Should I Train Or Should I Go? Estimating Treatment Effects of Retraining on Regional and Occupational Mobility

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Abstract

In this paper, we estimate heterogeneous causal treatment effects of retraining, a specific government subsidized training program for the unemployed, on regional and upward occupational mobility. While retraining leading to a vocational degree usually entails horizontal occupational mobility, its effect on vertical occupational mobility is not clear. Moreover, if (horizontal) occupational mobility is an alternative to regional mobility in the search process of the unemployed, participation in the program may make it less likely that an unemployed person will move. Using the Modified Causal Forest approach and administrative data for Germany, we find that retraining participation significantly increases upward occupational mobility and decreases regional mobility. Furthermore, for individuals in unemployment insurance, the substitution of regional mobility in favour of occupational mobility after retraining is larger than for welfare recipients.

JEL-Codes: J62, J61, J08
Keywords: retraining, occupational mobility, regional mobility, machine learning

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1 Introduction

Government subsidized training measures are one of the more common programs of active labor market policy (ALMP), designed to help reintegrate the unemployed into the labor market. Participation in these measures is intended to increase the labor market opportunities of the unemployed by providing qualifications that are in demand on the labor market. In fact, a large body of research indicates that continuing training for the unemployed increases the likelihood of returning to employment (e.g. Card et al. (2010)). If an unemployed person's pre-existing skills are not in demand in the local labor market, an alternative to investing in human capital can be regional mobility; unemployed people can move to where their existing skills are needed. The question this paper strives to answer is how participation in retraining, which is the most extensive training program for unemployed individuals in Germany, influences upward occupational and regional mobility.

Unemployed individuals without a usable vocational degree can obtain such a degree by participating in retraining which is subsidized by the German Federal Employment Agency (FEA). For most participants retraining typically automatically entails (horizontal) occupational mobility.[1] If occupational mobility can actually be considered as an alternative to regional mobility, participation in retraining could reduce regional mobility of job-seekers. Although participation in retraining should increase horizontal occupational mobility, the effect on vertical occupational mobility is less clear. While participants gain new qualifications and skills that can help them advance in their careers, some of them are starting out in a completely new career field in which they have not yet had the opportunity to gain work experience.

To analyze the effects of participating in retraining on regional and upward occupational mobility, we use German administrative data and apply the Modified Causal Forest approach by Lechner (2018) to estimate not only average but also heterogeneous causal treatment effects. For our main analyses we consider entries into retraining in

[1]Most individuals receive retraining in an occupation from a different occupational field than the one in which they were last employed. However, it is also possible that low-skilled individuals who were last employed in an unskilled job pursue a degree in the same occupational field.

the third quarter 2013 and report results up to five years after retraining started. Vertical occupational mobility, in this paper, is defined at the level of positions, e.g. moving from unskilled tasks to specialist positions. Our estimations show that, after a lock-in period, retraining participation has positive effects on the employment probability as well as on upward occupational mobility and negative effects on regional mobility. These effects are most pronounced for participants receiving unemployment insurance benefits who are typically closer to the labor market than welfare benefits recipients.

Our paper plays into several fields of research. First, it contributes to the growing field of applied Machine Learning and, in particular, of Causal Forests (e.g. Athey and Imbens (2016), Wager and Athey (2018)). Second, focusing more on qualitative dimensions, we contribute to the body of literature around the effects of ALMP (e.g. Lechner et al. (2007); Fitzenberger and Völter (2007); Dengler (2019); Doerr et al. (2017)) and occupational mobility (e.g. Kruppe and Lang (2018); Dauth and Lang (2019), Grunau and Lang (2020)). Last, we add to the literature concerning migration decisions and regional mobility in Germany (e.g. Lehmer and Ludsteck (2011), Lehmer and Möller (2008)).

The rest of the paper proceeds as follows. Section 2 presents an overview over the current literature. In section 3 we introduce the method, Modified Causal Forests, and data used for the analysis. Section 4 presents the results and section 5 concludes.

2 Background and Related Literature

Subsidized training for the unemployed improves participants' chances on the labor market by teaching them skills that are in demand on the labor market. By far the most comprehensive further training measure in Germany is retraining. There are two groups of unemployed workers who have access to this measure. On the one hand, these are individuals within the unemployment insurance system (according to Social Code III (SGB III)) who receive unemployment benefits. These were usually employed before entering unemployment and can receive unemployment benefits for a certain period (usually one year), which in turn depends on their previous income. On the other hand, unemployed workers in the welfare system (according to Social Code II (SGB II)) can also participate in retraining. They are not entitled to unemployment benefits, but receive a means-tested benefit. Typically, the first group of unemployed in the unemployment insurance system is closer to the labor market than the second.

Individuals who take part in retraining learn a (new) occupation; the qualification is equivalent to a regular initial vocational qualification. This is why these courses last a very long time, in many cases around two years. There are three target groups for retraining: (Unemployed) workers without a vocational degree, those with a vocational degree who can no longer practice their profession, and those with a vocational degree who have not worked in this occupation for several years. The retraining courses are intended to take place in occupations with a high demand for labor, so that the participants' chances of integration after completing the retraining courses are high. It is at the discretion of the caseworker whether an unemployed individual is assigned to a retraining program, where the selection of the target occupation is not only based on the interests and skills of the unemployed worker, but also on regional labor market needs.

