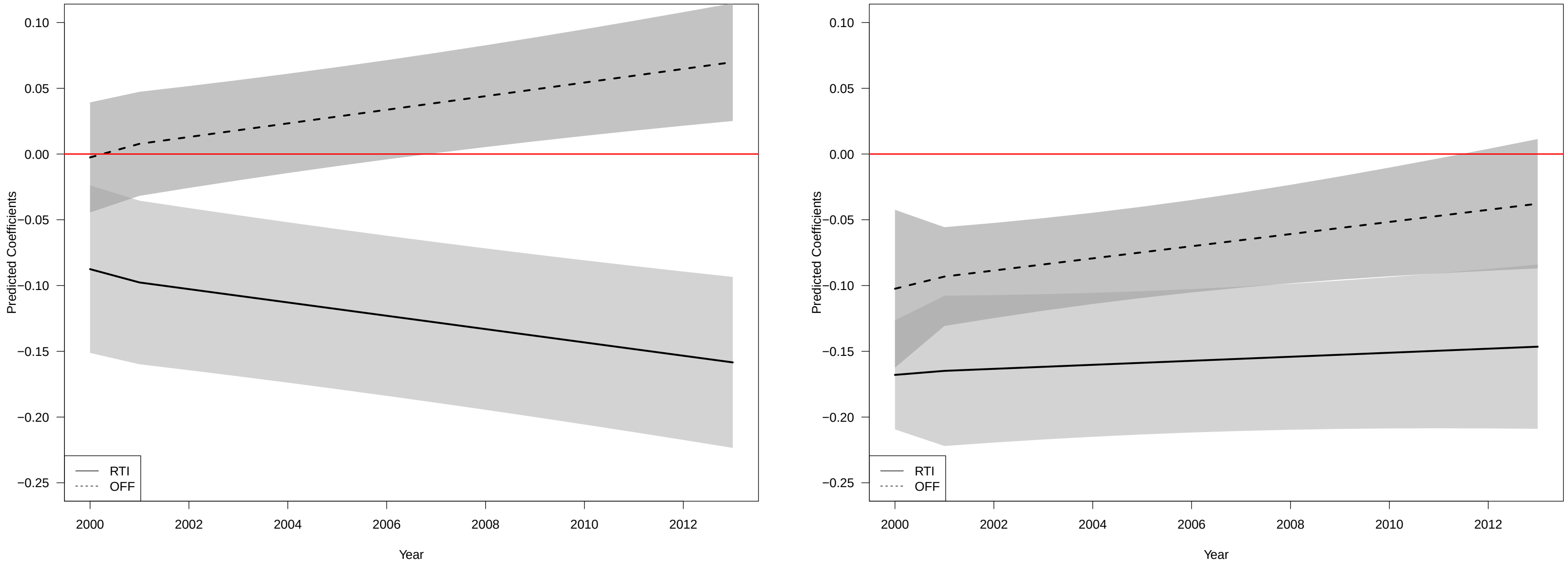
c. Training Hazards Men



d. Training Hazards Women

The upper part of the figure presents the smooth daily exit hazards from unemployment to employment estimated separately for the upper and lower third of the RTI and OFF distribution. The lower part presents smoothed training assignment hazards for the same two groups. The indices are based on Autor and Dorn (2013) and Blinder and Krueger (2013), and were mapped to European classification as in Goos et al. (2014). Hazards were smoothed using the method outlined in Müller and Wang (1994).

Figure 2: Impact of RTI and OFF on Re-Employment Hazard over Time

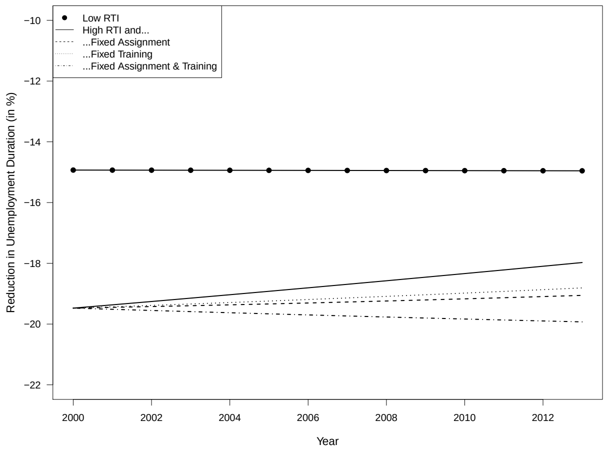


a. Men

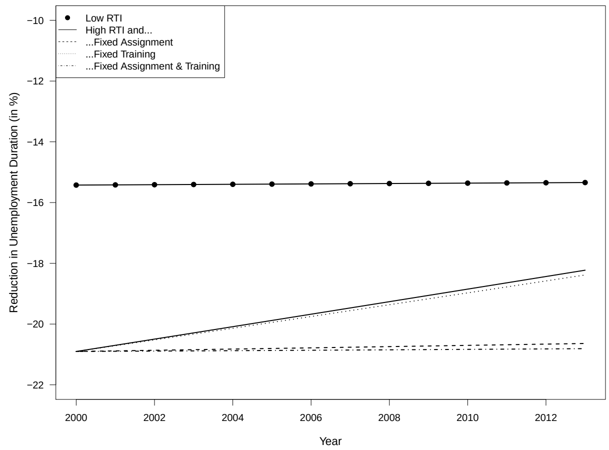
b. Women

The figures depict the estimates of our coefficient on the RTI and OFF for the linear time trend model together with 95% Confidence Intervals for the Re-Employment Hazard. The coefficients for linear time trend model of the RTI (OFF) are depicted by the solid (dotted) line.

