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ABSTRACT

Active Labour Market Policies for the Long-Term Unemployed: New Evidence from Causal Machine Learning*

We investigate the effectiveness of three different job-search and training programmes for German long-term unemployed persons. On the basis of an extensive administrative data set, we evaluated the effects of those programmes on various levels of aggregation using Causal Machine Learning. We found participants to benefit from the investigated programmes with placement services to be most effective. Effects are realised quickly and are long-lasting for any programme. While the effects are rather homogenous for men, we found differential effects for women in various characteristics. Women benefit in particular when local labour market conditions improve. Regarding the allocation mechanism of the unemployed to the different programmes, we found the observed allocation to be as effective as a random allocation. Therefore, we propose data-driven rules for the allocation of the unemployed to the respective labour market programmes that would improve the status-quo.

JEL Classification: J08, J68

Keywords: policy evaluation, Modified Causal Forest (MCF), active labour market programmes, conditional average treatment effect (CATE)

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1 Introduction

Bringing means-tested benefit recipients back to work is among the hardest tasks for employment agencies. Still, it is of high interest for all, the society, the state, and most importantly for the unemployed, to increase their chances to find decent jobs and leave long-term unemployment. The classical approach of employment agencies in industrialised countries is to provide active labour market programmes (ALMP), such as job-search and training programmes, to selected unemployed individuals. It is therefore of great interest to labour market authorities to understand whether those ALMP are beneficial for the long-term unemployed and to understand which programme works best and for which types of unemployed persons. Furthermore, a key issue is to learn how to allocate the programmes efficiently.

This study shares the interest of policy makers in gaining a better understanding of the employment agencies' tools by evaluating the existing ALMP and finding ways to improve the counselling process and allocation of ALMP. Previous empirical evaluation of labour market programmes focused on specific questions or investigated the effectiveness of the job-search, training, and other programmes for a small number of different participant groups and/or programme types (e.g., Bernhard and Kopf (2014), Hohmeyer (2012), Kopf (2013)). Those more general findings are of interest; however, there is still a huge potential for analysing the effects on more granular levels, and subsequently for allocating participants of training programmes in a more individualised way.

While estimating average effects for a population is well established in the microeconometric literature, systematically investigating treatment effect heterogeneities is a more challenging task. The recent, steadily growing literature on causal machine learning, which combines the predictive accuracy in statistical learning tools (see Hastie, Tibshirani, and

Friedman (2009) for an overview) and causal principles that have been known for years, offers promising solutions to these challenges.

Several approaches are proposed in the literature to modify machine learning tools in such a way that they become useful for causal inference (for overviews, see e.g., Athey (2018), Athey and Imbens (2019)). In an extensive empirical simulation study, Knaus, Lechner, and Strittmatter (2021) evaluated many of those methods and found forest-type estimators (e.g., Wager and Athey (2018), Athey, Tibshirani, and Wager (2019)) to perform well in many situations. In this study, we use the Modified Causal Forest (MCF) subsequently proposed by Lechner (2018), since it enables us to investigate multiple treatments and systematic effect heterogeneities on different levels of aggregation within one estimation approach.[1]

The literature on active labour market policy evaluation is substantial (e.g., the meta studies of Card, Kluve, and Weber (2010), Card, Kluve, and Weber (2018) and Kluve (2010) or less recent surveys on ALMP evaluation of Heckman, LaLonde, Smith (1999) as well as Martin and Grubb (2001)). Usually, the focus is on estimating average effects for broader populations, i.e., the average treatment effect (ATE) or the average treatment effect on the treated (ATET). However, there is less evidence for smaller, more homogeneous and diverse groups. This study is among the early papers in policy evaluation to systematically analyse treatment effect heterogeneity using causal machine learning (CML) methods. In a LASSO-based approach to analyse heterogeneous treatment effects, Knaus, Lechner, and Strittmatter (2020) evaluate a job-search programme in Switzerland. Using administrative data from 2003, they find heterogeneity in the short run, but effects become more homogeneous in the long run. Knaus (2020) uses the same data and applies double machine learning methods (cf. Chernozhukov et al. (2018)). In his analysis of training and job-search programmes in a multiple treatment setting, he finds substantial effect heterogeneity by gender and previous labour

[1] While the estimation in this paper have been conducted with the Gauss version of the estimator, a Python version of it can be downloaded from PyPy.

market success. In an application to a temporary public works programme, Bertrand, Crépon, Marguerie, and Premand (2017) use data from randomised controlled trials to analyse treatment effect heterogeneity. Using a causal forest algorithm (cf. Wager and Athey (2018)), they find differential effects during the lock-in period. The same method is also used in an RCT application to summer jobs in Davis and Heller (2017) and Davis and Heller (2020).

The study most similar to ours is the work of Cockx, Lechner, and Bollens (2019) investigating heterogeneity in employment effects of Flemish training programmes. In their work, they use the MCF to investigate multiple training programmes, providing treatment effects on various levels of aggregation. Especially, they find important heterogeneities associated to language, migration status, and employability.

A special feature of our study is that we observe the universe of job-search and training programme participants among German means-tested benefit recipients. Having a broad range of administrative data for over 300,000 mainly long-term unemployed individuals, we investigate three different ALMP, namely *job-training*, *reducing impediments,* and a *placement service*, with participation starting in the first quarter of 2010. For those three ALMP, the unconfoundedness assumption needed for identification is credible as these administrative data are available, for which we provide additional evidence in a placebo test. For a fourth programme, *in-firm training*, the placebo exercise rejects the unconfoundedness hypothesis. This programme is therefore excluded from the analysis.

When the programmes that we analyse were introduced in 2009, the German government attempted to create schemes that allow the job centres considerable leeway in the programme's design to meet the individual needs of participants. In turn, participation should positively influence the employment perspectives of most participants. It is therefore important that we analyse the heterogeneity of participation effects and estimate Individualised Average Treatment Effects (IATEs). In fact, we primarily find that all investigated training and job-search programmes lead to positive employment effects for the participants. This can be found not only on average, but most of the individuals are likely to realise additional days in regular (i.e., unsubsidised contributory) employment if participating.

Average results for women range from 26 to 54 more days in employment in three years after starting the participation in the respective programmes; for men the effect is in the range of 35 - 45 more days in regular employment. Effects emerge quickly and are long-lasting. While *placement service* is the programme with the highest effects, we find substantial effect heterogeneity. In general, those individuals with a worse labour market history benefit more than those with a better record. For women, the place of residence and local labour market conditions are decisive. Those located in regions with better local labour market conditions benefit substantially more from participating in the job-search and training programmes than those women living in areas with worse labour market conditions.

With regard to the allocation mechanism in place, we find a random allocation to perform equally well. While effect-based black-box allocation approaches lead to 14% higher effects for the reallocated subpopulation, even an easy and transparent rule leads to 6% higher effects.

The rest of the paper is structured as follows: Sections 2 and 3 introduce the institutional setting, the database used in the analysis and some descriptive statistics. The methodology is described in Section 4, and the results of the empirical analysis are presented in Section 5. Allocation mechanisms for the unemployed are discussed in Section 6. Finally, Section 7 discusses the findings, and Section 8 offers some concluding remarks.