Most studies on the effectiveness of retraining in Germany find that participation significantly increases the employment probability of the unemployed as well as their earnings (e.g., Lechner et al. (2007); Fitzenberger and Völter (2007); Fitzenberger et al. (2008); Doerr et al. (2017)). The extent of the positive employment effects may also depend on the respective target occupation of the retraining (Kruppe and Lang (2018); Dauth and Lang (2019)). Although there is clear empirical evidence for positive quantitative employment effects, there are few studies on qualitative aspects of employment. Dengler (2019) finds that further vocational training (including retraining) has positive effects on some qualitative dimensions of the job, such as stable employment and occupational exposure. Grunau and Lang (2020) show that retraining has a positive effect on the job match quality as retraining participants are more likely to take up a job for which their educational degree is required and are more likely to be employed in occupations they trained for. We focus on another qualitative outcome dimension, the mobility of unemployed workers. More precisely, we analyze the effects of retraining on the upward occupational mobility as well as regional mobility of job-seekers[2].

First, note that participation in retraining should in most cases lead to (at least horizontal) occupational mobility. Participants receive training for a new occupation or for the first time ever. Upon successful completion, it can usually be expected that a large proportion of participants will change occupations (see also the results found by Grunau and Lang (2020)). Considering upward occupational mobility, both direct and indirect effects of retraining may play a role (Grunau & Lang, 2020). The overall effect may strongly depend on how skilled a worker was before potential retraining participation and whether she was working in a skilled or unskilled job before becoming unemployed. As retraining increases not only occupation-specific but also general human capital, and thus overall employability, participation in retraining can improve the chances of finding new jobs not only in the newly learned profession but also in general. Hence, participants may also have better chances of finding a low-skilled job, which would not involve upward or may even involve downward occupational mobility, depending on the pre-training professional position. Moreover, when training participants start a job in the newly learned occupation, they often have no work experience in the occupational field and may (re)enter employment at a lower career level than they had before retraining. In contrast, unemployed non-participants who find a job in the occupational field in which they were previously employed may be less likely to experience downward occupational mobility (depending on the depreciation of their (occupation-specific) human capital during unemployment).

However, besides workers with a vocational degree who can no longer practice their profession or who have not worked in this occupation for several years, the main target group for retraining is unemployed individuals without a vocational degree. With retraining, the unemployed workers obtain a vocational degree and thus the probability that they will find qualified employment increases. This suggests that

[2]In a robustness check we also consider downward occupational mobility, see Section 4.2

participating in retraining can have a positive effect on upward occupational mobility especially for workers who entered unemployment from low-skilled work. Thus, the overall effect of participation in retraining on upward occupational mobility is not clear. Although the participants obtain new qualifications and skills that can help them move up the career ladder, most of them may start out in a completely new occupational field in which they have not yet been able to gain any work experience.

With regard to regional mobility, the economic theory on migration states that individuals move when the net returns to migration exceed the costs on the individual or household level (Sjaastad (1962); Mincer (1978)). The regional labor market situation plays an important role in the decision to move, along with family ties, educational background and other factors. Additionally, in the case of Germany, there are strong regional differences in unemployment rates or wage levels (in our data the unemployment rate in the third quarter of 2013 varies between 1.7 and 14.6 percent between employment agency districts). If unemployed people live in a region with poor labor market conditions, moving to a region with good labor market conditions can be associated with high returns. Indeed, Caliendo et al. (2017) analyze the effect of a measure that is directly targeted at regional mobility of unemployed workers, a subsidy which covers the moving costs to incentivize job seekers to search for jobs in more distant regions. They find that participants in this subsidy program move more often to a distant region, have higher wages and find more stable jobs compared to non-participants. They additionally show that the positive effects mainly run through a better job match due to the increased search radius.

Arntz (2005) finds that in West Germany, unemployed individuals react to local labor market conditions and that they are more likely to leave regions with worse reemployment opportunities. Huttunen et al. (2018) analyze the migration behavior of displaced Norwegian workers and show that job displacement increases regional mobility. However, occupational mobility could be an alternative to regional mobility to improve labor market outcomes. Reichelt and Abraham (2017) argue that these two mobility types act as substitutes when employees want to improve their labor market opportunities, where restrictions on both types of mobility determine which one is chosen. Since successful participation in retraining leads to occupational mobility - at least if a large proportion of the reemployed retraining participants take up a job in the newly learnt occupation (e.g. Grunau and Lang (2020)) - we expect participants to be less likely to move to improve their labor market opportunities than non-participants. This hypothesis is further supported by the fact that employment agencies select the target occupations for retraining based on the regional occupation-specific labor demand, which should increase the chances of finding a qualified job in the new occupation in the region where the retraining participant lives.

However, there is also a potential channel that points in a different direction. Various studies from the US show that regional mobility is positively related to education (Chetty et al. (2016), Molloy et al. (2011)). In this case, retraining could also increase regional mobility.

