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How do Automation and Offshorability Influence Unemployment Duration and Subsequent Job Quality?*

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Abstract

We analyze the effect of automation and offshorability on unemployment duration and post-unemployment outcomes such as wages and employment stability. Our rich administrative data allow us to evaluate the importance of providing unemployment training in this context. Employing a multivariate mixed proportional hazard model to deal with selectivity, we find that both the routine content in tasks as well as the probability of off-shoring negatively affects the re-employment possibilities. Labor market training is helping workers to ameliorate these negative effects and is remarkably on the spot. For workers who find re-employment, our results show that offshorability (but not automation) affects future job duration and wages positively. Our analysis reveals interesting differences by gender.

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1 Introduction

Over the past years, there have been substantial changes in the labor market with employment increases overwhelmingly concentrated at the lower and upper part of the wage distribution (Acemoglu and Autor, 2011). This "hollowing out", also known as polarization, has been documented for numerous developed countries such as the US (Autor et al., 2006, 2008; Autor and Dorn, 2013), 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 large part of the existing literature, which explores this phenomenon, traces its development back to an increasing routinisation of tasks in jobs found at the middle of the wage distribution and a rising risk of offshorability (e.g. Autor et al. (2006), Autor et al. (2008), and Firpo et al. (2011)). Making tasks routinisable is seen as a main pre-condition for later automation of these tasks.[1] On the one side, workers who are directly affected by changing occupational requirements face diminishing employment possibilities, especially when trying to re-enter employment from an unemployment spell (see also Cortes, Jaimovich, Nekarda and Siu (2016)). On the other hand, some workers might benefit from these changes as they can complement labor and increases employment opportunities (see, for example, Graetz and Michaels (2015) and Caselli and Manning (2017)).

Despite the growing literature on automation and offshoreability of jobs surprisingly little is known about the individual consequences, especially the impact on unemployed workers. Occupational changes can not only affect the search behavior of unemployed workers but also their post-unemployment wages and match stability. For example, workers who are negatively affected by automation might have pro-longed unemployment spells and lower re-employment wages. Assignment to active labor market policy (ALMP), in particular providing training episodes, might mitigate these negative impacts. Understanding the connection between previous job contents, post-unemployment outcomes, and training programs is important for at least two reasons.

First, the risks of automation as well as offshorability are likely to affect both the search behavior of unemployed individuals and their ability to find stable post-unemployment matches.

[1] 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. See also Acemoglu and Restrepo (2018) on the effect of robots on employment in different industries.

Unemployed individuals who have been negatively affected by such work environments 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. This lowers tax payments and increases the strain on public finances.

Second, given that training programs are in general one of the most expensive labor market programs available and their financing adds to the burden of tax payers, one would hope that these are capable of mitigating the impact of structural changes. As routinisation and offshorability will continue to pose considerable threats to employment, understanding the effect of ALMP to ameliorate these problems is very important. Evidence on this is, however, scant.

In this work, we evaluate the effect of changes in occupational requirements caused by both an increasing automation of routine jobs and a rising risk of offshorability on the job search behavior of unemployed workers and post-unemployment labor market outcomes. In order to measure occupational changes, we make use of the one-dimensional indices suggested by Autor and Dorn (2013) and Blinder and Krueger (2013). In our model, we explicitly account for the impact of ALMP on the unemployment duration and the chosen exit destination, and allow for selection into the training assignment based on unobservable workers' characteristics. We allow the impact of ALMP to depend on both automation and offshorability which gives a measure of its effectiveness in the current work environment. To the best of our knowledge, this is the first research which not only provides a comprehensive analysis of the impact of changes in occupational requirement on unemployed workers' labor market outcomes but also an assessment of the efficiency of provided ALMP.

We find that both automation as well as offshorability significantly decrease the likelihood of re-employment. The importance of each factor differs, however, strongly by gender. For men, we find that offshorability is the dominant force with a one standard deviation increase in our offshorability measure reducing re-employment by 22% compared to 6.5% for a similar increase in our automation measure. For women, we find that automation is more important. Here, a one standard deviation decreases the likelihood of re-employment by 30% compared to 23% for the same increase of our offshorability measure.

Looking at outcomes beyond unemployment duration, we find that offshorability increases future job stability and wages for men and women. In contrast, automation has in general a negative impact on future wages and employment duration. Taken our findings together, our results imply that while job opportunities for workers previously employed in highly offshoreable jobs decrease, those who are able to secure a job enjoy higher employment stability and wages. Workers affected by automation have, however, lower job finding probabilities and job stability as well as lower expected earnings.

Evaluating the effectiveness of ALMP, our results show that training assignment is incredibly on the spot: training measures are predominantly assigned to persons with the largest problems. ALMP also increases, in general, the re-employment likelihood to a large extent – in particular of those who suffer the most from automation or offshorability. The impact of ALMP on later wages or future employment duration is more mixed.

The remainder of this paper is organized as follows: In the next section, we discuss the data used in our analysis and describe our measures of automation and offshorability. In Section 3, we provide preliminary evidence on the effect of our measures on the re-employment probability and show that, despite the shift in employment, medium-skilled occupations do not completely disappear. Our estimation method is described in Section 4. We present and discuss our estimation results in Section 5. Section 6 concludes.

2 Data and Measures of Skill Requirements

2.1 Data

Our analysis is based on the Austrian Social Security Data, a high-quality administrative data set which comprises the whole universe of Austrian workers employed in the private sector. As documented in Goos et al. (2009) and Goos et al. (2014), Austria has experienced a similar path of employment polarization from the 1990s onward as most other European countries and the US.

Our data at hand contains daily information about the labor market spells of an individual, demographic characteristics and yearly incomes, which can be transferred into daily wages. A unique person identifier enables us to link every individual to firms. Zweimüller et al. (2009) provide an extensive discussion. A drawback is that we cannot observe the occupation of re-employment in our data. Hence, we cannot study whether switching out of a highly routinisable job is worthwhile.

For our analysis, we choose all individuals who had at least one unemployment spell during the years 2012 and 2013, a period marked by stable economic growth[2], and were, at the start of the spell, between 25 and 60 years old. We set the lower age bound at 25 years as younger individuals might choose to return to full-time schooling. The upper bound is chosen to be around the official early retirement age, as we are interested in how changing skill requirements affect the decision to leave the labor force, in particular toward out of labor force and retirement. We exclude individuals previously employed in the mining sector or in the provision of utilities such as energy or waste disposal.