2 Institutional setting

The German means-tested benefits (unemployment benefit II – UB II) are regulated in the system of basic income support called Social Code II (SC II). The official term of employment agencies in this system is "job centres", which we use in the following. Welfare recipients in this system are often long-term unemployed individuals running out of unemployment insurance benefits.[2] Although the pool of welfare recipients is rather heterogeneous, people with substantial employment impediments are frequently found among the unemployed receiving UB II. Both, unemployed and employed individuals can receive UB II if their household income is below the poverty line so that they and their household members pass the means test. In 2021, UB II amounted to € 446 per month for a single adult (plus the costs for heating and accommodation). By comparison: for those living as a couple, each partner receives € 401 per month, while children under the age of six receive € 283 per month. Thus, the household composition determines the amount of benefits a household receives.

ALMP play a major role in supporting unemployed welfare recipients in their integration in the labour market. The programmes are supposed to help to increase their employability and labour market attachment. The ALMP of interest in this paper are specific subtypes of the "schemes for activation and integration" (SAI). SAI consist of different training programmes within firms and in classrooms as well as placement services run by private providers. The schemes are characterised by a high flexibility as the job centres have considerable leeway in the programme's design. This allows them to adapt the programme to the individual skills and situations of the participants (see also Goller, Lechner, Moczall, and Wolff (2020) as well as Harrer, Moczall, and Wolff (2020) who were among the first to analyse SAI for UB II recipients).

Among the different SAI subtypes, we particularly focus on the following four: (1) guiding into apprenticeship and into work (in the following "*job-training*" or *JT*), (2) determining, reducing, and removing employment impediments (in the following "*reducing impediments*", or *RIM*), (3) placement into contributory employment (in the following

2 This is the other benefit type. The benefit level is 60 % (67 %) of the last net wage for childless adults (for parents). Unemployed persons receive this benefit up to one year if they are younger than 50 years (and up to two years for the older age groups).

"*placement services*", or *PS*), and (4) *in-firm training* (*IFT*). *JT* and *RIM* both take place at private training providers, *PS* are conducted by private placement services, while *IFT* are organised by companies as a type of internship.

During *job-training*, participants learn to choose suitable job offers and to write application letters and CVs. This is supposed to improve their job-search effectiveness. *Reducing impediments* focuses on the participants' individual skills and employability. *RIM* aims at overcoming the participants' employment impediments by increasing participants' knowledge about certain occupational fields, for example. *Placement services,* in contrast, aim at finding work or vocational training for participants. *IFT* provide participants with the possibility of getting accustomed to regular work schedules and the employment situation in the company hosting *IFT*. The duration of these programmes is rather short. *IFT* are short per se as they can last for only up to four weeks.[3] Accordingly, 99.0% of *IFT* inflows between January and March 2010 had a programme duration of less than one month.[4] For *JT* and *RIM* inflows, the shares of programmes lasting less than three months were 92.9% and 94.5%, respectively. Here, *JT* were even shorter on average than *RIM* (77.0% vs. 41.0% of inflows with a duration of less than one month). The respective shares were smaller for *PS* inflows between January and March 2010 (53.2% of inflows with a duration of less than three months and 13.0% with a duration of less than one month). Yet these programmes can still be classified as rather short.

Further SAI subtypes we do not consider in this paper are (1) guiding into self-employment, (2) stabilisation of existing employment, (3) activation focusing on young participants, and (4) combined measures. We did not include these subtypes as either they were quantitatively rather unimportant, i.e., not allowing us to perform group analyses ((1) to (3)),

[3] Compare article 46 paragraph 2, SC III, version of January 2009. SC III: Social Code III (Sozialgesetzbuch – Drittes Buch – Arbeitsförderung).

[4] Source: DataWareHouse of the Statistics Department of the German Federal Employment Agency.

too selective in their targeting (3) or too heterogeneous in their design and did not provide enough information on the programmes' content, i.e., impeding proper interpretation of our results (4). Neither did we include *IFT* in our main analyses (but in the placebo analysis) because employers might be involved in the selection of the welfare recipients into *IFT* participation. For instance, employers might partly select *IFT* participants that they would have hired anyway so that the results would reflect some deadweight loss (Kopf (2013)). Hence, it is likely that the decision process involving the employers cannot be convincingly modelled by just relying on the confounders of our analysis.

Table 1: Inflows into the SAI subtypes of interest

	Men	Women	Overall
Job-training	12,329	9,350	21,679
Reducing impediments	8,721	6,678	15,399
Placement services	7,375	4,713	12,088
In-firm training	11,869	6,564	18,433

Notes: Inflows between January and March 2010 among our sample members. Restriction to people who at the sampling date of the 31st of December 2009 were: (1) aged 25 to 54 years, (2) registered as unemployed, (3) receiving UB II. Source: Integrated Employment Biographies and further individual data.

Therefore, we focused on the SAI subtypes of *JT*, *RIM* and *PS* to get rather homogeneous treatments and clarity about each programme's contents. The distinctive subtypes differing in their aims allow us to answer the question of whether participants might have improved their labour market chances if they were assigned to another treatment. Moreover, the three subtypes are quantitatively important, providing us with sufficiently high numbers of observations to use the elaborated econometric methods of machine learning and group analyses (see Table 1).

3 Data

Our rich administrative dataset stems from the Statistics Department of the German Federal Employment Agency (FEA) and contains information on (registered) jobseekers and benefit recipients (see Goller, Lechner, Moczall, and Wolff (2020) and Harrer, Moczall, and Wolff (2020) for more detailed information on this database).

We were able to use a rich set of observable characteristics relevant for welfare recipients' labour market integration as we included information at the individual, the household, the district, and the job centre level. The full list of the covariates can be found for men in Table 10 in Appendix A.1 and for women in Table 11 in Appendix A.2. In detail, we included sociodemographic characteristics (see Panel A in the respective tables), a large set of variables on the labour market history of our sample members (Panel B) and, in particular, information on the last job (Panel C) and the labour market status in December 2004, i.e., before the introduction of the SC II (Panel D). Among the covariates at the individual level, we included variables such as age, gender, children living in the same household, the last occupation, and work experience. Older age, care responsibilities, and work experience that was made long ago decrease the probability of leaving unemployment and welfare receipt (Hohmeyer and Lietzmann (2020)) or at least slow down the transition from welfare receipt into self-sufficient employment (Achatz and Trappmann (2011), Beste and Trappmann (2016)). Including rich information on the labour market biographies (e.g., not only on work experience but also on unemployment and ALMP programme experience), we indirectly controlled for unobservable characteristics such as motivation or personality traits (Caliendo, Mahlstedt, and Mitnik (2017)).