The few studies that examine how ALMP affect the mobility of the unemployed arrive at different results, depending on the measure. Lindgren and Westerlund (2003) compare participants in a Swedish training program to participants in two other ALMP programs and to individuals in open unemployment. They find that participants in the training program have a higher probability of employment, migration, and commuting than participants in the other two programs and also a higher probability of mobility than the openly unemployed. This is due to the training participants having a higher probability of commuting compared to individuals in open unemployment, which predominates a lower probability to migrate. Arntz (2005), in turn, finds no evidence for a locking in effect of ALMP on the interregional mobility of male unemployed in West Germany and only weak evidence for minor lock-in effects for females.

To sum up, from a theoretical perspective it is not clear how participation in retraining will affect vertical occupational and regional mobility. Previous empirical studies on ALMP do not allow a clear conclusion for the training measure considered here. Furthermore, it is possible that there is a variation in effects between distinct groups of unemployed individuals. In order to identify possible differences, we apply the

Modified Causal Forest approach by Lechner (2018) to estimate heterogenous causal treatment effects. Although machine learning (ML) methods originally aimed primarily at making predictions, the methodological literature on ML to identify causal treatment effects has been growing rapidly in recent years (e.g. Chernozhukov et al. (2018), Athey and Imbens (2016), M. C. Knaus et al. (2021)). There is also a number of studies with applications of ML in labor economics to identify heterogeneous causal effects, e.g. of ALMP programs (M. C. Knaus et al. (2020), Lechner et al. (2020)).

3 Econometrics

3.1 Causal Forests

In this study, we use the Modified Causal Forest (Lechner, 2018) to estimate heterogeneous causal treatment effects. The idea of a Causal Tree, introduced first by Athey and Imbens (2016), is to split a sample sequentially into more and more homogeneous strata. When the splitting is finalized based on some stopping criterion, the treatment effect is computed within each stratum, called a "leaf", by taking the difference of the mean outcomes of treated and controls. Thus, effect heterogeneity is exposed while at the same time selection effects may be tackled. Since sequentially splitting the sample leads to unstable leaves, Wager and Athey (2018) proposed Causal Forests, whereby, taking a random selection of all available covariates or features, many trees are built from random subsamples of the original data. The final prediction is then averaged over all trees. Lechner (2018) finally proposes three modifications to the Causal Forest approach. First, a splitting rule that takes selection bias directly into account by penalizing splits with a low propensity score heterogeneity. Second, a method to aggregate the disaggregated Individualized Average Treatment Effects (IATE) into a number of discrete variables of interest: Group Average Treatment Effects (GATE). Finally, the approach allows to perform unified inference for all aggregation levels and extend the framework to a multiple treatment framework.

The Modified Causal Forest approach seems particularly helpful in our analysis.

In a comparison of several machine learning methods with respect to their theoretical properties as well as their performance M. Knaus et al. (2018) concluded that Random Forest-based estimators seem to outperform alternative estimators. Furthermore, in the case of retraining, selection bias seems particularly important: There may be both self-selection into the program and selection by the caseworkers. Last, this approach enables us to compute Group Average Treatment Effects (GATEs) for policy variables of interest, such as gender and social security status.

3.2 Data

The data used in this analysis stems from the Integrated Employment Biographies (IEB), German administrative data from the federal employment agency. We use the total population of retraining participants for the years 2013 and 2014 together with a random sample of control workers who did not participate in retraining in those years. Since our data is available through the end of 2019, this will allow us to observe participants' future employment histories for at least up to five years after they begin retraining. For each individual we observe socio-demographic characteristics, such as age, gender, residence at the district-level, and education. We also draw their employment biographies and calculate the days in employment, unemployment, and training measures up to 10 years prior to entry into unemployment. Tables 1 and 2 provide summary statistics of our covariates for the third quarter in 2013[3]. As most retraining programs start in the third quarter, we will focus our analysis on treated individuals with training start within the third quarter of 2013. However, as robustness, we also present results for other quarters, both for 2013 and 2014.

Covariates measuring the employment history are calculated based on the start of the relevant unemployment spell directly prior to retraining. For the control group, we estimate hypothetical retraining start dates based on an elastic net estimator. As outcome measures we use the probability of employment, change in residence, and upward occupational mobility within five years and for each year separately up to five

[3]For the full set of covariates used in our estimations see Table 6 in the Appendix

Table 1: Summary Table

	Treated	Control	Difference
Panel A: Socio-demographics			
Age	35.84	38.17	-2.33***
	(7.36)	(8.96)	
Share female	0.51	0.45	0.06***
	(0.49)	(0.49)	
Education			
No degree	0.09	0.1	-0.01
	(0.29)	(0.3)	
vocational degree	0.62	0.57	0.05***
	(0.49)	(0.49)	
High School degree	0.03	0.01	0.02***
	(0.17)	(0.12)	
High School & vocational degree	0.17	0.15	0.02***
	(0.38)	(0.36)	
Panel B: Employment history			
days worked 1yr pre-treatment	94.95	112.38	-17.43***
	(114.27)	(126.56)	
days worked 5yrs pre-treatment	616.7	602.8	13.9**
	(512.94)	(526.11)	
days worked 10yrs pre-treatment	980.44	968.92	11.52
	(812.10)	(837.96)	
days in ALG I 1yr pre-treatment	45.95	27.1	18.85***
	(71.41)	(58.47)	
days in ALG I 5yrs pre-treatment	81.91	62.53	19.38***
	(109.74)	(97.75)	
days in ALG I 10yrs pre-treatment	143.85	120.53	23.32***
	(163.92)	(151.53)	
Number of Observations	4367	12437	

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020. **Notes:** Standard deviations in brackets. ***, **, * indicate levels of significance at the 1, 5, and 10 % level, respectively.

years after (hypothetical) treatment start.