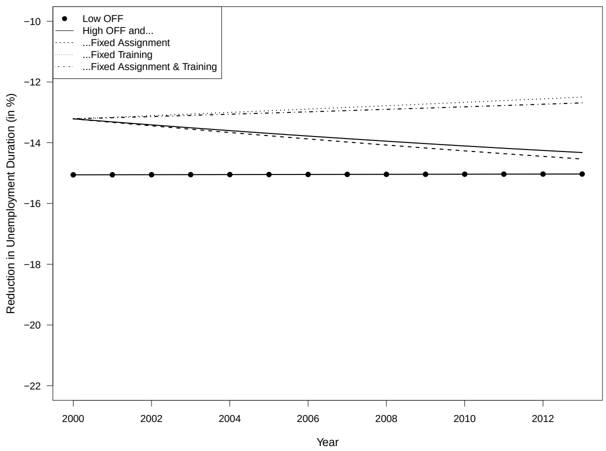
Figure 3: Benefits of Provided Unemployment Training



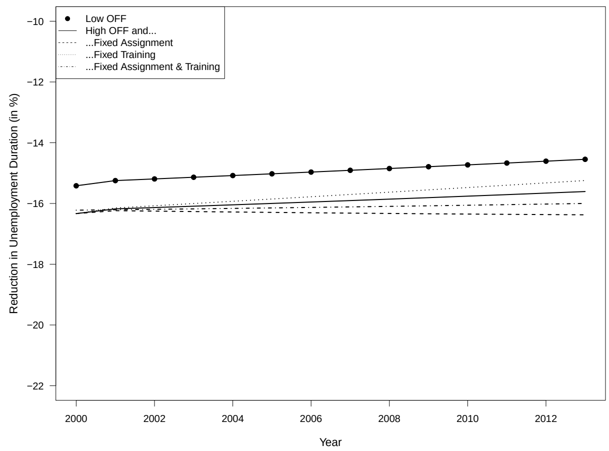
a. Men - RTI



b. Women - RTI



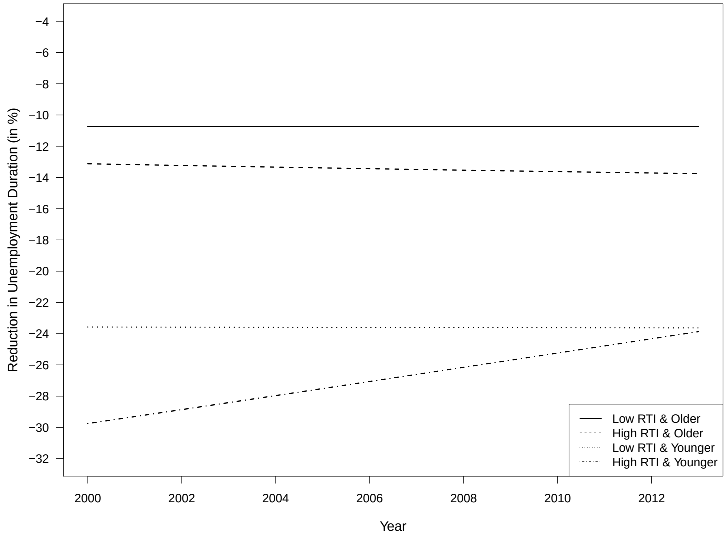
c. Men - OFF



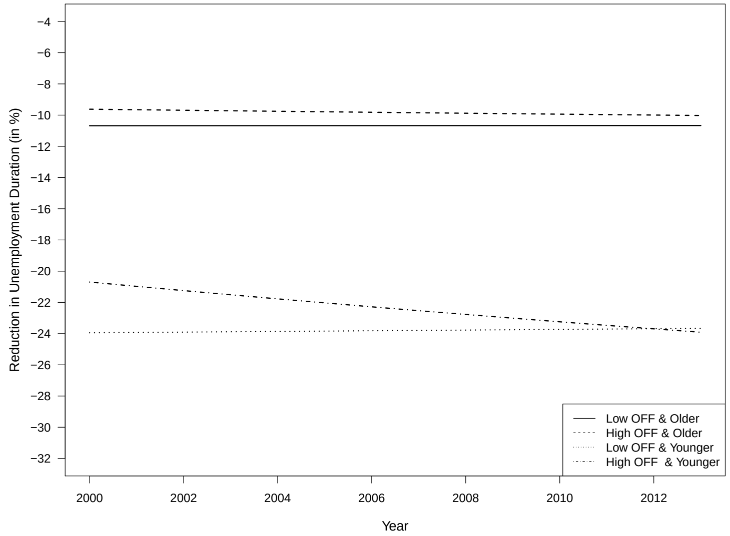
d. Women - OFF

The figure shows the benefits of providing unemployment training over our sample period for high and low values of our RTI (Panel a and b) and OFF (Panel c and d) respectively. The values were obtained by first calculating for each group the expected duration until training, then using these simulated values to calculate the duration until re-employment using the average of our covariate in 2000 and our estimates reported in Table 3. To obtain the benefits of provided unemployment training, the obtained durations are standardized by the expected duration until re-employment if no training had occurred; see Section 4 for details. The solid line represents the relative benefits of training setting RTI and OFF to 1 (high). The solid-dotted lines shows the relative benefits of training setting RTI and OFF to 0 (low). Setting RTI and OFF to 1, the dashed and dotted line shows the results if either training assignment or the training programs had had a similar impact as in 2000. Similarly, the dotted-dashed line presents the relative benefits if both assignment mechanism and the impact of programs are as in the year 2000 throughout the sample period.