At the household level, we considered e.g., the income and composition of the household (Panel E). In particular, we controlled for the number and age of children in the household as (high numbers of) especially young children diminish the chances to exit unemployment and welfare receipt (Hohmeyer and Lietzmann (2020)). We further differentiate by gender in our analyses because care responsibilities due to such compositional situations are more likely to negatively affect the labour market prospects of women than of men (see Achatz and Trappmann (2011)). Further, (potential) welfare receipt might affect household composition in particular in SC II (due to the amount of received benefits). Possible composition changes (e.g., divorce, cohabitation, or birth of children) in turn may lead to changes in the household's risk of welfare receipt (Blank (1989)). We also included information on the partner if living in the same household (Panel F) because the partner's work experience and education determines his or her employment prospects which overall affects the household's chances to leave UB II. Lastly, we included district-level labour market indicators such as the unemployment rate (Panel G) and information at the job centre level, such as the client-staff ratio in the job centres (Panel H). We did so because the local situations in job centres and labour markets are likely to influence welfare recipients' labour market prospects (as e.g., found by Carpentier, Neels, and van den Bosch (2014) in observing social assistance exit rates for Belgium).

Our sample consists of individuals who were unemployed and received UB II at the end of 2009. We further modified this dataset to get our final sample. The three treatment groups used in the main analyses consist of the population of unemployed welfare recipients starting *JT*, *RIM* or *PS* in the first quarter of 2010. Moreover, there is a group of *non-participants* (*NP*), which represent a 20 percent random sample of the stock of unemployed UB II recipients at the end of 2009 who did not enter any SAI programme during the following three months. If individuals participated in several of our observed SAI subtypes, the very first of these subtypes determines to which of the three treatment groups the individuals belong. We only included unemployed welfare recipients aged 25 to 54 due to the different ALMP assignment rules the FEA has for younger and older welfare recipients. In our observation window, special rules for individuals aged less than 25 years lead to more intense activation compared with older welfare recipients. This was a consequence of rules that were concerned with a quick integration of young welfare recipients into jobs, training or work opportunities.[5] Moreover, by excluding very young welfare recipients, we also make sure to get (un)employment biographies more complete, thus being able to indirectly control for unobservable characteristics that are highly related to the employment biographies. As we focus on *JT*, *RIM*, and *PS* in this study, we also

[5] Article 3 paragraph 2, SC II, version of August 2009.

excluded welfare recipients participating in one of the other SAI subtypes during our treatment window (January to March 2010).

Table 2: Descriptive statistics – Outcome and selected covariates

Variable	Men		Women	
	Participants	Non-participants	Participants	Non-participants
Cumulated days in regular employment in the 3 years after treatment (Outcome)	250 (325)	181 (291)	188 (300)	137 (261)
Personal characteristics				
Age at sampling date (in years)	38.3 (8.52)	39.7 (8.57)	38.9 (8.38)	39.9 (8.41)
Days since last employment	1,478 (1,598)	1,822 (1,774)	1,949 (2,128)	2,115 (2,287)
Days in regular employment in the previous 5 years	293 (401)	224 (358)	178 (343)	138 (298)
Days in welfare receipt in the last year	297 (112)	318 (91)	317 (98)	332 (79)
Receiving income from dependent employment (yes=1)	0.17	0.18	0.22	0.27
Region (west=0, east=1)	0.25	0.35	0.26	0.33
Foreigner (yes=1)	0.23	0.20	0.20	0.22
Job centre characteristics				
Job centre district - client-staff ratio	158 (28)	162 (26)	159 (28)	162 (27)
Job centre district - sanction intensity due to violations of duties (in percent)	0.54 (0.25)	0.51 (0.24)	0.54 (0.25)	0.52 (0.24)
Job centre district - sanction intensity due to failure in reporting (in percent)	0.71 (0.25)	0.71 (0.25)	0.71 (0.26)	0.71 (0.26)
District-level characteristics				
District unemployment rate (in percent)	10.4 (3.3)	11.0 (3.5)	10.3 (3.3)	10.8 (3.6)
District unemployment rate of welfare recipients (in percent)	7.4 (3.0)	7.9 (3.3)	7.4 (3.0)	7.7 (3.3)
N	28,425	136,691	20,741	116,769

Notes: Means of the covariates. Standard deviations in parentheses. The treated group in this table contains all individuals of our initial three treatment groups (*JT*, *RIM* and *PS*). We computed the mean of covariates over all treatment groups here.

Next, we excluded individuals who found contributory employment or left welfare receipt between the sampling date and their (hypothetical) programme start. Finally, we deleted observations from our sample due to missing values in the covariates used. All in all, this leads to 302,626 observed individuals (see Table 2). It is straightforward to measure outcomes for the treated individuals from their programme start onwards. To compare participants with non-participants, we would have liked to measure the outcomes for the latter in the same way, but for them no programme start is available. This was resolved by assigning a hypothetical programme start to each of the non-participants. It was randomly drawn from the distribution of actual programme starts among participants (similar to e.g., Gerfin and Lechner (2002), Sianesi (2004), and Goller, Lechner, Moczall, and Wolff (2020)).

In Table 2, we present some selected covariates and distinguish between non-participants and a combined group of treated sample members. The whole covariate set distinguished by non-participants and *JT*, *RIM*, and *PS* participants can be found in the Tables 10 and 11 in the Appendix A.1 and A.2. On average, participants show more beneficial characteristics than non-participants as e.g., participants experienced less cumulated days in welfare receipt in the last year but more days in regular employment in the last five years. The differences are more pronounced among men. Moreover, men's non-employment duration is shorter than women's (days since last regular employment). This holds for all participants and non-participants (with higher levels among the latter). Table 2 thus indicates some positive selection into treatment. Additionally, the Appendix Tables 10 and 11 show that this positive selection varies across the three participation groups.

4 Econometrics

4.1 Notation and framework

To describe our multiple treatment model under conditional independence (Imbens (2000), Lechner (2001)), we use Rubin's (1974) potential outcome framework. Participation in one of the programmes is indicated with D_i as the (multiple) treatment variable, while $D_i = 0$ indicates non-participation of the individual i $(i = 1, .., N)$ and $D_i > 0$ participation in one of the three job-search and training programmes. Let $Y_i^d \coloneqq Y_i(D_i = d)$ denote the potential outcome if individual i receives treatment $d_i \in \{0,1,2,3\}$.[6] For each individual we observe the particular potential outcome related to the treatment status to which the individual is assigned, the others remain counterfactual: $Y_i = \sum_{d=0}^{3} \underline{1}(d_i = d) Y_i^d$. Further, for each individual we observe the variables $X_i \in (\tilde{X}_i, Z_i)$. While $\tilde{X}_i$ represents those variables needed to account for confounding, Z_i contains those variables in which we are interested in the heterogeneity analysis.[7]

There are three estimands of interest on different levels of aggregation:

$$IATE(m,l;x,\Delta) = E(Y^m - Y^l | X_i = x),$$

$$GATE(m,l;z,\Delta) = E(Y^m - Y^l | Z_i = z, D \in \Delta),$$

$$ATE(m,l;\Delta) = E(Y^m - Y^l |\, D \in \Delta).$$

The Average Treatment Effects (ATE) represent the population average effects on the highest level of aggregation for treatment status m compared to treatment status l belonging to treatment groups Δ, where Δ denotes all treatments of interest. Please note that if Δ relates to the population $D = m$ we obtain the Average Treatment Effect on the Treated (ATET). On the contrary, the estimand on the lowest aggregation level is the Individualised Average Treatment Effects (IATE), i.e., conditional on characteristics x. An estimand on the intermediate aggregation level, which is of main interest for policy analysis, is the Group Average Treatment Effect (GATE) according to the heterogeneity variables Z_i. Both special cases of the Conditional Average Treatment Effects (CATEs) last mentioned, the GATEs and IATEs, are useful to detect heterogeneities, which are otherwise "hidden" in the homogenous ATE

[6] We use the convention that (usually) capital letters denote random variable, while small letters denote some fixed value of these random variables.