Table 1 shows that retraining participants are on average younger and more often female than non-participants. Participants and non-participants also differ with regard to previous days spent in employment and unemployment. Retraining participants spent significantly fewer days in employment in the previous year before becoming unemployed. In addition, they received unemployment benefits more frequently (in the unemployment insurance system, SGB III), spent more days in ALMP measures, but had somewhat fewer days with welfare receipt in the last year (or unemployment benefits II, SGB II). Moreover, Panel B reveals clear differences with regard to the position in the last job. The share of unskilled workers is at 44 percent much higher for participants than for non-participants. This is reasonable as unskilled workers are one target group for training. The fact that participants on average have higher educational degrees than non-participants is not necessarily inconsistent with this. Participants may be reclassified as "unskilled again" in case they have not worked in their learned occupation for some time. Moreover, it is possible that (e.g., for health reasons) they can no longer work in their old occupation.

We use the probability of employment as the tree building variable and the two mobility outcomes as secondary outcomes. In our first specification, we look at the outcome for the first employment within five years after (hypothetical) retraining. That is, the dummy measuring employment is one if a person has (at least) one employment spell within five years after retraining. The dummy measuring occupational mobility equals one if, for the first employment spell within five years, a person moves upward in their occupation, that is, e.g. from an unskilled position to specialist, and zero otherwise. The dummy measuring regional mobility equals one if, for the same spell, a person changes her place of residence with a distance of at least 50km. The place of residence is measured at the district level and we use the haversine formula to compute the distance between the places of residence. The second specification follows the same principle, but taking the first employment spell in the fifth year after the (hypothetical) start of retraining as basis. Table 3 provides descriptives for our four outcome variables. Quite clearly, there are marked differences even at this stage between the share of treated and control workers concerning their probabilities of employment and mobility.

In section 4.1 we further analyse heterogeneity in treatment effects. One dimension, for which we computed the GATEs, is whether a participant is in the unemployment insurance or welfare system. It is categorized into three dimensions. SGB equals one, if a person receives welfare benefits (unemployment benefit II). SGB equals two for workers within the unemployment insurance system, who are typically closer to the labor market and zero if the information is missing.

3.3 Identification

The present chapter introduces the estimation equation and our identification strategy. We define the estimand using the potential outcomes framework developed by Rubin (1974). Let X_i be a vector of covariates for individual i, where $X_i = [X_i', Z_i]$. X_i' represents confounders needed to correct for selection bias and Z_i variables that define groups of population members. For Treatment $D = [0, 1]$ and (potential) outcome of interest Y we estimate:

$$IATE(D, x) = \mathbf{E}(Y^1 - Y^0 | X = x, D \in \delta) \tag{1}$$

$$GATE(D, x, z) = \mathbf{E}(Y^1 - Y^0 | Z = z, D \in \delta) = \int IATE(D, x) f_{X|D\in\delta}(x) dx \tag{2}$$

$$ATE(D) = \mathbf{E}(Y^1 - Y^0 | D \in \delta) = \int IATE(D, x) f_{X|D\in\delta}(x) dx \tag{3}$$

The IATE measure the mean impact of treatment $d = 1$ compared to no treatment $d = 0$ for units with features x. These are the causal parameters at the finest granular level. The ATE measure population averages, and the GATE the treatment effects for groups z; both calculated as weighted averages of the IATEs.

The set of unconfoundednes assumptions required are Conditional Independence, Common Support, Exogeneity and Stable Unit Treatment Value. The conditional independence assumption states that no other features than X, the set of confounders and covariates that define groups of population members, jointly influence treatment and potential outcomes. As we use rich administrative data from the German Federal Agency with information on socio-demographics as well as the individual's employment biography, we can safely assume conditional independence to hold. The stable unit treatment value assumption rules out spillover and treatment size effects by requiring that the observed value of treatment does not depend on treatment allocation of other population members. Exogeneity requires that the observed values of the confounding and heterogeneity variables do not depend on the treatment status. First, treatment allocation is based on a fixed available retraining capacity per year per federal state. Then, it is at a given caseworker's discretion whether or not to offer retraining to an unemployed person. Only at this point the unemployed may decide on participation. As both retraining capacity as well as caseworker allocation is exogeneous, we assume that exogeneity holds. Last, we did not detect any common support problems.

If these identifying assumptions hold, the IATE are identified and can uniquely be deduced from the expectations of observables.