After these adjustments our data consist of around 286,000 individuals. From these data, we randomly draw 35,000 males and females, respectively, and for each individual we record the number of unemployment spells during the time span under consideration. 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 has received training during the current spell. We observe the last possible exit at the 31st of May 2014, implying that some individuals are censored after 2 1/2 years while others are censored after 6 months, depending on the start of the unemployment spell. Table 1 provides summary statistics for our data.

[Table 1]

From the table one can see that each individual is on average observed twice in our data. The outflow rate out of unemployment is 86% for both men and women, but there are substantial gender differences in the chosen exit destinations. Around 60% of all men transit from unemployment into new employment, while only slightly over 50% of women do so. In contrast, 33% of all women and 27% of men leave the labor force.[3] These statistics highlights the importance to allow for non-employment as an additional exit option in our analysis.

In terms of background characteristics, one can see that while women have slightly higher tenure in the previous job they earned substantially less. They are also less likely to hold an apprenticeship or high-school degree, but are more likely to have received at most compulsory schooling. The difference in the share of highly educated individuals between men and women

[2] Jaimovich and Siu (2015) show that routine intensive occupations are in particular affected by recessions and Hershbein and Kahn (2016) argue that this is due to a movement toward high-skilled workers and labor saving technology.

[3] We consider an individual as out of labor force if she is not registered as unemployed anymore and the next employment spell starts at least 60 days after that date.

is, however, small as is the age difference. Given the large divergence in important background variables such as previous labor market performance, exit state, and training received, we will conduct our analysis separately for men and women.

2.2 Measuring Occupational Skill Requirements

We are interested in how changing occupational requirements affect the search behavior of unemployed workers. In order to capture these effects, 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). We define routine tasks as tasks which can be fully and exactly described, as is e.g. done in a computer program. Workers in occupations with a higher routine task intensity are therefore at higher risk of being replaced by computers or robots (see also Autor et al. (1998)). The RTI summarizes the routine task activities in an occupation and 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. The measure is increasing in the importance of routine tasks within an occupation. It has been used in various studies which investigate the effect of a changing work environment, such as Goos et al. (2014).[4]

Solely concentrating on the effect of routine tasks on unemployment duration might miss important points in determining the effects of a changing work environment on unemployment duration. While high routine workers are at higher risk of being replaced by computers and robots, individuals working in occupations which can be easily migrated to different countries might also have lower career prospects. In order to measure this effect, we will make use of the preferred measure of Blinder and Krueger (2013). They use the Princeton Data Improvement Initiative to derive three measures of offshorability which are self-reported, inferred, and based on professional coders. The last one is preferred by Blinder and Krueger (2013) which we will call

[4] 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.

Offshorability Index (OFF) hereafter. The OFF index determines the risk that tasks required by an occupation, and therefore employment, might be “offshored” or outsourced to a different country. It measures a different dimension compared to the RTI as it captures the risk for tasks or jobs where the geographic location does not matter for fulfilling the job requirements. Thus, a high RTI does not necessarily imply a high OFF index. 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[5].

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 the respective samples. In Appendix A, we provide further details on the occupations used in our analysis, the share of each occupation within our sample and average pre- and post-unemployment wages.

3 Descriptive information

In this section, we present results from a preliminary analysis. The goal is to investigate the relationship between our measures of occupational task requirements and both the allocation into training and the likelihood of finding new employment. We do so by first dividing our sample into different parts according to the individual position in the distribution of both the RTI and OFF index. We then concentrate on those individuals who worked before the unemployment spell in occupations which fall into either the bottom third or the upper third 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 in the case of the RTI and Science Professionals and Machine Operators in the case of the OFF index. 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, Jamovich and Siu (2016)

[5]As it is the case with the RTI, we make use of the mapped index provided by Goos et al. (2014)

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 propensity 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.

Looking first at the transition rates from unemployment to employment at the upper panel of the figure, two features become immediately apparent. First, for both men and women transition rates into re-employment are substantially higher at lower values of our indices during the first six months of the spell. This is true for both the RTI and OFF index and provides preliminary evidence that occupational skill requirements do indeed affect the probability of finding a new job, especially in the short run. For long term unemployed individuals, the occupational characteristics matter less which may imply that the previous occupation does not matter any more, but stigma effects as a long-term unemployed may prevail (e.g. Eriksson and Rooth (2014)). Second, one can see pronounced gender differences in what type of occupational requirements are more important. Men with lower OFF index have a slightly higher transition rate into employment. The opposite is true for women. Those previously employed in low routine occupations have a 0.25 Percentage point higher transition rate after 2 months. This is likely to be the result of gender specific sorting into occupations (e.g. Black and Spitz-Oener (2010)).

[Figure 1]

One explanation for our preliminary findings might be that jobs affected by structural change simply disappear. To investigate this further, we also look at vacancy postings during our sample period 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.[6] Table 2 contains the yearly share of vacancies

[6]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

posted by 1-digit levels and the annualized growth rate.

Groups associated with both a high RTI and OFF index, such as office clerks, have experienced a lower growth in the share of open positions over time. In contrast, positions associated with management or professional positions have seen a rise in the relative share of vacancies posted. The vacancy postings provide suggestive evidence that our measures of occupational changes are related to job opportunities. The figures also show that, despite the well documented fall in the employment share in certain occupations, there is no evidence that these types of jobs completely disappear.[7]

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, if firms specialize in certain tasks (Cortes and Salvatori, 2016) the total number of vacancies posted for a certain occupation decreases but remaining firms might have higher productivity and are able to offer higher wages and better job stability. We will explore this implication later in our work.

We find less clear evidence when looking at the impact of occupational requirements on training assignment. The results are shown at the lower panel in Figure 1. At the beginning of the unemployment spell, men at the upper part of the OFF index distribution do not receive more likely training compared to those with high RTI values; later on there is a slight divergence after 4 to 6 months. For women, we see small differences at the beginning of the spell. Those at the upper part of the OFF distribution are more likely to receive training.

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 if decision makers are aware of the consequences. The simple analysis presented here has, however, obvious shortcoming in order to form the grounds of a well-defined policy debate. We have abstracted from covariates and unobserved heterogeneity of individuals which are certainly important for a detailed analysis. In addition, we did not take the joint timing and the decision process of the training assignment together with the exit decisions into account. Allowing for correlation between these processes is certainly important.

document "Offene Stellen lt. Offene-Stellen-Erhebung nach ausgewählten Merkmalen, Jahresdurchschnitt 2011 bis 2016".