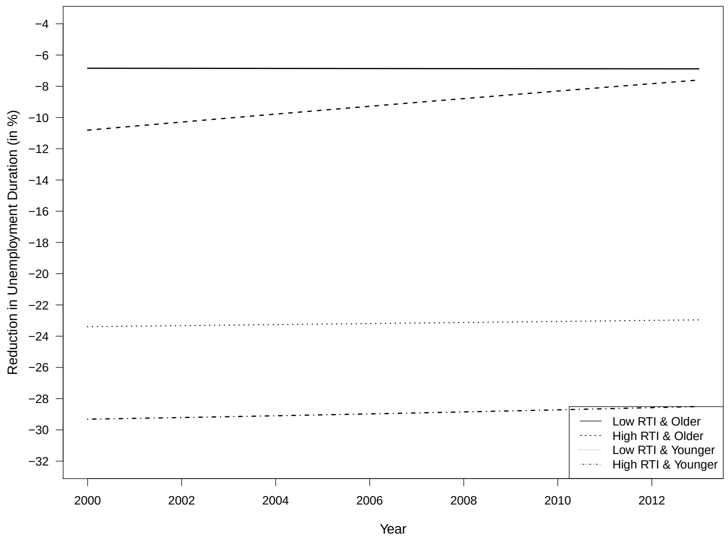
Figure 4: Relative Benefits of Provided Unemployment Training over Time by Age Groups



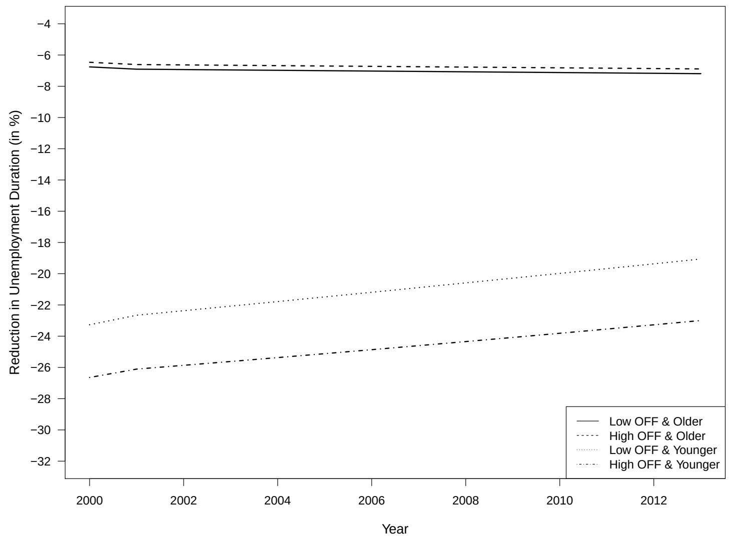
a. Men - RTI



b. Men - OFF



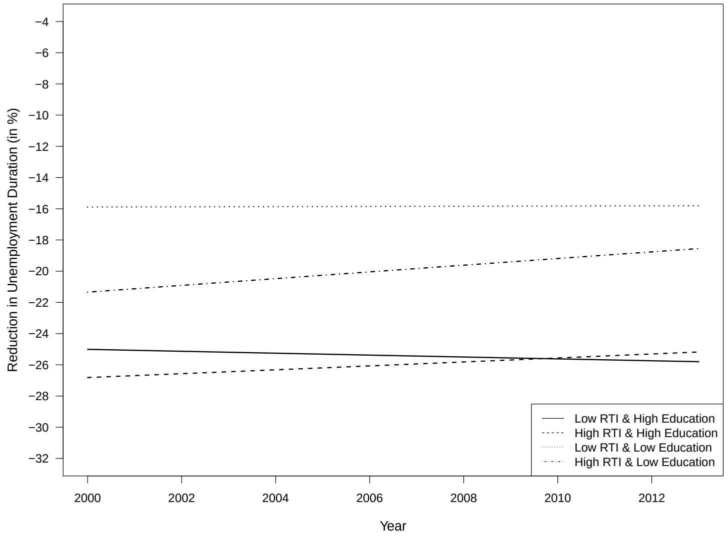
c. Women - RTI



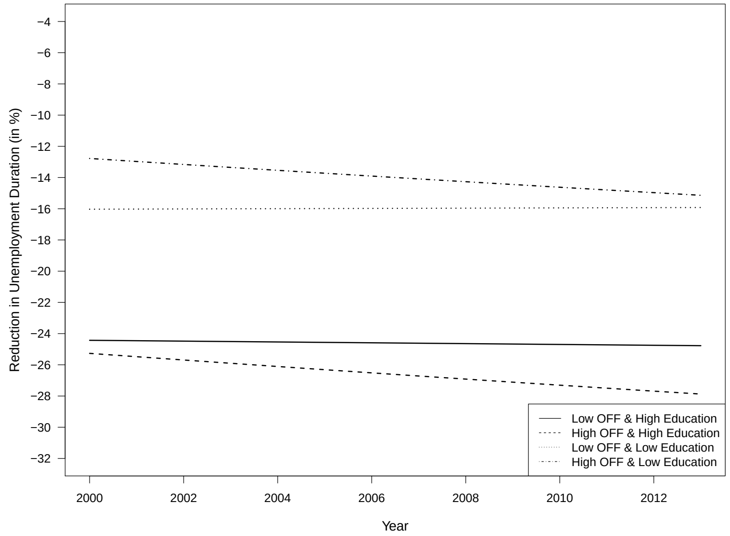
d. Women - OFF

The plots show the relative benefits of providing unemployment training when increasing RTI (Panel a. and c.) and OFF (Panel b. and d.)by one standard deviation. The simulation takes into account that high and low RTI/OFF workers have different baseline unemployment durations and different assignment probabilities. The relative benefits of provided training are calculated using Equation (9) and the expected durations are calculated using the estimates from Table **??** setting all other covariates to their average in 2000. Older workers are all male (female) workers who were at the start of the unemployment spell 41 years (40 years) old.