Table 2: Summary Table - cont'd

	Treated	Control	Difference
Panel B: Employment history			
days in ALG II 1yr pre-treatment	14.94	17.23	-2.29***
	(50.92)	(53.87)	
days in ALG II 5yrs pre-treatment	88.3	89.6	-1.3
	(183.61)	(186.6)	
days in ALG II 10yrs pre-treatment	194.94	197.65	-2.71
	(291.45)	(308.58)	
days in ALMP program 1yr pre-treatment	38.31	24.42	13.89***
	(78.32)	(61.44)	
days in ALMP program 5yrs pre-treatment	150.29	115.9	34.39***
	(232.33)	(208.37)	
days in ALMP program 10yrs pre-treatment	293.88	235.16	58.72***
	(377.72)	(352.4)	
days in Mini-Job 1yr pre-treatment	12.89	14.94	-2.05***
	(46.44)	(52.42)	
days in Mini-Job 5yrs pre-treatment	95.52	98.99	-3.47
	(207.32)	(217.29)	
days in Mini-Job 10yrs pre-treatment	210.88	205.19	5.69
	(370.34)	(371.36)	
last wage	47.2	53.06	-5.86***
	(33.69)	(45.06)	
Position at occupation			
unskilled	0.44	0.3	0.14***
	(0.5)	(0.46)	
skilled	0.48	0.52	-0.04***
	(0.5)	(0.5)	
specialist	0.05	0.08	-0.03***
	(0.22)	(0.27)	
expert	0.03	0.1	-0.07***
	(0.17)	(0.3)	
Panel C: Other			
Unemployment benefit receipt according to			
SGB II	0.29	0.41	-0.12***
	(0.45)	(0.49)	
SGB III	0.71	0.58	0.13***
	(0.45)	(0.49)	
unemployment rate	5.25	5.24	-0.01
	(2.16)	(2.04)	
retraining rate	0.004	0.003	0.001***
	(0.005)	(0.003)	
Number of Observations	4367	12437	

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020. **Notes:** Standard deviations in brackets. ***, **, * indicate levels of significance at the 1, 5, and 10 % level, respectively.

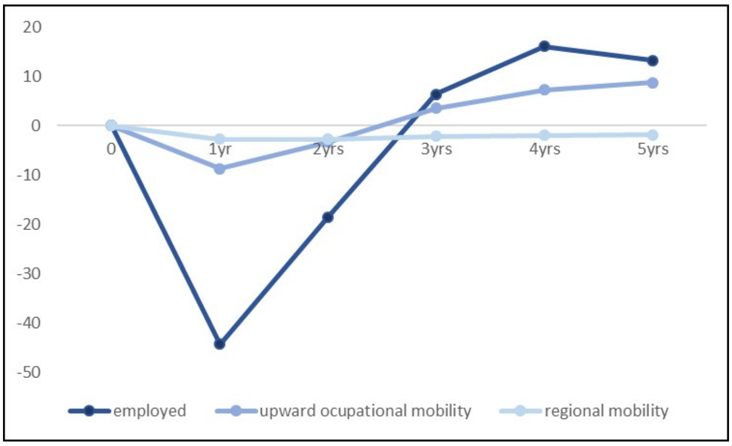
Table 3: Summary Table of Outcome Variables

	Treated	Control	Difference
employed	0.71	0.57	0.14***
	(0.45)	(0.49)	
upward occupational mobility	0.33	0.23	0.1***
	(0.47)	(0.42)	
no downward mobility	0.78	0.7	0.08***
	(0.42)	(0.46)	
regional mobility	0.06	0.09	- 0.03***
	(0.24)	(0.29)	
Number of Observations	4367	12437	

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020. **Notes:** Standard deviations in brackets. ***, **, * indicate levels of significance at the 1, 5, and 10 % level, respectively.

4 Results

Before diving into the detailed ATEs, we first present yearly point estimates of the effects of retraining on the employment probability, upward occupational mobility, and regional mobility for up to 5 years after the start of retraining. Figure 1 clearly traces the short-term lock-in effects of retraining. One year after the start of retraining, participation in the program reduces the probability to be employed by 44.34 percentage points. After three years the ATEs on employment turn positive and reach its maximum of 16,09 percent four years after treatment start. Similarly, for upward occupational mobility we also find lock-in effects during the first two years and an increase in the positive effects afterwards. The ATE on regional mobility is negative for the whole observation period and increases from -2.8 after one year to -1.8 percentage points after five years. All of the ATEs presented in Figure 1 are statistically significant.



Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020.

Figure 1: Timeline of ATEs

In Table 4 we present results from two different specifications. The first specification concentrates on the first employment within five years after the (hypothetical) training spell, whereas the second specification is related to figure 1 but only deals with the first employment spell in the fifth year after the (hypothetical) retraining (which corresponds to the last data point in Figure 1). While there is a large positive effect on employment of 13.3 percentage points for the second specification, there is no significant ATE for the employment probability for the first employment within five years.