[7] 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".

4 Econometric Framework

Disentangling the effect of occupational requirements from unemployment training is a difficult task. Assignment to training during the unemployment spell is related to numerous factors and it certainly may be 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 heterogeneity, occupational changes, 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 multi-spell data which facilitates identification. Abbring and van den Berg (2003*b*) show that the effect of the ALMP can be identified without any parametric assumption or exclusion restriction.[8] An additional advantage of the method is the possibility to model the treatment effect in a flexible way (see Richardson and van den Berg (2013)). We will exploit this when evaluating the effectiveness of ALMP in relation to structural changes.

The key underlying identifying assumption of our model is the so-called no-anticipation assumption. This assumption implies that future program participants do not foresee the exact assigned start of the course and, as an immediate implication, it is required that training only has an effect on the exit hazard from the actual participation date onward. However, 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, but they should not know the exact date of an assignment. 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), Osikominu (2013).

Given the recent discussion in the literature (see, for example, Cortes, Jamovich and Siu (2016)), we consider both the exit into new employment (NJ) and the transition into out of labor force (OLF) in our analysis. By incorporating the possibility of choosing OLF as an exit destination, we are able to measure the effect of job contents on the most likely selective decision to participate in the labor market in the first place.

We assume that the exit and treatment transition rates have a mixed proportional hazard

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

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

$$\theta_e(T|x, \nu_e, D) = \lambda_e(T) exp(x'\beta_E + \gamma_e^{RTI} RTI + \gamma_e^{OFF} OFF + \delta(x)\mathbb{1}(T > D) + \nu_e) \qquad (1)$$

In our exit hazard, $\lambda_e(T)$ represents the baseline hazard, displaying individual duration dependence, which is fully flexible. The vector x consists of individual observable characteristics and ν_e captures the unobserved heterogeneity on the exit rate. We are particularly interested in the coefficients on RTI, our Routine-Index, and OFF, the risk of employment being offshored. The parameter $\delta(x)$ captures the shift in the exit hazard due to labor market policies. We allow $\delta(x)$ to depend on covariates. For example, in order to evaluate if training is more effective in dampening the effect of changing task requirements or outsourcing, we model the treatment effect to depend on routinisation and offshoreability job contents. [9] If an individual receives training, we "stop the clock" and the time spent in training does not contribute to the unemployment duration. We do this as individuals are likely to stop actively looking for new work during the training activity.[10]

Likewise, we model the arrival rate of labor market policies (treatment hazard) as

$$\theta_P(D|x, \nu_P) = \lambda_P(D) exp(x'\beta_P + \gamma_P^{RTI} RTI + \gamma_P^{OFF} OFF + \nu_P) \qquad (2)$$

Here ν_P captures unobserved heterogeneity on the treatment hazard and the vector x consists of possible confounding factors. γ_P^{RTI} and γ_P^{OFF} capture the dependence of ALMP on the previous job content.

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 transition 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

[9] The identification of this model was proven in Richardson and van den Berg (2013).

[10] 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.

Singer (1984). The associated probability for having M possible mass points is parametrized in the following way

$$p_m = P(\nu_{NJ} = \nu_{NJ}^m, \nu_{OLF} = \nu_{OLF}^m, \nu_P = \nu_P^m) = \frac{exp(\alpha_m)}{\sum_{m=1}^{M} exp(\alpha_m)} \tag{3}$$

Parameterizing the probabilities in this fashion avoids constrained maximization. In our empirical specification 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_i (or censoring) and the time to having a job $D_{i,}$ (or censoring) for each of these individuals, the log-likelihood function for our empirical model is defined as

$$\begin{aligned} L = \sum_{i=1}^{N} \log \Bigg\{ \sum_{m=1}^{M} p_m \prod_{j=1}^{J_i} \prod_{e=1}^{E} \theta_e(T_{ije}|x_{ije}, \nu_e^m, D_{ije})^{\Delta_{ij,e}} \exp\left(- \int_0^{T_{ije}} \theta_e(T_{ije}|x_i, \nu_e^m, D_{ije}) \right) \\ \theta_P(D_{ij}|x_{ij}, \nu_P^m)^{\Delta_{ij,P}} \exp\left(- \int_0^{D_{ij}} \theta_P(D_{ij}|x_{ij}, \nu_P^m) \right) \Bigg\} \end{aligned} \tag{4}$$

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

Note 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 restriction greatly facilitates identification of our model and has the big advantage that the chosen exit state is allowed to depend on the unobservable characteristics of the workers (Abbring and van den Berg, 2003*b*; Abbring and Van den Berg, 2003*a*) . This is important in our setting as we allow for selectivity in labor market participation..[11]

[11] In certain circumstances it might be possible that an estimated heterogeneity parameter takes a large negative value, which makes it impossible to invert our 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 heterogeneity points of less than -20. Furthermore, in the optimization process we account for possible degenerate distributions; see also

We are not only interested in the effects of routine content and offshorability on unemployment duration but also how these job contents affect post-unemployment wages and job stability.[12] As we have access to daily labor market spells, we can model the duration of the first employment spell *after* exiting unemployment in a similar way as in Equation (1). Here, the parameters give us estimates how both unemployment training and previous job content is affecting re-employment stability. In order to investigate the effect on subsequent wages, we make use of the estimator suggested by Donald et al. (2000). It allows us to estimate the distribution function of wages in a similar way as hazard functions and can be incorporated in our model in a straightforward manner. We will discuss this approach in greater detail in Section 5.4 below.

5 Estimation Results

5.1 Basic Model

We start with a very basic specification where we assume a homogenous effect of training, regardless of the previous occupation on the exit hazards. This is our baseline model and we call it Model (I) in the following. In the next section, we discuss a simple extension where δ is allowed to depend on both RTI and the OFF index. We report the estimation results using seven mass points of support in our analysis, but the estimates do not depend on the exact number of points chosen.[13]

Table 3 contains the estimation results of our Model (I). For the sake of brevity, we only report the coefficients on our variables of interest. Panel A of the table contains the effect of routine job content and offshorability as well as an interaction effect on the transition probabilities. These are the main variables of interest in our analysis. We first discuss the effect for men and concentrate on the hazard to employment.

Our results confirm available macro studies: both automation and offshorability have a significantly negative impact on the hazard towards a new job. An increase in the RTI and offshorability index by one standard deviation is associated with a fall in the re-employment probability by 6.47% and 22% respectively.[14] These effects are significant at the 1-Percent

Gaure et al. (2007*a*) and Gaure et al. (2007*b*) for more details on the optimization approach.