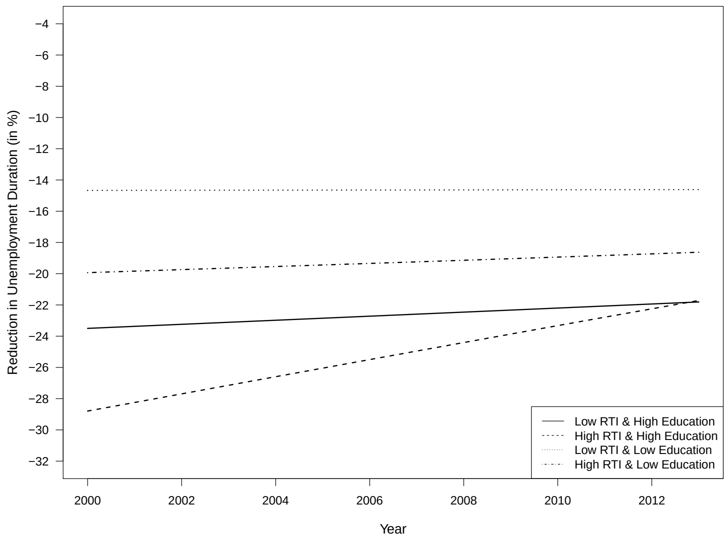
Figure 5: Relative Benefits of Provided Unemployment Training over Time by Education Groups



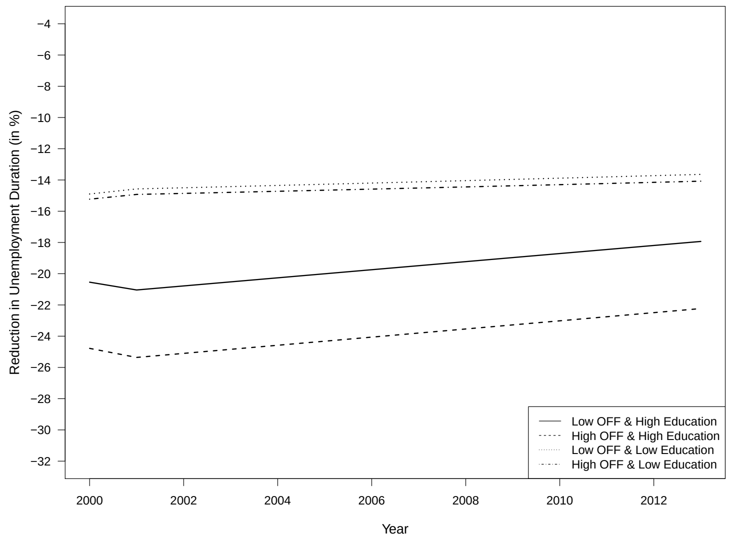
a. Men - RTI



b. Men - OFF



c. Women - RTI



d. Women - OFF

The plots show the relative benefits of providing unemployment training when increasing RTI (Panel a. and c.) and OFF (Panel b. and d.)by one standard deviation. The simulation takes into account that high and low RTI/OFF workers have different baseline unemployment durations and different assignment probabilities. The relative benefits of provided training are calculated using Equation (9) and the expected durations are calculated using the estimates from Table **??** setting all other covariates to their average in 2000. Low educated workers are all individuals who hold at most a high-school degree/ apprenticeship.

Online Appendix for "Automation, Offshoring, and the Role of Public Policies"

Bernhard Schmidpeter

Rudolf Winter-Ebmer

June 24, 2019

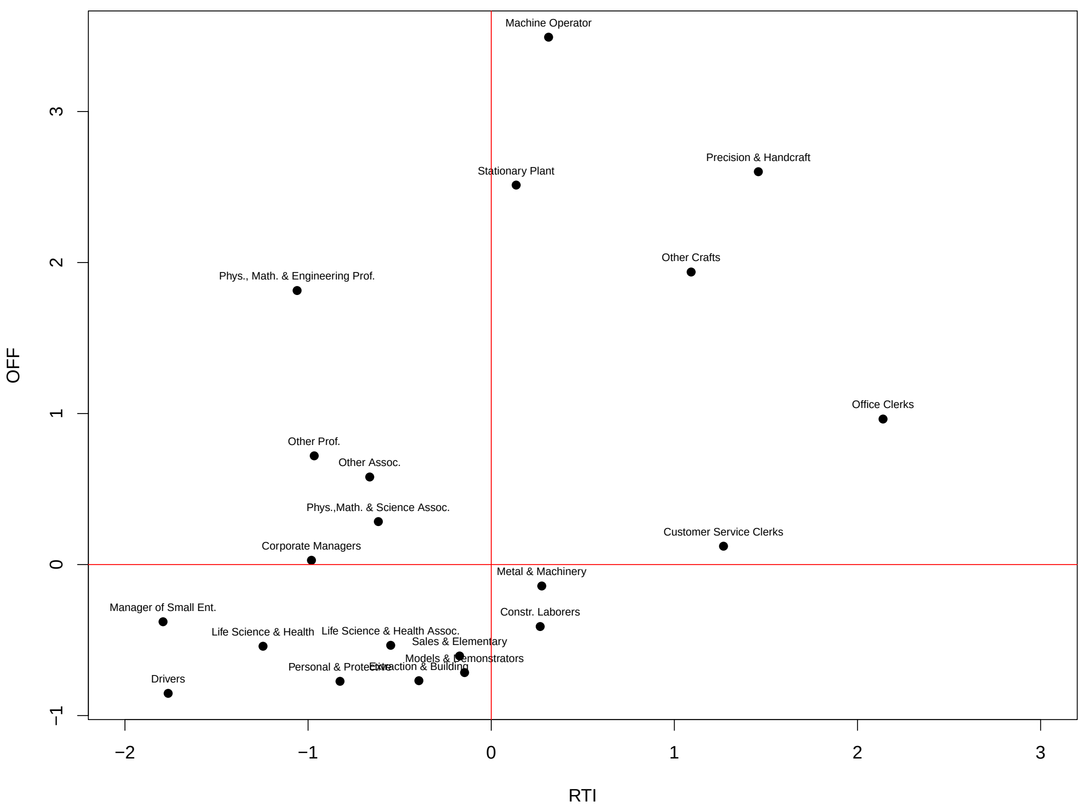
A Occupations

Our data contains information about the last occupation of the unemployed worker using the Austrian public labor market administration (AMS) occupational classification. The AMS also provides a cross-walk file which allows us to map their classification into the 4-digit ISCO 88 classification. Goos et al. (2014) provide a mapped version from the US occupational classification system of the RTI and OFF index of Autor and Dorn (2013) and Blinder and Krueger (2013) to ISCO 88 on a two digit level. We use this information and the AMS mapping file to merge both the Routine Task Intensity Index (RTI) and Offhosreability Index (OFF) to our data. We then normalize these indices to have a mean of zero and a standard deviation of one in our estimation samples.