Table 4: ATEs

	(1) ATE	(2) ATET	(3) ATEUT
Specification I: First employment within 5 years			
employed	-1.21	-2.61***	-0.76
	(0.98)	(0.9)	(1.06)
occupational mobility	8.87***	8.18***	9.09***
	(0.87)	(0.75)	(0.96)
regional mobility	-1.63***	-1.56***	-1.65***
	(0.52)	(0.49)	(0.57)
Specification II: Employment in fifth year			
employed	13.3***	12.49***	13.57***
	(0.86)	(0.82)	(0.93)
occupational mobility	8.74***	7.02***	9.33***
	(0.89)	(0.82)	(0.98)
regional mobility	-1.83***	-1.88***	-1.81***
	(0.51)	(0.47)	(0.55)
Number of Observations	16804	4367	12437

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020. **Notes:** Standard deviations in brackets. ***, **, * indicate levels of significance at the 1, 5, and 10 % level, respectively. Both specifications use the employment dummy as a tree-builder, with a minimum leaf size of 5, an alpha regularity of 0.2, 11 features in the splitting process and an average size of leaves of 9.6.

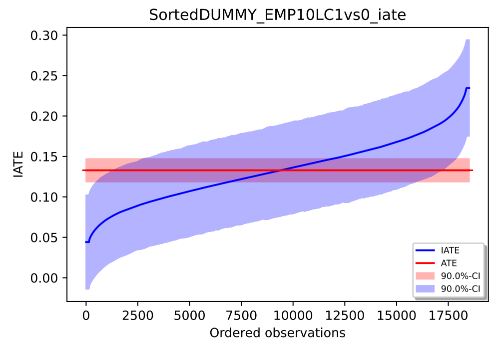
That is, retraining has a strong positive effect on employment probability for the employment probability in the fifth year after retraining. However, there is no difference between treated and non-treated individuals for the first employment within five years after the retraining took place. This should not be surprising, as most individuals - retrained or not - will have found an employment within five years.

The ATEs for the other outcomes do not differ much between both specifications. Compared to non-participants, retraining participants are 8 percentage points more likely to register upward occupational mobility and almost 2 percentage points less likely to move to another region. As only 8.5 percent of all individuals in our sample live in another region after five years, the relative effect is more than 20 percent.

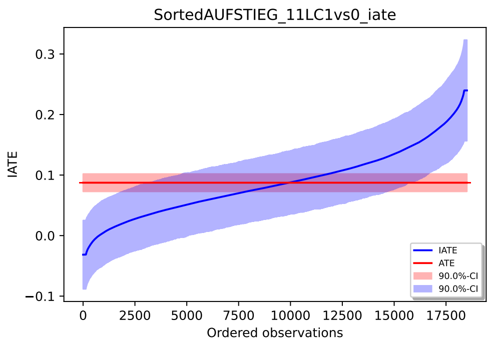
Turning to the ATE of the Treated (ATET) and the untreated (ATEUT), the effects do not seem to differ too much in comparison to the ATEs in general and between both specifications. However, for the ATET, there is a significant and negative effect of treated individuals on the employment probability within 5 years after training. This should be due to the short term lock-in effect of retraining participation (Fitzenberger et al., 2008), as also visually detectable in figure 1.

4.1 Heterogeneity in Treatment Effects

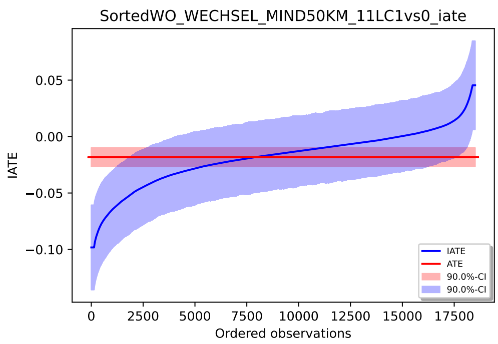
The previous section demonstrated clear and significant positive average treatment effects with respect to employment probability and vertical occupational mobility as well as negative effects regarding regional mobility. This section now sheds some light on heterogeneities in treatment effects.



(a) IATEs employed



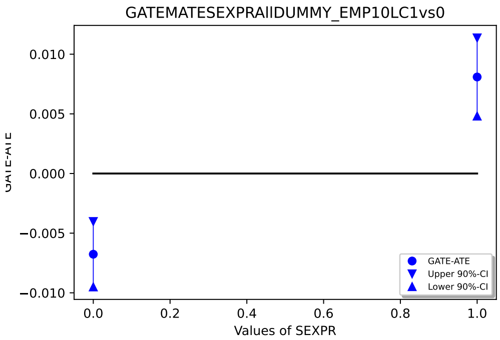
(b) IATEs occupational mobility



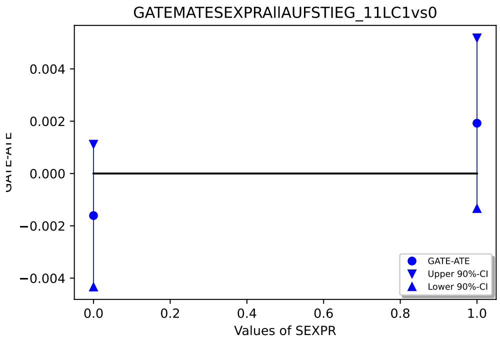
(c) IATEs regional mobility
Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020.