[7] In principle, $\tilde{X}_i$ and Z_i might contain distinct variables or overlap, partly or completely. In this work Z_i is a subset of $\tilde{X}_i$ selected ad hoc. The heterogeneous treatment effects that are based on this selection of variables are of considerable interest for policy makers, society, and academia.

estimate. Worth noting is the relationship of those three estimands. Averaging the IATEs by the groups $Z_i = z$ results in the GATEs. Averaging over the GATEs then leads to the ATEs.

4.2 Identification

As mentioned, only one of the potential outcomes is observable, since exactly one of the four treatment statuses can be realised, the others remain counterfactual. In the literature this is referred to as the 'fundamental problem of causal inference' (Holland (1986)). To 'solve' this, a credible identification strategy for estimating causal effects is crucial. We rely on a selection-on-observable approach and need to impose some assumptions to identify the estimands of interest in our multiple treatment setting (see Imbens (2000), Lechner (2001)):

CIA: $Y^d \perp D|\tilde{X}_i = \tilde{x}$,

CS: $0 < P\big(D = d\big|\tilde{X} = \tilde{x}\big) < 1$,

SUTVA: $Y = \underline{1}(D = d)Y^d$.

Exogeneity: $\tilde{X} = \tilde{X}^d$

The Conditional Independence Assumption (CIA) states that all the potential outcomes are independent of the treatment assignment, conditional on the observed confounders. This implies that there are no further characteristics that are jointly related to the potential outcomes and the treatment. Common Support (CS) is ensured if every treatment status might be observed for all realisations of covariates. The Stable Unit Treatment Value Assumption (SUTVA) requires that there are no spill-over effects across the treatment groups, and for Exogeneity covariates are not affected by the treatment.

As discussed in Section 3, the available covariates capture a wide range of potential confounders. Most of the quantifiable information, which the caseworker responsible for the assignment to the programmes can see are contained in our data set. Among those are the most important confounders as identified by other evaluation studies (Heckman, Ichimura, Smith, and Todd (1998), Lechner and Wunsch (2013)). In addition, we include more characteristics related to the individuals' labour market history in the last five years, since means-tested benefit recipients to a higher degree consist of people who did not work for various years. Therefore, having this rich administrative data set, the CIA in this work is arguably credible. While this assumption is untestable, we provide a placebo study below to strengthen the argument.[8] Since the observed programmes are rather small compared to the labour force, there should not be any spill-over effects rendering the SUTVA incredible. Exogeneity is given as we measure all covariates at our sampling date (12/31/2009) and before they are assigned to any treatment status.

4.3 Method

Recently, many new estimators were proposed, which combine the predictive power of machine learning tools and the causal structure known from classical microeconometric literature (see e.g., Athey (2018), Athey and Imbens (2019) for an overview). Those methods, branded as causal machine learning, turn out to be especially useful if the interest is in estimating treatment effects beyond the average effects.

For our empirical analysis, a well performing estimator for multiple treatments, which can provide us with estimates on the various levels of aggregation and inference for those estimates, is needed. Simulation-based evidence (e.g., Knaus, Lechner, and Strittmatter (2021)) finds a general observation that forest-based causal machine learning estimators perform especially well in many situations (Athey, Tibshirani, and Wager (2019), Wager and Athey (2018)).

The Random Forest was introduced in Breiman (2001) as an ensemble of many regression trees. The idea of a regression tree is to recursively split the space of covariates into non-

[8] The placebo study does provide evidence for the CIA to hold for the three treatments investigated. It also confirms our choice to not include another, fourth treatment *IFT*, for which the assignment mechanism is probably driven by some external factors, which are not observable for us.

overlapping areas by minimising the MSE of the outcome prediction until some stopping criteria are reached. The resulting structure is reminiscent of a rotated tree, as one observes the trunk with all the observations in the beginning, split-up into finer branches the further one goes down. The final predictions result from the averages of the outcomes falling into the same end-nodes, so called leaves. The combination of many randomly constructed trees gives the final prediction of the random forest. To accommodate this prediction tool in the causal framework, Athey and Imbens (2016) developed a causal tree. Many of those causal trees can be combined to a Causal Forest in different forms (Wager and Athey (2018), Athey, Tibshirani, and Wager (2019)).

Lechner (2018) further develops this idea by improving on the splitting rule for the individual trees, proposing the Modified Causal Forest (MCF). The MCF is especially well suited for the purpose of this study. It enables the estimation of heterogeneous effects in a multiple treatment setting on various levels of aggregations. With an approach for unified inference for the highest (ATE) and lowest level (IATE) of aggregation as well as the intermediate level for variables of policy interest (GATE), this estimator is computationally attractive and well fitted for the empirical challenges in analysing active labour market policies. For technical details, the interested reader is referred to Lechner (2018).

4.4 Practical implementation

With regard to sample selection, our overall sample consists of 302,626 observations, as discussed in Section 3. We do the estimations using observations of women and men separately for two reasons. First, we expect different effects with regard to gender and second, for computational reasons.

The respective subpopulations are randomly divided in shares of 75% for training and 25% for prediction of the various causal effects. From the training data, 20% of the observations are taken for a feature selection procedure to reduce the extensive set of potential confounders to a smaller, most relevant set of covariates. For a detailed motivation and introduction to this procedure, the interested reader is referred to Appendix E.

Tuning parameters, like the minimum leave size and the number of features available in each split, are determined in a grid search by out-of-bag minimising the MSE. The share of subsampling is fixed to 2/3 of training observations, the number of trees is set to 1,000. To investigate the implied sensitivity, several of those choices are varied, while the conclusions drawn are unaffected.[9]

5 Results

In this section, we report and discuss the main results, while additional results can be found in the Appendix. First, in Section 5.1 the usual population average effects are discussed, as is also done in most previous empirical research in ALMP evaluation. This enables us to evaluate the overall effectiveness, in terms of additional days in regular employment, of the three investigated training and job-search programmes, compared to each other as well as non-participation in any programme. Second, in Section 5.2 we investigate more fine granular effects on the policy relevant group average levels (Section 5.2.1) and individualised level (Section 5.2.2).