Figure A.1 provides an overview over the occupations used in our estimation together with their RTI and OFF index. As one can see from the figure and discussed in the main part of the paper, RTI and OFF are not perfectly correlated. There are numerous occupations with a low value of RTI and a high BK and vice versa. For example, tasks performed by individuals in Physic, Mathematical, and Engineering Professional occupations have a relatively high risk of being offshored but a low risk of being automated. Likewise, the tasks performed by Customer Service Clerks are at a low risk of being offshored but at a high risk of being automated. By including both RTI and OFF index in our model, we are able to capture both effects on the carrer of unemployed workers.

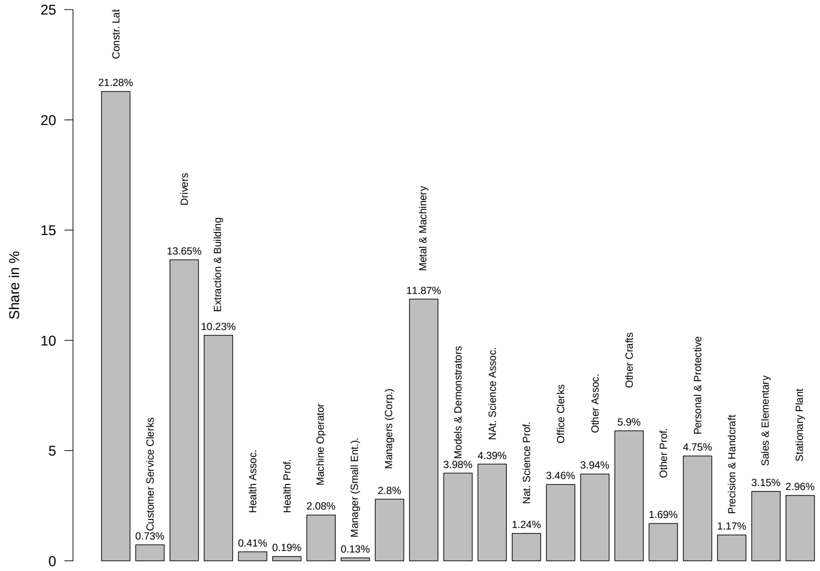
Figures A.2 and A.3 give an overview of the share of unemployed workers within each occupation in our sample and across time respectively. For men, individuals who used to work in the construction sector are the largest group in our sample, followed by Drivers, and Metal and Machinery. For women, individuals who were employed in Model & Demonstrator occupations, Office clerks, as well as those who used to work in Protection & Personal service are the three largest groups. As can be seen in A.3, the distribution of the occupational shares also remained relatively stable throughout our sample period.

Figure A.1: Occupations

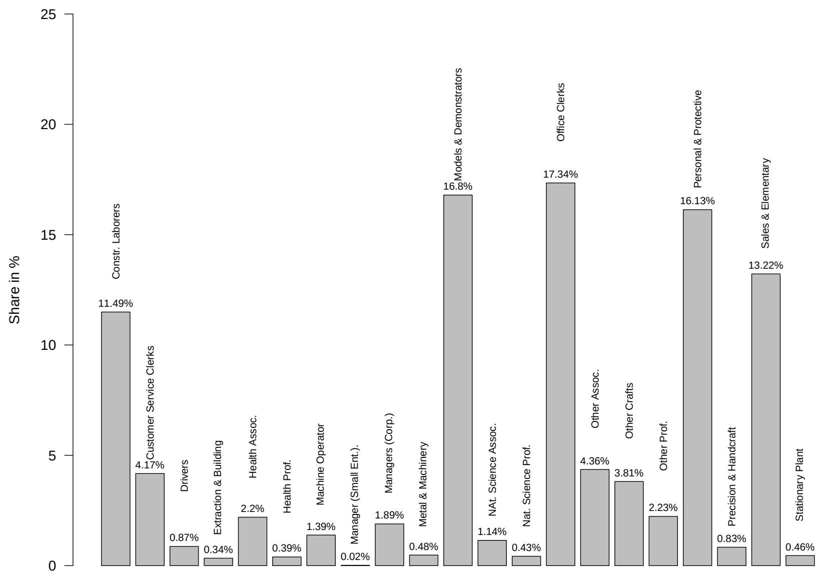


The figure presents a scatter plot of occupations used in our analysis. The x-axis depicts the Routine Task Index (RTI) of Autor and Dorn (2013) and the y-axis the Offshoring Index (OFF) of Blinder and Krueger (2013). Both indices were mapped to European occupational classifications by Goos et al. (2014) and are standardized to have a mean of zero and a standard deviation of 1.