Figure 2: Plots of IATEs for the employment probability in the fifth year

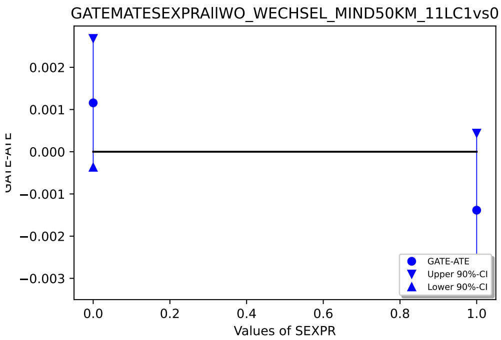
As table 4 has shown, both specifications do not differ much in the magnitudes of the ATE estimates on upward occupational and regional mobility. For the remainder of the paper, we will stick to specification II, the employment probability in the fifth year.



(a) GATEs employed



(b) GATEs occupational mobility



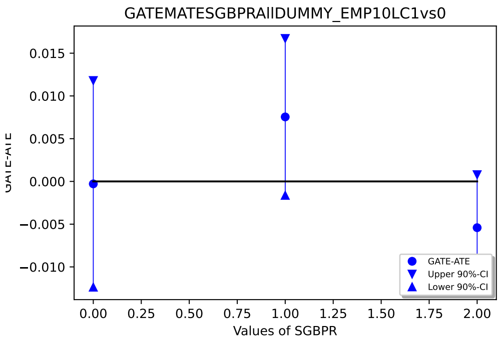
(c) GATEs regional mobility

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020.

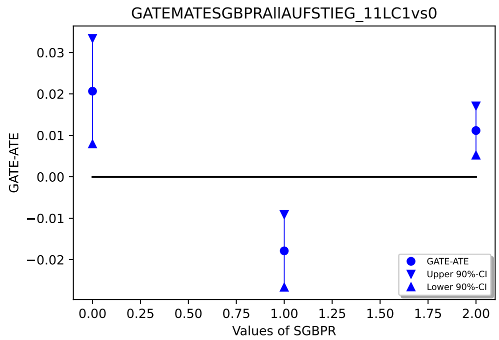
Figure 3: Plots of GATEs for the first Employment in fifth year, by gender

Sorting the IATEs, we detect a somewhat marked variance and differences from the ATEs, which hints at heterogeneities in treatment effects. Figure 2 presents the sorted IATEs for the three outcomes employment probability (figure 2a), upward occupational mobility (figure 2b), and regional mobility (figure 2c). The IATEs for employment are positive for all individuals and larger than the ATE of 13.3 percentage points for 54 percent. Furthermore, as to upward occupational mobility, the large majority of the IATEs is positive (95.9 percent) and almost 48 percent are above the ATE. Considering regional mobility, more than 80 percent of the individuals experience negative IATEs. Two potential dimensions that could determine differences in magnitudes of the IATEs are gender and the social security status, which we will now turn to.

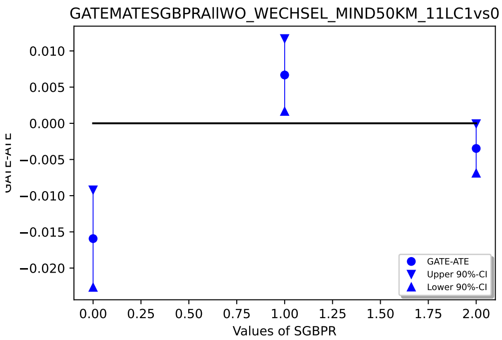
Figure 3 presents three graphics plotting the difference of the GATEs to the ATEs for



(a) GATEs employed



(b) GATEs occupational mobility



(c) GATEs regional mobility

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020.

Figure 4: Plots of GATEs for the first Employment in fifth year, by SGB status

men and women, where sex equals 1 if a person is female. Regarding the employment probability, women profit more than average from retraining participation, which is in line with existing research (Biewen et al., 2014). Neither occupational nor regional mobility show any significant gender-related treatment differences.

Individuals in the unemployment insurance system (SGB III) exhibit larger than average effects in their probability of being employed. Welfare recipients (SGB II) show smaller than average treatment effects of retraining on employment and upward occupational mobility and larger, that is less negative, effects on regional mobility. Participants belonging to SGB III exhibit smaller than average treatment effects regarding regional mobility probability and larger than average effects in occupational mobility. It seems like these individuals, who may, generally, be considered to be closer to the labor market, profit most from retraining participation. They are more likely to become employed and, when employed, their probability for upward occupational mobility is higher than average. Additionally, they are less likely to move to another region.

Altogether, we see pronounced effects in both regional and occupational mobility, in line with our hypotheses. Training participants exhibit a larger probability in being employed, showing upward occupational mobility, and a lower likelihood of spatial mobility. Additionally, we detect heterogeneous effects in employment probability by social security status and gender and in occupational and regional mobility. Individuals within unemployment insurance profit most from retraining, regarding their employment probability, as well as show the most pronounced substitution effect between occupational and spatial mobility.

4.2 Robustness

As robustness check, we present quarterly estimates of our outcomes for all four quarters in 2013 and all but the fourth quarter for 2014. As table 5 shows, estimates stay roughly similar along all quarters. Strong positive effects of retraining on upward occupational mobility are contrasted with clearly negative effects on regional mobility.