5.1 Average effects

Table 3 presents the ATEs for the three different programmes (*job-training*, or *JT*; *reducing impediments*, or *RIM*; *placement services*, or *PS*) and *non-participation* (*NP*) against each other as well as ATETs for the respective participants groups. For the primary outcome, cumulated days in regular employment in three years after the treatment, results are presented in Panel A. We find all programmes to be effective compared to non-participation for men and

[9] Those sensitivity checks also include the feature selection described above. Results on all sensitivity checks are available upon request from the authors.

women, with *PS* to be the most effective for men (45.1 days) and women (54.1 days more in regular employment). For men, the effects are non-significantly different when the different programmes are compared. For example, *RIM* is 1.7 days less effective compared to *JT*, but with a standard error of 7.8 statistically insignificant. For women, *PS* seems to be preferable to *JT*, resulting in 28.5 days more in regular employment if allocated to *placement services* compared to *job-training*. On the main diagonal of Table 3, Panel A, the potential outcomes in the respective treatments are documented. Generally, those are higher for men compared with women, showing that the gains of participating in one of the programmes are higher in relative terms for unemployed women.

Table 3: Average Treatment Effects

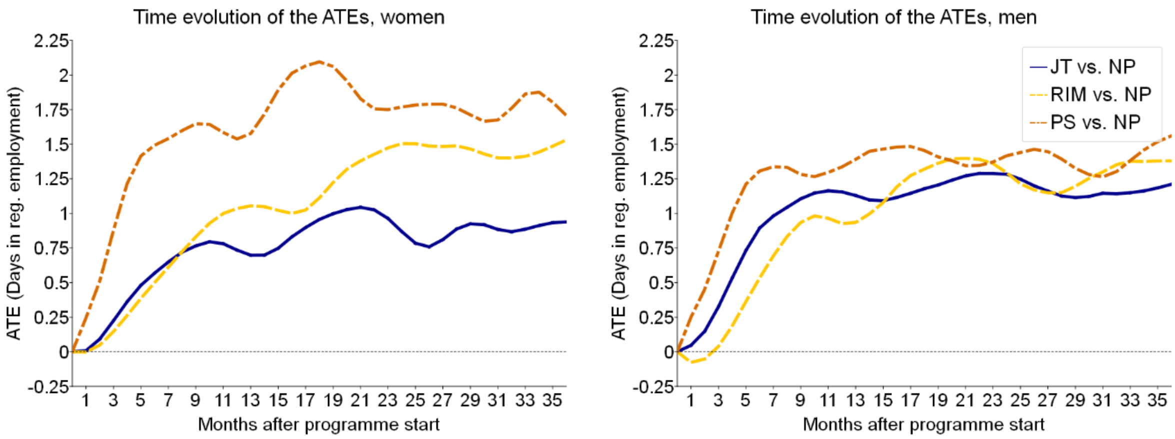
	Men					Women				
N	136,691	12,329	8,721	7,375		116,769	9,350	6,678	4,713	
	NP	JT	RIM	PS	ATET	NP	JT	RIM	PS	ATET
Panel A: Cumulated Days in Employment in 36 months after start of treatment (outcome)										
NP	181.1					137.6				
	(2.1)					(2.2)				
JT	**36.3*****	217.4			*35.0****	**25.7*****	163.3			*23.6****
	(5.4)	(4.9)			*(6.2)*	**(5.6)**	(5.1)			*(5.9)*
RIM	**34.6*****	**-1.7**	215.7		*34.1****	**36.8*****	**11.2**	174.4		*34.7****
	(6.3)	**(7.8)**	(6.2)		*(6.8)*	**(6.7)**	**(8.3)**	(6.4)		*(6.9)*
PS	**45.1*****	**8.8**	**10.5**	226.2	*46.7****	**54.1*****	**28.5*****	**17.3**	191.7	*64.1****
	(7.8)	**(9.0)**	**(9.6)**	(7.0)	*(7.6)*	**(8.7)**	**(10.0)**	**(10.7)**	(8.4)	*(9.1)*
Panel B: (Cumulated) Days in Employment in months 25-36 after start of treatment (outcome)										
NP	81.5					65.4				
	(1.0)					(1.0)				
JT	**12.7*****	94.2			*13.1****	**11.3*****	76.7			*11.4****
	(2.5)	(2.3)			*(2.7)*	**(2.7)**	(2.5)			*(2.8)*
RIM	**15.7*****	**3.0**	97.2		*15.8****	**15.2*****	**3.9**	80.6		*15.5****
	(3.0)	**(3.6)**	(2.8)		*(3.2)*	**(3.2)**	**(4.0)**	(3.1)		*(3.3)*
PS	**18.0*****	**5.3**	**2.3**	99.5	*20.2****	**17.5*****	**6.2**	**2.3**	82.9	*19.3****
	(3.7)	**(4.2)**	**(4.5)**	(3.5)	*(3.6)*	**(3.8)**	**(4.5)**	**(4.8)**	(3.7)	*(4.1)*

Notes: Outcomes are measured in days in regular employment after starting the treatment. ATEs is in bold font; ATET (relative to no treatment only) is in italics; Potential outcomes are on the main diagonals. Standard errors are in parentheses. *** indicate that the p-value of a two-sided significance test is below 1%. The programmes are labelled as NP: *non-participation*, JT: *job-training*, RIM: r*educing impediments,* PS: *placement services*.

The ATET estimates might help to understand the effects of caseworkers' selection of the unemployed to the programmes. In case the ATET is larger than the ATE, which is the case for *PS* when we regard the female sample, the caseworkers' selection is effective, while otherwise, as in *RIM* and *JT* for both, men and women, the allocated participants to the programmes are not the best choices, though differences are small. We investigate this more formally in the course of the study.

Panel B focuses on the long-term effects in the third year after the start of the programme. We find every programme to be still beneficial for participants in the third year compared to non-participation. Further, *RIM*, especially for men, unfolds its effect somewhat later and might be even more beneficial if looking at a longer time-horizon.

Figure 1: Evolution of ATE over time



Notes: Outcome is the cumulative days in regular employment for each month after start of participation in the respective programme. After month 4, all estimates are significantly different from zero at conventional levels. Exemplary, standard errors for month 10 (women: 0.19, 0.23, 0.31; men: 0.19, 0.23, 0.28), month 20 (women: 0.24, 0.28, 0.37; men: 0.23, 0.27, 0.33), and month 30 (women: 0.25, 0.30, 0.39; men: 0.24, 0.28, 0.33) for JT vs. NP, RIM vs. NP, and PS vs. NP, respectively.

To complete the picture, Figure 1 presents how the effects of participation in the specific programmes versus non-participation evolve over time. First to mention is that we do not observe severe lock-in effects for any of the programmes. This is to be expected as the data mainly covers long-term unemployed individuals, as described in Section 3, for whom it is hard to find a job in general and who often show higher programme participation effects (see e.g., Blázquez, Herrarte, and Sáez (2019) for Spain). Second, the programmes' durations are rather short, i.e., programme participation holds off welfare recipients from job-search only for a short time. Lastly, for women, *PS* is always the most beneficial, with a quick realisation period in the first year and a rather constant benefit of about 1.6 - 2.0 more days in employment per month for participants after the first year. As *PS* is designed to push participants into the labour market, this finding is not surprising. *RIM* steadily increases employment until 36 months after participation. Such training programmes often unfold their effectiveness in particular in the medium to long run (see Lorentzen and Dahl (2005) for Norway or the meta-analyses of Card, Kluve, and Weber (2010, 2018)).