[12] Arni et al. (2013) use a similar strategy by looking how sanctions and warnings affect subsequent employment stability and wages in Switzerland.

[13] Detailed results for different specifications and covariates are available upon request.

[14] Remember, we normalized our indices to have mean zero and a standard deviation of 1.

level. What is striking is that the estimated impact of offshorability is almost four times as high as our estimates for the RTI. While automation seems to have played the predominant role in explaining changes in the occupational share, at least in Europe (e.g. Goos et al. (2014), and Heyman (2016)), on a micro level offshorability is more important when explaining the re-employment possibilities of unemployed male workers. The negative impact of both the RTI and OFF index on the employment hazard is somewhat dampened by the positive interaction effect (0.133 with a s.e. of 0.008). This means that routinsation and offshoreability share some characteristics.

[Table 3]

Looking at the impact on the transition into out of labor force, one can see that offshorability not only decreases the re-employment probability but also increases the likelihood of leaving the labor force. The estimated coefficient is significantly estimated but with an implied magnitude of 4% rather small compared to the effect on the re-employment hazard. We do not find any significant effect of automation (coeff. of -0.017 and s.e. 0.012). The effect of occupational changes on selective labor market supply is only from secondary importance.

To put our results more into perspective, consider two individuals with similar background characteristics but one worked as an office clerk while the second person worked in Personal Service & Protection. As shown in Table A.1 both occupations pay, on average, very similar pre-unemployment wages. The office clerk has, however, a 18% lower likelihood of finding re-employment probabilities and a 7% lower likelihood of leaving the labor force. These differences are quite substantial.

We find that both measures of occupational requirements have a large and significant negative effect on the re-employment hazard. An increase of the RTI and OFF index decreases the re-employment probability significantly by 30% and 23% respectively. Compared to our estimates for men, the estimates for the RTI is 5 times and for the OFF index more than twice as large. These findings imply that women are stronger affected by structural change compared to their male counterparts, which is in line with the findings of Black and Spitz-Oener (2010). This might be partially traced back to gender specific sorting where women move from high routine occupations such as office clerk to professional occupations.[15] The estimated positive

[15]Unfortunately, our data provide no information on the re-employment occupation. Autor and Dorn (2013)

cross-effect dampens the overall impact somewhat.

Looking at the estimates for the hazard out-of-labor force, we come to a similar conclusion as for men. The coefficient on the OFF index is 0.047 (s.e. 0.012) comparable to the 0.039 estimated for men. We do not find any significant impact of the RTI on labor participation decision. As before, the impact of our measures on selective participation is only of minor importance.

5.2 Simple Training Effects

Having seen negative employment prospects for persons coming from jobs with a high degree of routinisation and/or offshorability, we ask ourselves, whether labor market training could ameliorate some of these problems. In fact, we see, for both men and women, that case workers do assign persons with job contents consisting of more routinisation or more offshoreability earlier into training. Remarkably, this increased intensity corresponds exactly to the disadvantage they have in the job search market: As men are more hit by offshoring, their training assignment is faster than in the case of routinisation (11% vs 4.25%); the opposite patterns applies to women: here routinisation is more job-search prolonging – we also find a faster assignment into job training. For both, men and women, the existence of both a high degree of routinisation and a high risk of offshoreability does not lead to a corresponding increase in training assignment. Case workers do not see these risks as cumulative – and they are right: we see the same phenomenon in the employment hazard discussed above. If a worker faces the risk of routinisation and the risk of offshorability, the interaction effect increases the hazard rate into employment.

In Panel B of Table 3, we report the effect of training assignment on the transition probabilities. In line with the literature on unemployment training, as for example Richardson and van den Berg (2013), we find that training has a significant positive effect on the re-employment probability for men and women – Once an individual receives training, the log hazard rate increases by 0.415 (s.e. 0.038) for men and 0.888 (s.e. 0.040) for women. Expressed differently, the probability of an exit increases by 51% for men and 142% for women compared to someone without training. The latter effect is comparable to recent estimates for Sweden (Richardson and van den Berg, 2013).

Interestingly, we also find a significant positive effect of training on the transition into

provide evidence that a higher routine task share is associated with an increase in the female share in Manager, Professional, Technical, Financial, and Public Service occupations.

inactivity for both genders. The log hazard rate increased for men by 0.321, which translates into a 38% higher probability of leaving the labor force relative to someone without training. Our results for women are similar with an estimated impact of training on the probability of leaving the labor force by 33%. One explanation might be that training increases productivity and therefore the reservation wage of an individual. This, in turn, increases selectivity of the worker which type of job to accept. Those who receive a job below their reservation wage are unwilling to accept and, as the job offer arrival rate falls with the duration in unemployment, they may finally opt to exit the labor market.[16] We investigate the effect of training on post-unemployment wages further in Section 5.4.

Another reason might be that the result is mainly driven by older workers who use training assignment to bridge the time until official retirement. Our results, however, do not indicate that older workers are more likely to be assigned to training or more likely to transit into out of labor force (results not shown). The results imply, however, that the benefits of training are ambiguous.

The results presented in this section extend previous findings of Goos et al. (2014) on a micro-level and show that jobs which are routine-intensive and which are easily offshorable impact the transition rate of unemployed workers. Our findings show that different measures of occupational change have different gender-specific effects and that using only the risk of automation in the analysis is likely to conceal important points, which is also the conjecture of Cortes, Jamovich and Siu (2016). While there is a significant positive effect of ALMP on the assignment of training to the most vulnerable and also a positive effect of training on the hazard out of unemployment into employment, we want to explore ALMP effects further.

5.3 Can Training Ameliorate Specific Disadvantages Due To Job Content?

One natural extension of Model (I) is to allow the training effect to depend on our measures of changing occupational requirements. This enables us to assess if current ALMP are able to counteract the negative effect of routinization and offshorability on re-employment probabilities. We do so by modeling the treatment effect now as $\delta(x) = \delta + \beta_\delta^{RTI} RTI + \beta_\delta^{OFF} OFF$. We call this Model (II). If positive, the coefficients β_δ^{RTI} and β_δ^{OFF} can be interpreted as the additional

[16] This explanation implies that the reservation wage of a worker changes only with human capital and not with the unemployment duration. Schmieder et al. (2016) show that reservation wages are non-binding for unemployed workers in Germany. Given the close institutional proximity between Austria and Germany it is highly likely that the same is true for our sample.

benefit of assigning ALMP for those at high risk of routinization and Offshorability.