As an additional measure for occupational mobility, we added estimates measuring the scenario of no downward mobility, which equals 1 if a person's occupational position does not change to a lower position, e.g. from a specialist to unskilled work, and 0 otherwise. Especially for unemployed at higher positional levels, upward mobility might not be realizable - even though these do not form the majority of retraining participants (see table 2). For all quarters retraining participants have a higher likelihood not to exhibit downward occupational mobility by 5 to 7 percentage points. Generally, estimates for upward and no downward occupational mobility are within the same range.

Table 5: ATEs per quarter

	q1	q2	q3	q4
2013				
employed	12.78***	15.17***	13.3***	13.84***
	(1.62)	(1.39)	(0.86)	(1.26)
occupational mobility	10.36***	6.77***	8.74***	9.97***
	(1.73)	(1.44)	(0.89)	(1.37)
no downward occ. mobility	7.23***	6.8***	6.63***	6.98***
	(1.5)	(1.31)	(0.78)	(1.17)
regional mobility	-1.69**	-1.67**	-1.83***	-1.76**
	(0.85)	(0.82)	(0.51)	(0.76)
Number of Observations	20563	17893	16804	20892
2014				
employed	7.91***	11.19***	10.62***	-
	(0.97)	(1.29)	(0.91)	-
occupational mobility	9.07***	8.51***	8.57***	-
	(1.01)	(1.35)	(0.92)	-
no downward occ. mobility	5.66***	6.03***	5.4***	-
	(0.86)	(1.21)	(0.83)	-
regional mobility	-2.36***	-1.1	-3.73***	-
	(0.49)	(0.75)	(0.48)	-
Number of Observations	25788	19097	14893	23196

Source: IAB Integrierte Erwerbsbiografien (IEB) V15.00.00-201912 and Arbeitsuchendenhistorik (ASU) V06.12.00-202004, Nuremberg 2020. **Notes:** Standard deviations in brackets. ***, **, * indicate levels of significance at the 1, 5, and 10 % level, respectively. The employment dummy is used as a tree-builder, with a minimum leaf size of 5, an alpha regularity of 0.2 and 11 features in the splitting process and an average size of leaves of 9.6. For the fourth quarter in 2014 treatment estimation was not possible as there were not enough training participants.

5 Conclusion

As outlined before, a large body of literature both on retraining effects as well as determinants of occupational and regional mobility exists. Our paper is the first to combine the three dimensions. Using a relatively new machine learning approach, we estimate average treatment effects in retraining participation and investigate into effect heterogeneity. Our results show strongly significant effects of retraining participation on employment probability, upward occupational and regional mobility. Retraining reduces the probability to move within five years by almost 2 percentage points and increases the probability of experiencing upward occupational mobility by approximately 8 percentage points. Furthermore, we present evidence that these effects are strongest for unemployment insurance beneficiaries.

From literature, we know that regional mobility has higher returns compared to occupational mobility (Reichelt & Abraham, 2017) and that there exists an education gap in regional mobility (Molloy et al., 2011). It seems low-wagers, those who are generally less educated, are the ones that generally move less but are more likely to participate in retraining. At the same time, retraining further reduces regional mobility in favour of occupational mobility. Thus, it seems worthwile to think about who exactly should be offered retraining. Some unemployed (low-wagers) might profit more from regional mobility and policies aiming to increase job search radius or (financial) help with moving. Future research should look into who might profit most from moving compared to occupational mobility through retraining, and who might especially benefit from retraining as they cannot or would not move (e.g. due to family ties).

For this paper, we further plan to take a closer look at effect heterogeneity with regard to occupational position before potential treatment start. Additionally, we plan to divide retraining participants along target groups. Individuals with no vocational degree potentially reap different returns to retraining participation in comparison to those who can no longer practice their profession or those who have not worked in their occupation for a longer amount of time. Finally, we want to focus on groups of unemployed who are potentially less regionally mobile, such as parents, to see if retraining is particularly effective for these groups.

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A

Table 6: List of Features

Feature	
Demographics	
Age	
Education	
Share female	
Family Status	
Employment History	
days in employment	monthly, up to 60 months pre-training
Days in employment	1,5,10 years pre-training
Days in ALG I	1,5,10 years pre-training
Days in ALG II	1,5,10 years pre-training
Days in ALMP programms	1,5,10 years pre-training
Days in Mini-Jobs	1,5,10 years pre-training
Days in vocational training	1,5,10 years pre-training
Days registered as job searching	1,5,10 years pre-training
Number of employment spells	1,5,10 years pre-training
Number of spells in ALG I	1,5,10 years pre-training
Number of spells in ALG II	1,5,10 years pre-training
Number of spells in ALMP programms	1,5,10 years pre-training
Number of spells in Mini-Jobs	1,5,10 years pre-training
Number of spells in vocational training	1,5,10 years pre-training
Number of spells registered as job searching	1,5,10 years pre-training
last wage	
last position	
last occupation	
Other	
Share of unemployed	
Share of retrained	job agency district-level
Month of (hypothetical) Retraining	
Social Security Status	
Place of residence	job agency district-level