The effect of *JT* increases to about 0.8 additional days in employment after nine months and remains on this low level. Further, participation effects of this programme type often stay rather constant in the medium to long run. For men, the picture is different. While in the first months *PS* is the most beneficial programme, the effects of *JT* and *RIM* catch up and remain close to each other. Especially the effect of *PS* is lower for men throughout, compared to women (see similar findings in e.g., Bergemann and van den Berg (2008) and Dengler (2019)), leading to a benefit of about 1.1 - 1.4 more days in employment per month for participating in any programme for men in the long run.

In the following, we investigate how the effects from Table 3 differ for the different subpopulations of participants in the three programmes. The caseworkers are effective in allocating individuals to programmes if the group of selected individuals to a specific treatment benefit more from the treatment compared to the non-selected individuals. In other words, if the ATET is larger than the ATE (or the average treatment effects of those groups selected to none or a different training programme) the treated population is well selected. As already described above for *PS* compared to non-participation, the caseworkers' selection mechanism tends to be effective, i.e., the ATET is larger than the ATE. For *RIM* and *JT* compared to non-participation the selection mechanisms tend to be rather ineffective. Table 4 presents a formal

WALD test for equality of the effects in all four subpopulations, i.e., the three participant groups and non-participants.[10]

Table 4: Wald test of equality of effects in all four treatment specific subpopulations

Cumulative months in employment	JT vs. NP	RIM vs. NP	PS vs. NP	RIM vs. JT	PS vs. JT	PS vs. RIM
… in months 25 - 36 after start of treatment						
Women	29	9	24	37	6	2
Men	80	99	61	98	98	90
… in 36 months after start of treatment						
Women	<1	83	19	6	1	29
Men	57	92	85	94	72	97

Notes: P-values (in %) of the Wald test, distributed as Chi-squared (3) under the null of equality. The respective treatment effects of the specific subpopulations can be found in Appendix C.1.

Not being able to reject any of the 12 tests for men points to either a rather random selection of participants by the caseworkers or rather homogeneous effects for all subpopulations. For women, we find half of the tests to reject the null hypothesis of equality (at the 10% level). As can be seen in Table 14, in Appendix C.1, in four out of those six significant comparisons, the caseworkers' selected group achieves a higher ATET compared to the ATE, in two cases the selected group is not the most benefiting group. While we cannot say anything about the total effect by investigating this table, it indicates that there is a substantial potential to allocate participation to the specific programmes in a well-informed way, which is the topic of Section 6.

5.2 Heterogeneity

The evidence presented for the population and treatment specific subpopulation level documents the overall effectiveness of the programmes as well as the allocation of participants to the programmes. In this section, we investigate lower levels of aggregation, by starting on an intermediate level for characteristics that are of general or specific policy interest in Section 5.2.1. In Section 5.2.2, we continue with effects on the (almost) individual level. In the

[10] The respective treatment effects of the selected subpopulations, for which Table 4 presents the WALD tests of quality of effects, can be found in Table 14, Appendix C.1.

following, we focus on cumulative days in regular employment in three years, since the total effect is likely to be most policy-relevant.

5.2.1 Group effects

The analysis on the GATE level is of special policy interest and a good way to systematically investigate treatment effects on an intermediate level. Using all available potential variables for a heterogeneity analysis and reporting significant results only would be datamining and surely the wrong way. We therefore pre-specified a short-list of variables of special interest for policy makers, society, and academia in Table 5.[11]

Table 5: Short List - Wald tests for heterogeneity (p-values)

Variable	Women			Men		
	JT vs. NP	RIM vs. NP	PS vs. NP	JT vs. NP	RIM vs. NP	PS vs. NP
			Personal characteristics			
Age§	93	46	13	98	86	93
Family status	3	73	1	16	58	59
Educational achievement	14	24	6	2	61	95
Days in reg. empl. in the prev. 5 years§	99	83	70	94	85	65
			Regional characteristics			
Region (East vs. West)§	1	42	<1	38	66	93
District unemploym. rate§	<1	67	<1	31	99	99
			Job centre characteristics			
Client-staff ratio	8	63	5	79	99	99
Sanction intensity – violation of duties§	<1	96	2	35	99	99

Notes: P-values in % from Wald tests for heterogeneity. Variables indicated with § are discussed in the following.

Table 5 shows Wald test p-values for men and women indicating whether there are differential effects for groups of individuals with respect to the specific variable. A p-value below 10 / 5 / 1% rejects the null hypothesis of non-differential effects for the respective groups of individuals. While this is not a formal test for effect heterogeneity, it can be seen as indicative

[11] Further, we pre-specified a "long-list" of variables, which we only use to test for heterogeneity on a general level within the group (as can be seen in Tables 12 and 13 in Appendix B). We do not go into detailed heterogeneities here, but only use it for a general overview as discussed later.

for differential effects. Significant differential effects in Table 5 can be found mainly for women, specifically for *JT* and *PS* vs. *NP*. Variables indicated with "[§]" are discussed in the following, while results for the other variables are shown in the Appendix.

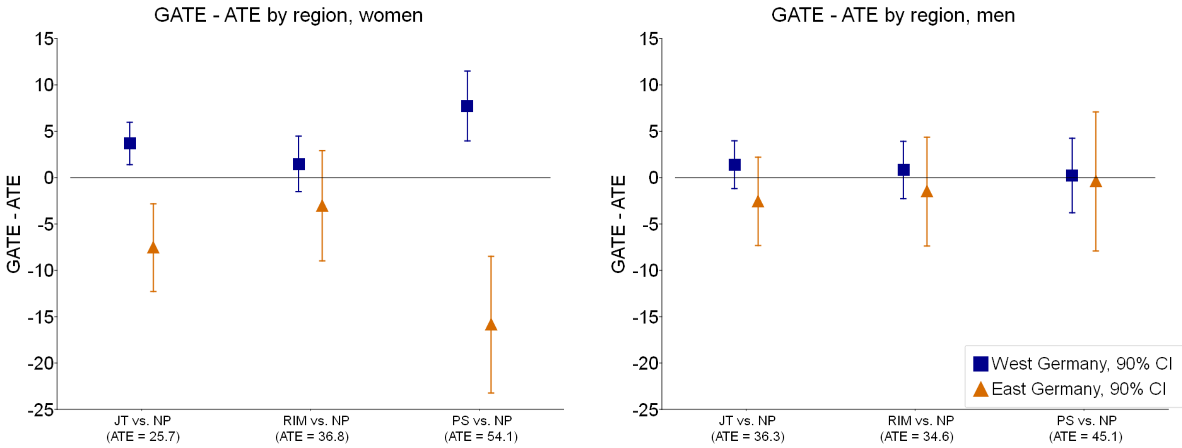
Due to historical reasons in many fields of the economy, there is still some discrepancy between the former GDR region and the western part of Germany. It is therefore interesting to analyse if training and job-search programmes are equally, more, or less effective in either of those regions. We complement this by regional economic conditions, since the economic conditions in East and West Germany are still very different, e.g., higher rates of unemployment and less vacancies in the East. Further, especially important for the labour market authorities are the labour market history of the individual as well as the age, since those are well observable characteristics and might indicate the general potential of the unemployed. The third party involved are the job centres, their structure and behaviour. Here, we are interested in the influence of the sanction intensity, so how many sanctions are imposed in the specific job centre as indication of the toughness of the caseworkers. All figures presented show differences of GATEs to the respective ATE for women and men separately to investigate how those effects differ compared to the average and with regard to gender.[12]