Table 4 contains our estimation results for Model (II). A likelihood ratio test of a homogenous treatment effect on our exit hazards results in a rejection of the null at all conventional levels. This shows that the individual training effect is indeed heterogenous.

[Table 4]

Comparing the selection into treatment from Model (II) to those obtained from Model (I), one can see that the coefficients are quite similar. Likewise, the constant δ in Model (II) is close to the estimated effect under a homogenous treatment effect. These findings support our modeling approach as by extending the treatment effect in a simple way our baseline estimates do not change by much.[17]

Looking at our heterogeneous effects for men, one can see that for persons with a strong routine job content, training does not help, whereas for those with a large offshoring perspective, the situation is different: A one standard deviation increase in the OFF index increases the log re-employment hazard by an additional 0.072. This implies that for this group training increases the re-employment probability by 64% in total compared to someone without training and by around 8% compared to a training assignee previously employed in an occupation with mean OFF index. We do not find any evidence that our heterogeneous training effect affects the decision to leave the labor force. Both estimated parameters are not significant at any conventional level.

For women, the estimated specific training effects for both of our measures are significantly positive. Similar as in our Model (I), we find that automation plays a more important role. The effect of the RTI on the log re-employment hazard is 0.138 (s.e. 0.024) which is almost twice as high as the coefficient on the OFF index (0.078 with a s.e. of 0.023). Both, the general and heterogeneous training effect are substantially higher for women compared to men. Women are more affected by changing occupational requirements, but there is also more to ameliorate: ALMPs can play a larger role to compensate women with particular disadvantages.

Summarizing these specific training effects, we see that training does help in three of the four cases and the training effects are - both for men and women - strongest in cases where the vulnerability of workers is highest. While it is important to know how structural changes affect

[17] As before, we do not report the full set of estimated coefficients, but the difference in coefficients between both models is small in general.

the search behavior of unemployed workers and how ALMP can interfere, it is also vital for a well-defined policy debate how these factors affect post-unemployment outcomes. We will do so in the next section.

5.4 Post-Unemployment Outcomes

In this section, we explore how occupational requirements influence re-employment wages and job stability. Considering post-unemployment outcomes adds another selection problem to our model. Taking up new employment or not is certainly endogenous and we need to take this additional type of selectivity into account. We do so by estimating post-unemployment outcomes simultaneously with training assignment and search behavior, and allow for correlation among unobservables across different states.

We model post-unemployment job stability, our Model (III), similar as in Equation (1) but take the duration in the new job into account. The hazard for the duration in new employment *after* exiting the unemployment spell (PE) is given by

$$\theta_{PE}(T|x, \nu_{NE}, D) = \lambda_{PE}(T) exp(x'\beta_E + \gamma_{NE}^{RTI} RTI + \gamma_{NE}^{OFF} OFF + \delta(x)\mathbb{1}(T > D) + \nu_{PE}) \quad (5)$$

where we model individual duration dependence as before. Notice that we now have a double censoring problem as we only observe individuals in new employment who actually left unemployment. Therefore, the likelihood contribution of an individual in this new model is given by $\left[\theta_{PE}(T_{NJ}|x, \nu_E, D)^{\Delta_{ij,PE}} S_{PE}(T_{NJ}|x, \nu_E, D)\right]^{\Delta_{ij,NJ}}$ where $S(\cdot)$ is the survival rate. Here $\Delta_{ij,PE}$ is a censoring indicator if the individual has left her new employment before the end of our sample period.

In terms of re-employment wages, our Model (IV), we use the estimator suggested by Donald et al. (2000); see also Cockx and Picchio (2013) for an extension. They show that the cumulative distribution function of wages can be modeled similar as duration hazards.[18] The wage hazard for new employment *after* exiting the unemployment spell (WE) is similar as above, but the interval points in $\lambda_{NW}(\omega)$ are chosen to occur at every 10th percentile of the observed distribution. As with post-unemployment job stability, we face a double censoring problem here. An individual contribution to the likelihood in this case is given by

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

$\left[\theta_\omega(\omega|x,\nu_E,D)^{\Delta_{ij,\omega}} S_\omega(\omega|x,\nu_E,D)\right]^{\Delta_{ij,NJ}}$ where $\Delta_{ij,\omega}$ is now the censoring indicator for wages. When estimating Model (III) and Model (IV) we follow the same strategy as outlined in Section 4.

Before presenting our results, we want to highlight that in terms of our post-unemployment outcomes negative coefficients on our variables of interest can be interpreted as having a *positive* impact. This is straightforward to see when considering job stability but it might be more complicated when considering wages. The wage hazard is the instantaneous probability of earning ω conditional on earning at least ω and has a similar interpretation as the unemployment exit hazard. One can show that under the MPH assumption imposed the sign of the impact on the wage distribution is *opposite* to the sign estimated on the coefficient of interest (Cockx and Picchio, 2013). Hence, a positive estimated coefficient *lowers* the conditional instantaneously probability of earning ω.

Tables 5 and 6 contain the results from Model (III) and Model (IV), respectively. Note that we do not know which job content in terms of routine and offshorability the new jobs have. Our basic estimates – for employment and out of labor force – are practically unchanged using our additional outcome variables, which is reassuring for our strategy. The results considering post-unemployment job duration presented in Table 5 suggest different effects of training by gender. For men, we estimate a negative effect of ALMP, which increases the hazard out of the new job by 27%. This implies that on the one hand ALMP increase the transition into new employment, but at the expense of less stable new jobs. For women, we find the opposite: ALMP actually decreases the hazard out of the new job by around 6%. Women seem to uniformly profit from these labor market policies both in terms of transition into re-employment and finding a stable new job.

[Tables 5 & 6]

How does routine job content or offshorability affect post-unemployment job stability? By and large, we see that persons with detrimental job contents end up in more stable jobs. This holds for both routinisation and offshorability for females; but only for offshorability in the case of men. As our data do not reveal which job (i.e. which occupation) these workers occupy after their unemployment spell, we cannot say whether these workers, in fact, apply a structural change into other occupations/industries to improve their future prospects or whether they just try to hold on this job more determined as otherwise.

It is interesting to see whether these positive post-unemployment tenure effects come at the expense of lower wages. Table 6 shows the results when using the wage rate in the new job as post-unemployment outcome variable. Note that – due to our formulation – a positive coefficient implies a lower wage rate.