Figure A.2: Distribution of Occupations in Total Sample



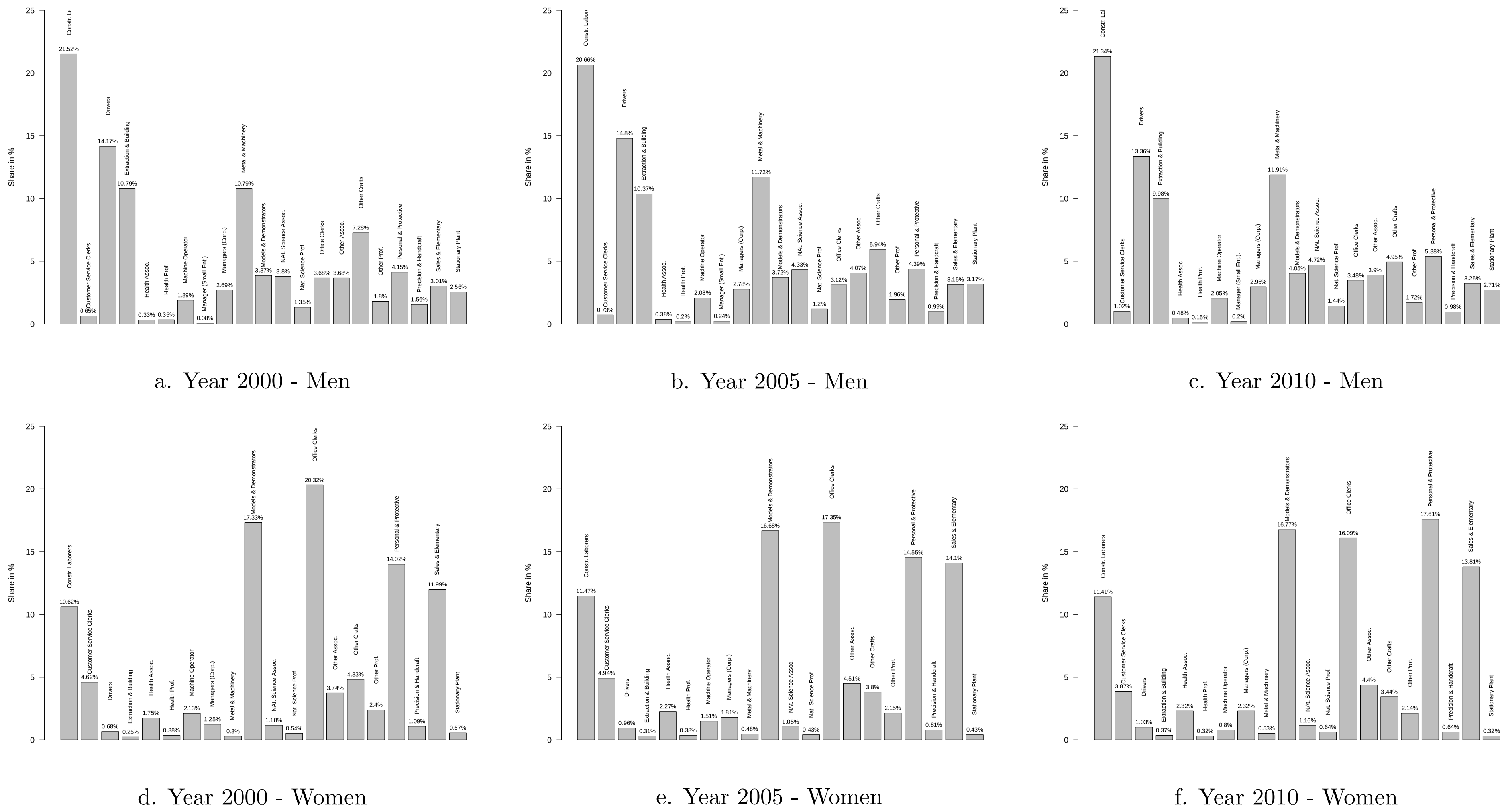
a. Total Sample - Men



a. Total Sample - Women

The figures shows the share of each occupation in our sample defined according to 2-digit ISCO-88 classification for the total sample.

Figure A.3: Distribution of Occupations Across Time



a. Year 2000 - Men

b. Year 2005 - Men

c. Year 2010 - Men

d. Year 2000 - Women

e. Year 2005 - Women

f. Year 2010 - Women

The figures shows the share of each occupation in our sample defined according to 2-digit ISCO-88 classification for selected years.