Figure 2 shows the results for the treatment effects of the programmes against non-participation by regions. We find the effects for the group of individuals located in the western part of Germany to be higher than for those located in the eastern part in every comparison. Therefore, programmes in general seem to work better in West compared to East Germany. Bernhard and Wolff (2008) found the same pattern for the contracting out to private placement providers (programme replaced by *PS*). However, in our paper we found significantly

[12] To obtain the "pure" GATE, the ATE provided in each figure has to be added to the point estimate of the respective group. Since the vast majority of the GATEs are significantly different from zero, we opted for presenting the GATE-ATE to focus explicitly on within group differential effects.

differential effects only for women in *JT* and *PS* compared to non-participation, while for men the GATEs are all close to the population average effects.

Figure 2: Difference of GATEs to ATE in West / East Germany

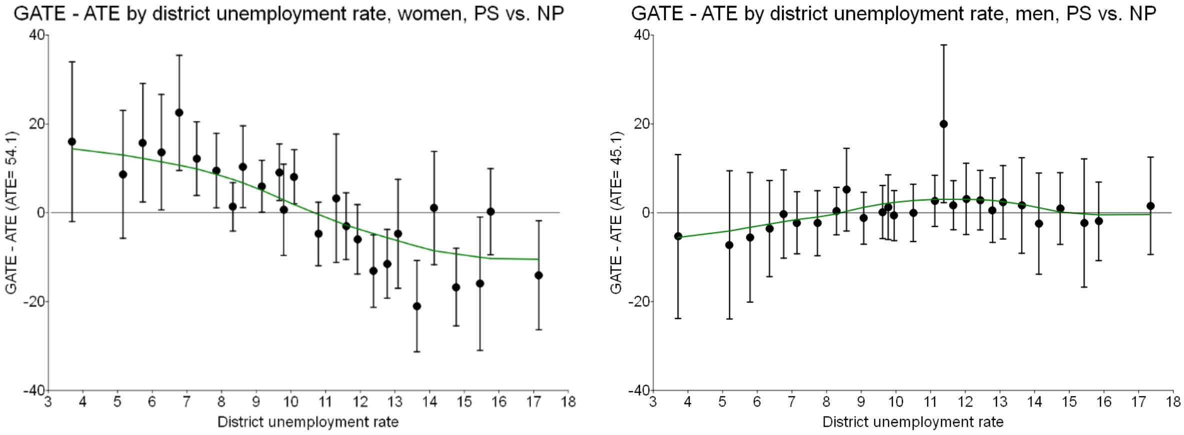


Notes: 90% confidence intervals (CI). ATE estimates in parentheses at the bottom of the graphs. Outcome is the cumulative days in employment in 36 months after start of treatment.

To investigate if this is driven directly by the local economic conditions, which are worse in East Germany compared to West Germany, we investigate the GATEs associated to the district unemployment rate. Indeed, we find in general higher treatment effects for those female participants in regions with a lower rate of unemployment, as shown in Figure 3.[13] As *PS* needs vacancies to unfold its effectiveness and lower unemployment rates might be correlated with higher amounts of available jobs, this finding is clear-cut. For men, the results of Figure 3 are in line with the findings in Figure 2, as the GATEs fluctuate around the ATE. The same pattern can be observed for GATEs associated to the unemployment rate of welfare recipients. Results for this alternative measure of the labour market conditions can be found in Appendix C.3, Figure 9.

[13] For the other treatment comparisons this tendency is equivalent, and the results can be found in Figure 8 in Appendix C.3.

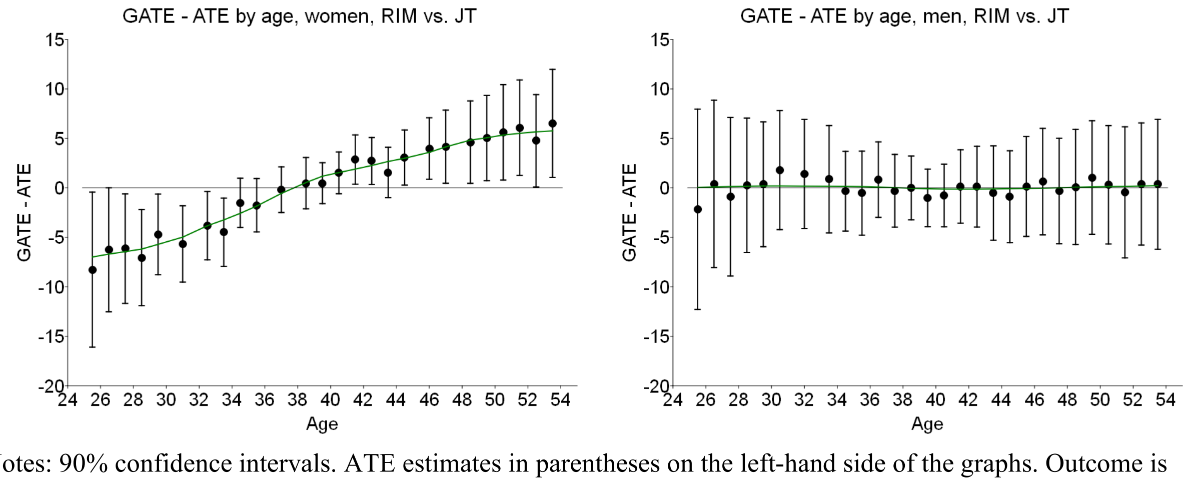
Figure 3: Difference of GATEs to ATE by district unemployment rate, PS vs. NP



Notes: 90% confidence intervals. ATE estimates in parentheses on the left-hand side of the graphs. Outcome is cumulative days in regular employment in 36 months after start of treatment. The green line represents the (kernel-)smoothed GATE estimates and is for illustration purposes only.

For previous labour market success, in form of days in regular employment in the previous five years, results can be found in Figure 11 in Appendix C.3. We do not find any clear pattern. In addition, confidence intervals become increasingly large due to fewer observations with many days in regular employment in the last five years. Thus, we refrain from further interpretation.