For men, the effects of specific job contents are similar with respect to post-unemployment wages as to job stability. Higher routinization is associated with a significantly higher wage, while a higher OFF index increases the wage. Hence, men in occupations which are affected by offshorability who found re-employment do not only benefit from a stable work relationship but also receive higher wages. Our results are similar for women. Routinization significantly reduces post-unemployment wages while offshorability increases them.

For both men and women, ALMP clearly has a negative effect on re-employment wages. For men, it seems that ALMP may have the primary goal of rapid re-employment with little regard to post-unemployment outcomes such as wages and job stability (see also the findings in Autor et al. (2017).) For women, our results suggest that job stability and wages are rather substitutes for unemployed workers.

The estimates in this section give important implications on the impact of changes in occupational requirement on unemployed workers. We find that higher offshorability increases both post-unemployment wages and job stability while routinization has in general a negative effect. These effects are, however, rather small compared to the impact on the re-employment hazards.

6 Conclusion

While there is a large amount of studies on aggregate effects of automation or offshorability on employment, we look at the effect of changing occupational requirements on the re-employment probability of unemployed workers and post-unemployment outcomes. In this line, we also evaluate the current state of provided unemployment training and evaluate its efficiency. We base our definition of changing occupational requirements on two one-dimensional indices which capture the risk of automation and offshorability.

Our results show that all these occupational risks can significantly reduce the re-employment probability of unemployed workers. There are pronounced gender differences in the size of these effects. For men, we find that workers previously employed in occupations with high risk of being offshored have a substantially lower re-employment probability compared to workers affected by automation. For women it is the opposite. In general, women face higher problems if they come from jobs that are at risk to be outsourced or to be replaced by a robot.

What can labor market policy do to ameliorate these problems for workers? Active labor market policy (ALMP) is in general helpful to these workers. Workers plagued by such risks, do in general receive more training, in particular workers most vulnerable. The effect of this training is also positive in 3 out of four cases, again with the highest positive effects for workers with the largest re-employment problems.

These are important results. Digitalisation and globalisation most probably lead to large gains to society, but – as in other structural changes – not all members of society will profit from them. Having shown that ALMP can, in principle, assist some losers of these processes may lead to larger policy potentials. One of them is a variant of the U.S. Trade Adjustment Assistance (TAA) program. Such a program could also be introduced to assist victims of digitalisation – and thus help a digitalisation strategy to fly.

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7 Tables

Table 1: Summary Sample

	Men	Women
Individuals & Spells		
Individuals	35,000	35,000
No. of Spells	1.95	2.08
Outflow & Training		
Outflow	86.80%	85.71%
to New Job	59.53%	52.14%
to Out of Labor Force	27.27%	33.57%
Training Received	14.83%	20.22%
Pers. Characteristics		
Age	43.18	42.83
Non-Austrian	18.37%	17.04%
at most Com. Schooling	17.74%	29.41%
Apprenticeship/ High-School	62.77%	51.84%
Matura/ University	19.49%	18.75%
Children	44.85%	63.34%
Married	40.79%	45.26%
Divorce	10.97%	15.76%
Others	48.24%	38.98%
Last Employment		
Tenure in Last Job (Days)	375.64	394.11
Daily Wage in Last Job (Euros)	76.74	49.83
Access to Extended Benefits	50.40%	41.79%
Inflow Year		
Year 2012	55.79	52.03
Year 2013	44.21	47.97

Out of Labor Force refers to the state when an individual exits unemployment and does not take up employment within 40 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. UE-Benefits denotes the share of spells in our sample where the individual is eligible for at least 20 weeks of unemployment benefits.

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

	Years				Ann. Growth Rate
	2011	2012	2013	2014	$\Delta^{2011-2014}$
Managers (1)	2.17%	2.31%	2.92%	2.72%	5.64%
Professionals (2)	11.67%	12.54%	11.21%	11.84%	0.36%
Technicians (3)	17.50%	18.44%	18.59%	18.24%	1.03%
Clerical Support Workers (4)	6.11%	6.77%	6.61%	4.96%	−5.20 %
Service and Sales Workers (5)	29.85%	25.07%	31.34%	29.92%	0.06%
Craft & related Trades Workers (7)	16.28%	19.31%	14.44%	14.08%	−3.63 %
Plant & Machine Operators, and Assemblers (8)	6.92%	5.33%	4.45%	5.12%	−7.53 %
Elementary Occupations (9)	7.87%	8.36%	8.14%	7.04%	−2.79 %

The table presents the share of average yearly vacancy 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). $\Delta^{2011-2014}$ is the annual growth rate 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: Model (I): Results for 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: Occ. Requirements						
γ^{RTI}	0.041	-0.067	-0.017	0.191	-0.362	0.00
	(0.017)	(0.009)	(0.012)	(0.017)	(0.014)	(0.012)
γ^{OFF}	0.101	-0.245	0.039	0.084	-0.265	0.047
	(0.019)	(0.012)	(0.014)	(0.017)	(0.015)	(0.012)
$\gamma^{RTIxOFF}$	-0.065	0.133	-0.020	-0.088	0.223	-0.018
	(0.014)	(0.008)	(0.009)	(0.011)	(0.010)	(0.008)
Panel B: Training						
δ		0.415	0.321		0.888	0.281
		(0.038)	(0.040)		(0.040)	(0.034)
Unobs. Heterogeneity	Yes			Yes		
Control Variables	Yes			Yes		
Log-Likelihood	-35,386.29			-44,080.61		

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 98 parameters were estimated. OLF refers to Out-of-Labor Force

Table 4: Model (II): Results for Heterogenous 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 $\theta_{\text{Out-of-Labor Force}}$
Paenl A: Occ. Requirements						
γ^{RTI}	0.045	−0.066	−0.017	0.192	−0.375	0.000
	(0.017)	(0.009)	(0.012)	(0.018)	(0.015)	(0.0129)
γ^{OFF}	0.100	−0.251	0.041	0.083	−0.273	0.043
	(0.019)	(0.012)	(0.014)	(0.017)	(0.015)	(0.013)
$\gamma^{RTI\text{x}OFF}$	−0.065	0.135	−0.021	−0.089	0.219	−0.0162
	(0.014)	(0.008)	(0.009)	(0.012)	(0.001)	(0.008)
Panel B: Training						
δ		0.425	0.312		0.871	0.282
		(0.038)	(0.040)		(0.040)	(0.034)
β_{δ}^{RTI}		−0.025	0.024		0.138	−0.018
		(0.028)	(0.029)		(0.027)	(0.024)
β_{δ}^{OFF}		0.072	−0.028		0.078	0.023
		(0.029)	(0.029)		(0.0274)	(0.023)
Unobs. Heterogeneity	Yes			Yes		
Control Variables	Yes			Yes		
Log-Likelihood	-35,355.59			-43,986.88		