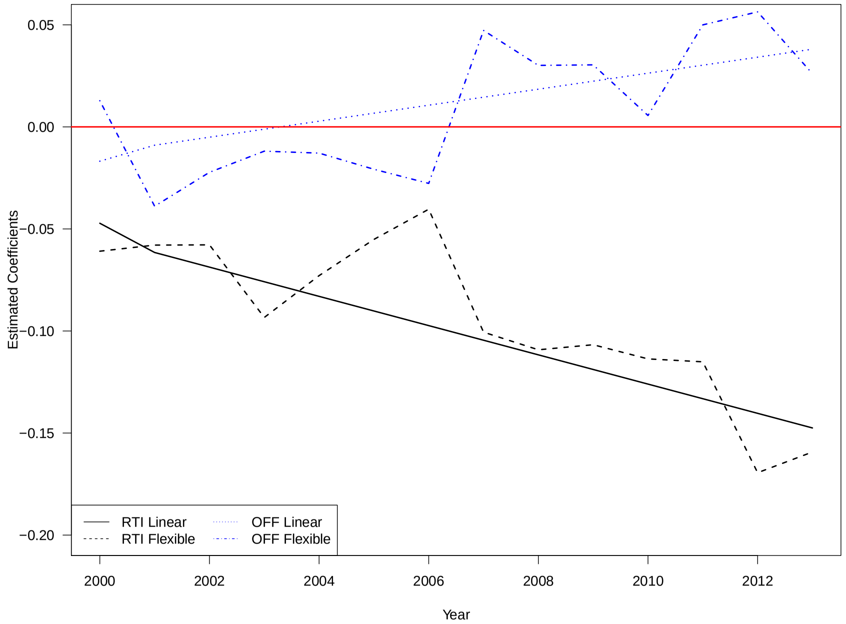
B Additional Results

B.1 Justification of Linear Time Trend

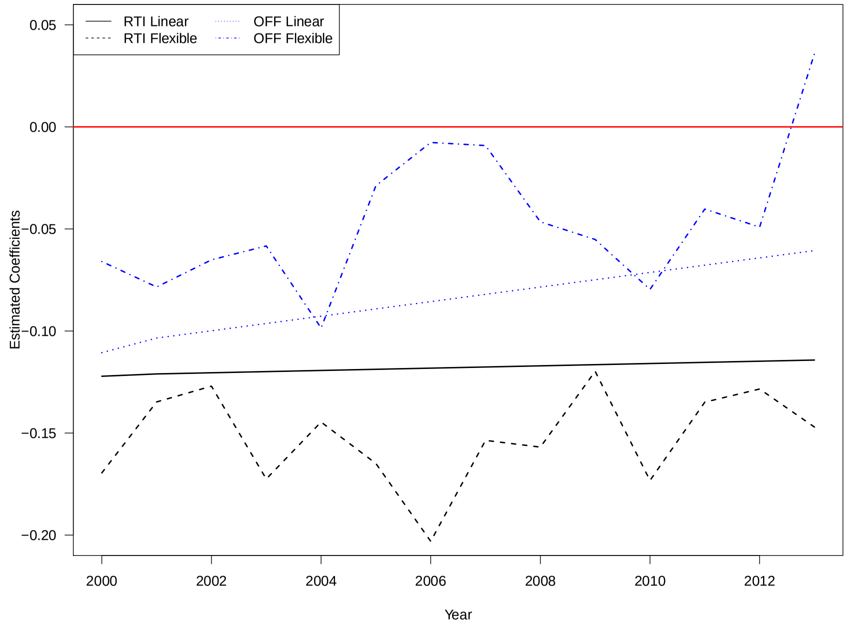
While we could estimate all models using a full set of interactions between our time dummies and the RTI and OFF index, this would substantially increase the number of parameters to be estimated and thus the estimation time. To circumvent this problem but still be able to gain insights into how the impact of occupational change has intensified, we estimate a model using linear time trends. Although simplistic, the model provides a good approximation when compared to a fully flexible model. Figure B.1 depicts the estimated coefficient for the re-employment hazard of our linear time-trend model and the coefficients from a model where the temporal impact of RTI and OFF is not restricted. Figures B.2 does the same for the treatment hazard.

From the figures it is clear, that using a linear trend to capture changes in employment possibilities related to occupational changes is a very good approximation. Our unrestricted estimates are very close to our linear approximation for both men and women for most of our time periods. Thus, we are confident that our simple way of capturing changes in the impact of RTI and OFF over time gives valuable insights with only little trade-off in terms of assumptions.

Figure B.1: Estimate of Coefficient in Fully Flexible and Linear Time Trend Model - Re-Employment Hazard



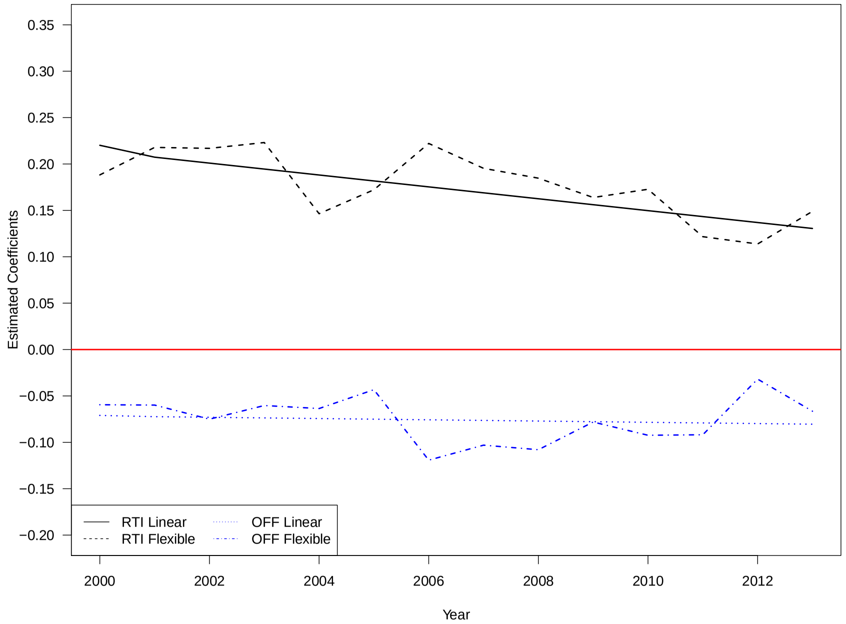
a. Men



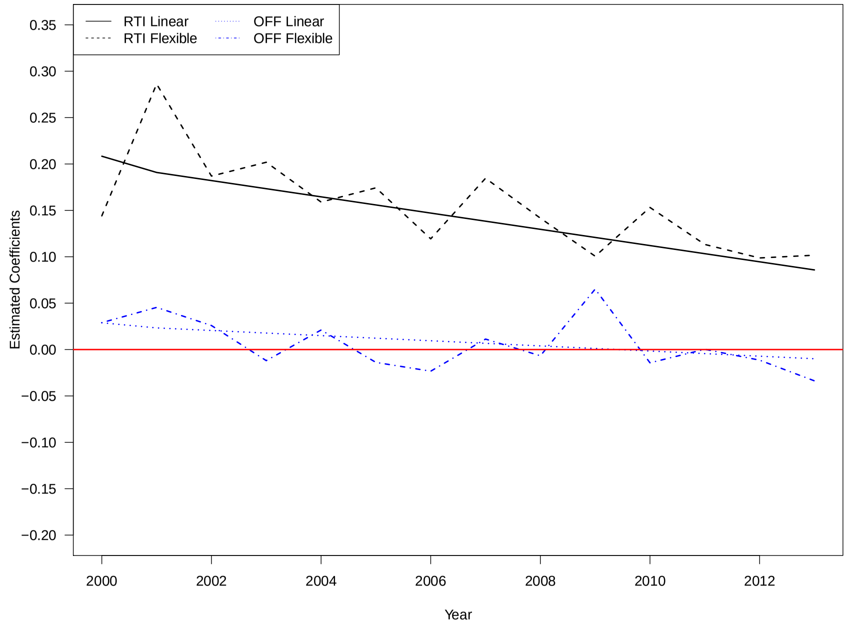
b. Women

The figures depict the estimates of our coefficient for the re-employment hazard on the RTI and BK for the fully flexible time trend model and linear time trend model separately for men and women. The coefficients for linear time trend model of the RTI (BK) are depicted by the solid (dotted) line. The coefficients for the fully flexible time trend model of the RTI (BK) are depicted by the dashed (dashed-dotted) line.

Figure B.2: Estimate of Coefficient in Fully Flexible and Linear Time Trend Model - Treatment Hazard



a. Men



b. Women

The figures depict the estimates of our coefficient for the treatment hazard on the RTI and BK for the fully flexible time trend model and linear time trend model separately for men and women. The coefficients for linear time trend model of the RTI (BK) are depicted by the solid (dotted) line. The coefficients for the fully flexible time trend model of the RTI (BK) are depicted by the dashed (dashed-dotted) line.

B.2 Estimates without Trend & Treatment Effect Heterogeneity

In this part of the Appendix, we present results from a very basic model where we ignore possible heterogenous training effects and time-varying impact of occupational changes. These estimates show the the importance of allowing for more flexibility in our estimation. Table B.1 shows the results from our simple model. For the sake of brevity, we only report the coefficients on our variables of interest. The upper panel of the table contains the effect of routine job content and offshorability on the hazards, the lower panel the effect of training on the re-employment and OLF hazard. We will discuss our results first for men and then for women.

Looking at the impact of RTI and OFF on the probability of training assignment for men, one can see that those previously employed in jobs with higher risk of automation are more likely to be assigned to ALMP while individuals in jobs with higher risk of offshoreability are less likely to receive unemployment training. The estimated coefficients are with 0.147 (s.e. 0.045) and -0.06 (s.e. 0.028) large in magnitude and highly significant. This implies that an increase of our RTI by one standard deviation, or entering unemployment as a cashier rather than as a welder, increases the likelihood of receiving training by around 16%. In contrast, an increase in our BK by one standard deviation, which corresponds to the distance between a plant and and a machine operator decreases the probability of being assigned to training by around 6%.[1]

We find almost the opposite impact of RTI and OFF, when looking on the re-employment hazard. Being at a higher risk of automation significantly reduces the likelihood of finding a new job. A one standard deviation increase in our RTI reduces the re-employment hazard by almost 10%. We do not find that OFF has any significant effect on re-employment and our estimated coefficient is very small in magnitude. Likewise, in our simple model, neither RTI nor OFF has an effect of leaving the labor force for men.

The second part of the table reports the results for women. Similar to what we have found for men, female workers previously employed in occupations at higher risk of automation have a significantly higher probability of getting assigned to training (coef. 0162 with s.e. 0.039). Unlike it was the case for men, we do not find that previous OFF status is affecting the case worker's decision. Our estimate for OFF is very close to zero.

We also find a similar but slightly bigger effect of our RTI on the re-employment likelihood and substantially lower effects on leaving the labor force for women. A one standard deviation increase decreases the likelihood of finding a new job by around 12% and the probability of leaving the labor force by around 10% . In contrast to our results for men, our estimates also indicate that the probability of re-employment and leaving the labor force also significantly depends on our OFF. A one standard deviation increase in our OFF decreases the re-employment likelihood by 8% and increases the likelihood of leaving the labor force by around 4%.

Our estimated training effects for women are comparable to those for men. Training assignment increases both the re-employment probability but also the likelihood of leaving the labor force. These estimates are highly significant.

Comparing our estimates to those presented in Section 4, one can see that this simple model conceals substantial heterogeneity both in terms of developments over time and the effectiveness of training assignment. These changes have, however, important implications when determining the effectiveness of training.

[1] Remember, we normalized the standard deviation to 1. A welder has a RTI of 0.27 and a cashier of 1.28. Plant and machine operators have a OFF of 2.51 and 3.49 respectively.

Table B.1: Homogenous Treatment Effects

	Male			Female		
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$
Panel a. Occupational Requirements						
γ^{RTI}	0.172^{***}	-0.083^{**}	-0.027	0.158^{***}	-0.146^{***}	-0.095^{***}
	(0.045)	(0.035)	(0.035)	(0.038)	(0.031)	(0.029)
γ^{OFF}	-0.072^{***}	0.006	0.029	0.004	-0.059^{***}	0.034^{*}
	(0.028)	(0.022)	(0.022)	(0.026)	(0.021)	(0.020)
Panel b. Training						
δ		0.402^{***}	0.106^{***}		0.488^{***}	0.086^{***}
		(0.017)	(0.018)		(0.018)	(0.018)
Linear Trend	No			No		
Unobs. Heterogeneity	Yes			Yes		
Individual Control Variables	Yes			Yes		
Time & Occupation Dummies	Yes			Yes		
Log-Likelihood	-95,491.41			-92,765.25		

OLF refers to Out-of-Labor Force. In addition to the reported variables, control variables for individual characteristics, time dummies, and occupational dummies defined one a 1-digit level are included in the estimation. Duration dependence was modeled using a flexible piece-wise constant function and the number of mass points for the distribution of unobserved heterogeneity was set to seven; see Section **??**. In total, 144 parameters were estimated. Standard errors are reported in parentheses.

References

Autor, D. H. and Dorn, D. (2013), 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market', *American Economic Review* **103(5)**, 1553–1597.

Blinder, A. S. and Krueger, A. B. (2013), 'Alternative Measures of Offshorability: A Survey Approach', *Journal of Labor Economics* **31**(2), S97–S128.

Goos, M., Manning, A. and Salomons, A. (2014), 'Explaining Job Polarization: Routine-Biased Technological Change and Offshoring', *American Economic Review* **104(8)**, 2509–2526.