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with a total of seven mass points. In total, 102 parameters were estimated. OLF refers to Out-of-Labor Force

Table 5: Model (III): Results including Post-Unemployment Job Duration

	Male				Female			
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$	NJ hazard $\theta_{\text{New Job}}$	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$	NJ hazard $\theta_{\text{New Job}}$
Panel A: Occ. Requirements								
γ^{RTI}	0.043	−0.068	−0.016	0.032	0.167	−0.312	−0.013	−0.125
	(0.016)	(0.009)	(0.011)	(0.011)	(0.017)	(0.014)	(0.012)	(0.014)
γ^{OFF}	0.096	−0.252	0.040	−0.080	0.073	−0.224	0.035	−0.187
	(0.019)	(0.012)	(0.013)	(0.014)	(0.016)	(0.014)	(0.011)	(0.015)
$\gamma^{RTIxOFF}$	−0.061	0.135	−0.018	−0.004	−0.077	0.194	−0.009	0.098
	(0.013)	(0.008)	(0.009)	(0.010)	(0.011)	(0.009)	(0.008)	(0.010)
Panel B: Training								
δ		0.393	0.338	0.237		0.810	0.238	−0.065
		(0.037)	(0.039)	(0.047)		(0.037)	(0.033)	(0.049)
Unobs. Heterogeneity	Yes				Yes			
Control Variables	Yes				Yes			
Log-Likelihood	-49,302.96				-54,122.42			

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 129 parameters were estimated. OLF refers to Out-of-Labor Force and NJ to the Duration in the New Job.

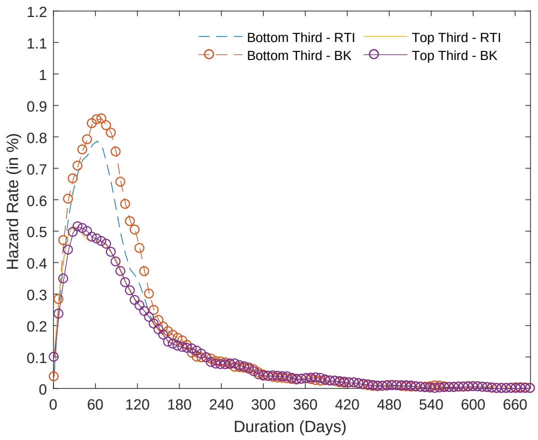
Table 6: Model (IV): Results including Post-Unemployment Wage

	Male				Female			
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$	Wage hazard θ_{ω}	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	OLF hazard $\theta_{\text{Out-of-Labor Force}}$	Wage hazard θ_{ω}
Panel A: Occ. Requirements								
γ^{RTI}	0.043	−0.067	−0.015	0.040	0.175	−0.306	−0.014	0.024
	(0.016)	(0.009)	(0.011)	(0.008)	(0.017)	(0.013)	(0.012)	(0.011)
γ^{OFF}	0.098	−0.238	0.038	−0.095	0.071	−0.233	0.041	−0.098
	(0.019)	(0.012)	(0.013)	(0.011)	(0.016)	(0.013)	(0.012)	(0.012)
$\gamma^{RTI\text{x}OFF}$	−0.062	0.127	−0.019	0.093	−0.077	0.190	−0.011	0.034
	(0.013)	(0.008)	(0.009)	(0.007)	(0.011)	(0.009)	(0.008)	(0.008)
Panel B: Training								
δ		0.398	0.343	0.329		0.815	0.281	0.152
		(0.036)	(0.040)	(0.033)		(0.037)	(0.033)	(0.036)
Unobs. Heterogeneity	Yes				Yes			
Control Variables	Yes				Yes			
Log-Likelihood	-41,002.15				-57,053.38			

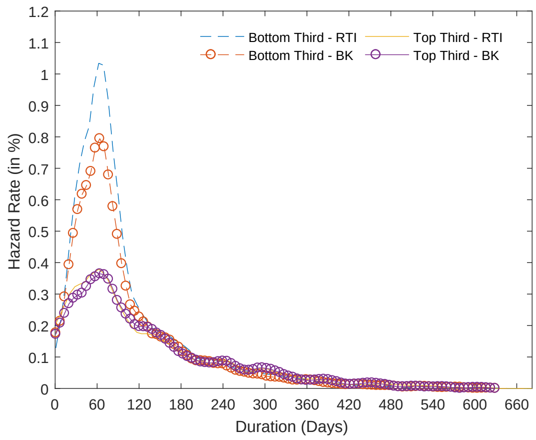
Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 129 parameters were estimated. OLF refers to Out-of-Labor Force.

8 Figures

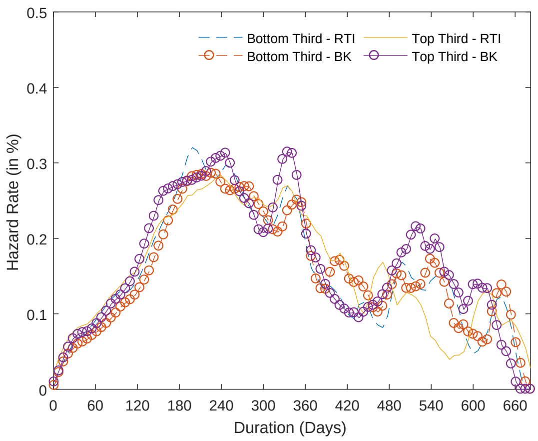
Figure 1: Empirical Transition Rates



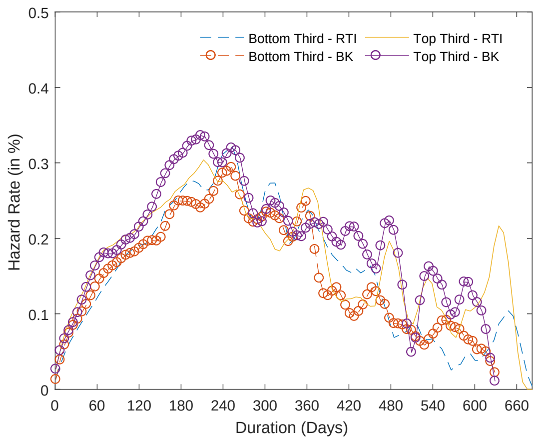
a. Exit Hazards Men



b. Exit Hazards Women



c. Training Hazards Men



d. Training Hazards Women

The upper part of the figure presents the smooth daily exit hazard from unemployment to employment estimated separately for the upper and lower third of the RTI and BK index distribution, the lower part present smooth training assignment hazard separately for the upper and lower third of the of the RTI and BK index distribution. 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).

Online Appendix for "When Routine Jobs Disappear: Task Input, Unemployment Duration, and Subsequent Job Quality"

Bernhard Schmidpeter

Rudolf Winter-Ebmer

September 19, 2017

A Routine Task and Off-Shorability Index

Our measure of both Routine Task intensity (RTI) and off-shorability (OFF) are based on the indices used in Autor and Dorn (2013) and Blinder and Krueger (2013). Goos et al. (2014) provide a mapped version from the US occupational classification system to ISCO 88 on a two digit level. In this analysis, we make use of their index.[1]. In our raw data, we have information on the occupation on a 4-digit level. In order to merge the information provided by Goos et al. (2014) to our index we convert the 4-digit level into 2-digit categories. Note that the OFF index measure the ease with which an occupation can be offshored to a different country. This does not mean that occupations with high value have actually been outsourced abroad. In our analysis, we standardize both indices to have a mean of zero and a standard deviation of one. This is in order to facilitate comparison.

Table A.1 gives an overview of the share in our study sample, RTI and OFF index, as well as past and future wages by 2-digit occupational category. In the male sample, the highest share of spells come from individuals previously employed in "Extraction & Building Trades" with 25%, followed by individuals previously employed in Personal & Protective Service occupations. In the female sample, 40% of the spells stem from inflows from Personal & Protective Service occupations, and 15% from Sales & Services. The figures in the table also highlight the fact that men and women sort themselves into different occupations with different RTI and BK index. This finding supports our decision to estimate our models separately by gender.

[1]The mapped indices can be found here https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509

Table A.1: Summary of Occupations - 2-digit Level

	Share in Sample	RTI	BK	Wage Prev.	Wage New
Panel a. Men					
Corporate Managers (12)	2.19%	−0.70	0.27	90.09	88.27
Science Professionals (21)	1.09%	−0.79	2.16	94.99	101.30
Life Science & Health Professionals (22)	0.09%	−1.03	−0.33	77.43	72.09
Other Professionals (24)	1.60%	−0.68	1.00	84.75	86.98
Science Associate Professionals (31)	3.41%	−0.24	0.54	91.51	92.10
Life Science & Health Associate Professionals (32)	0.49%	−0.15	−0.32	62.86	71.44
Other Associate Professionals (34)	3.30%	−0.29	0.86	77.28	79.69
Office Clerks (41)	1.04%	3.24	1.26	74.34	76.84
Customer Service Clerks (42)	0.91%	2.14	0.37	62.42	64.23
Pers. & Protective Services (51)	15.75%	−0.50	−0.57	68.29	73.04
Models, Salespersons & Demonstrators (52)	3.61%	0.36	−0.51	67.21	71.28
Extraction & Building Trades (71)	24.29%	0.04	−0.57	86.51	90.51
Metal, Machinery & Related Trades (72)	12.62%	0.89	0.09	79.12	81.79
Precision, Handicraft, Craft Printing & Related (73)	1.10%	2.38	2.99	77.69	77.38
Other Craft & Trades (74)	4.34%	1.92	2.29	69.08	73.40
Stationary Plant & Related Operators (81)	2.40%	0.71	2.90	83.24	88.66
Machine Operators & Assemblers (82)	0.94%	0.94	3.93	67.34	72.64
Drivers & Mobile Plant Operators (83)	14.04%	−1.68	−0.66	72.55	78.00
Sales & Services (91)	2.72%	0.32	−0.40	53.68	62.49
Laborers in Mining, Constr., Manufac. & Transport (93)	4.07%	0.88	−0.19	65.76	67.16

Continued on next page

Table A.1 – continued from previous page

	Share in Sample	RTI	BK	Wage Prev.	Wage New
Panel b. Women					
Corporate Managers (12)	2.00%	−0.92	0.57	78.52	71.07
Science Professionals (21)	0.37%	−1.03	2.96	82.25	80.81
Life Science & Health Professionals (22)	0.12%	−1.30	−0.20	77.64	60.12
Other Professionals (24)	2.23%	−0.90	1.49	72.38	74.38
Science Associate Professionals (31)	0.84%	−0.40	0.91	65.79	70.19
Life Science & Health Associate Professionals (32)	2.33%	−0.31	−0.19	56.41	56.33
Other Associate Professionals (34)	3.25%	−0.47	1.31	69.31	67.41
Office Clerks (41)	2.31%	3.50	1.82	61.42	60.02
Customer Service Clerks (42)	4.16%	2.27	0.69	48.74	53.02
Pers. & Protective Services (51)	40.56%	−0.70	−0.51	50.45	53.71
Models, Salespersons & Demonstrators (52)	17.21%	0.26	−0.43	47.25	48.13
Extraction & Building Trades (71)	0.40%	−0.09	−0.50	53.45	58.41
Metal, Machinery & Related Trades (72)	0.39%	0.86	0.34	51.59	63.29
Precision, Handicraft, Craft Printing & Related (73)	0.66%	2.54	4.02	48.38	50.43
Other Craft & Trades (74)	2.75%	2.02	3.13	42.72	45.23
Stationary Plant & Related Operators (81)	0.29%	0.66	3.90	50.27	47.95
Machine Operators & Assemblers (82)	0.65%	0.91	5.21	47.52	48.71
Drivers & Mobile Plant Operators (83)	0.93%	−2.03	−0.62	43.48	44.90
Sales & Services (91)	14.25%	0.23	−0.29	36.51	41.91
Laborers in Mining, Constr., Manufac. & Transport (93)	4.31%	0.85	−0.02	49.33	49.68

The table present summary statistics by occupations defined on the 2-digit level. The corresponding ISCO 88 code is reported in parentheses. Wages are expressed in Euros per Day. Wage Next Job is calculated using those who find new employment only. Both RTI and BK are normalized in the respective sample to have mean of zero and a standard deviation of one

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