Figure 4: Difference of GATEs to ATE by age, RIM vs. JT

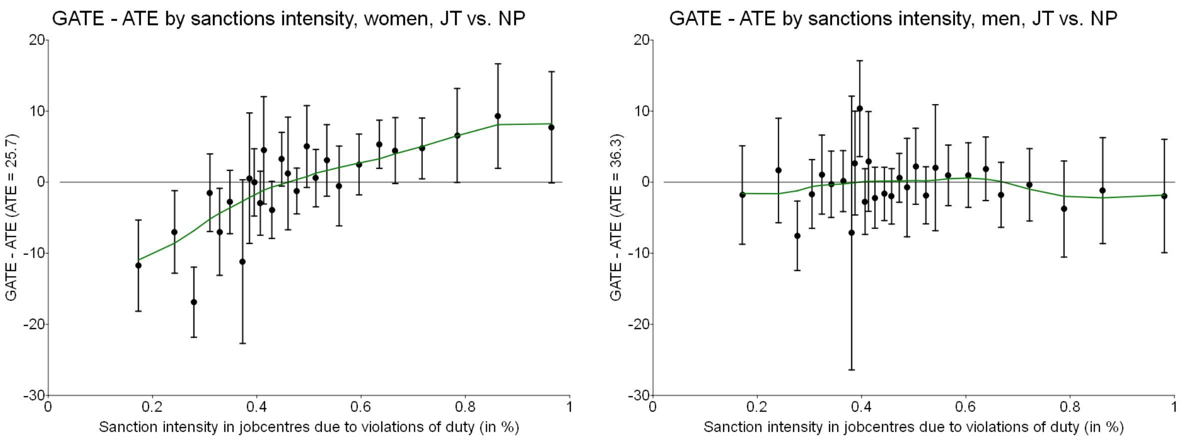


Notes: 90% confidence intervals. ATE estimates in parentheses on the left-hand side of the graphs. Outcome is cumulative days in regular employment in 36 months after start of treatment. The green line represents the (kernel-)smoothed GATE estimates and is for illustration purposes only.

Another interesting question is if younger and older people should be sent to the same or different ALMP. Figure 4 shows differential effects with individuals grouped by age for sending them to *RIM* compared to *JT*. While for men it does not seem to matter, with all GATEs around the ATE, for women this does matter. Younger women should rather be allocated to the *job-training* or *non-participating* (compare Figure 12 in Appendix C.3), older women benefit more from the *reducing impediments* programme. For older men, instead, the *placement services* programme seems to be more beneficial compared to *non-participation*, *job-training* or *reducing impediments*, while the latter two are more beneficial for younger men; results for this and the other comparisons can be found in Appendix C.3, Figure 12. That *JT* is more beneficial for younger participants is in line with Caliendo and Schmidl (2016) who found positive effects for young people participating in (solely) classroom-based training programmes (to which *JT* is the most similar of our observed programmes).

For job centres, imposing sanctions is a controversial tool to encourage means-tested benefits recipients to actively search for jobs, take part in training programmes, etc. From an academic point of view, it is interesting to investigate if those unemployed, who are supported by job centres imposing more sanctions do benefit more or less from participation. Figure 5 provides results for being allocated to *JT* compared to not being allocated to one of the training programmes associated to the job centres sanction intensity.

Figure 5: Difference of GATEs to ATE by job centre sanction intensity, JT vs. NP



Notes: Job centres' sanction intensity due to violations of duty. 90% confidence intervals. ATE estimates in parentheses on the left-hand side of the graphs. One outlier group is omitted for the sake of visibility. The full graph can be found in Appendix C.3, Figure 10. Outcome is cumulative days in regular employment in 36 months after start of treatment. The green line represents the (kernel-)smoothed GATE estimates and is for illustration purposes only.

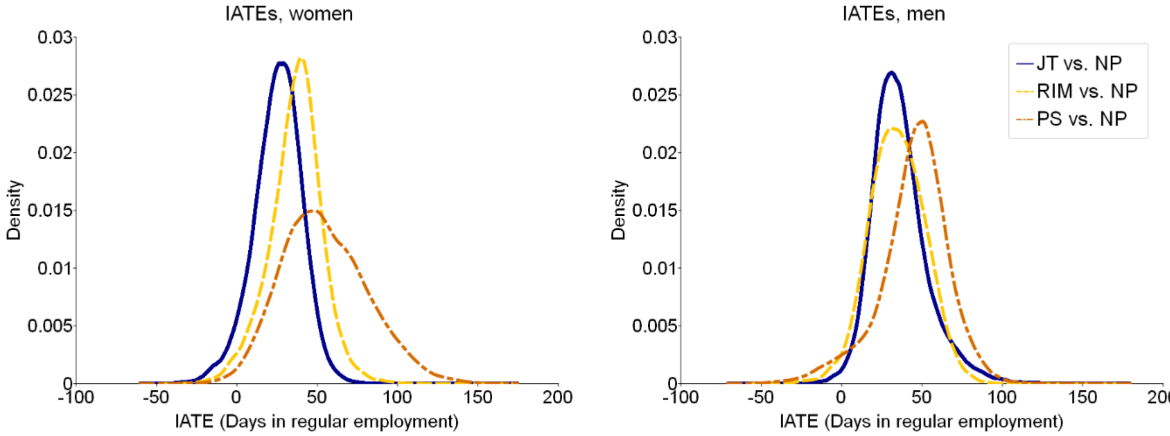
We find that for the effects for women associated to job centres with a higher sanctions' intensity is indeed above the average effect, while those associated to a job centre imposing less sanctions benefit below average. Again, for unemployed men there are no differential effects. The same pattern is found for the comparison of the other treatments to non-participation and results can be found in Figure 10 in Appendix C.3.

To finally support the impressions already gained, that particularly for women, and less for men, there is substantial effect heterogeneity we extend the set of heterogeneity variables to a larger set in Appendix B. With this extended set we test every treatment comparison with a WALD test for effect heterogeneity. We find several significant within-group differences of effects for women (Table 12, Appendix B.1) and very few for men (Table 13, Appendix B.2). This is all the more remarkable when one considers that we have fewer observations, and therefore higher standard errors, for women than for men.

5.2.2 Individualised average effects

On the lowest level of aggregation, Figure 6 presents the distributions of estimated IATEs for participating in one of the treatments against non-participation. The first observation is that for all labour market programmes most individuals realise positive effects. Table 6 documents this with shares of 94.5 - 99.2 % of individuals having a positive effect from participating in either programme. This is manifested in the substantial shares of individuals with significant positive effects. Another conclusion from Figure 6 is that *PS* leads to the largest gains in days in regular employment on average, like discussed in the previous subsection, as well as for a substantial share of individuals.

Figure 6: Distribution of estimated IATEs



Notes: IATE density plots. Outcome is the cumulative days in regular employment in 36 months after start of treatment.

Table 6: IATEs, descriptions

	Women				Men			
	Share >0	Share >0 (**)	Std	SE (aver.)	Share >0	Share >0 (**)	Std	SE (aver.)
JT vs. NP	94.5 %	44.4 %	15.14	16.18	99.2 %	59.1 %	17.39	18.69
RIM vs. NP	97.7 %	55.2 %	16.58	19.48	97.6 %	49.1 %	17.54	21.44
PS vs. NP	99.0 %	63.8 %	26.85	24.53	95.7 %	57.6 %	21.98	24.98

Notes: Share of positive IATEs. Share significantly larger than zero indicated with ** on the 5% level. *Std* stands for the standard deviation of the respective distribution, *SE (aver.)* is the standard error averaged over all IATEs.

Comparing the distributions of men with those of women, it is especially noteworthy that the distribution of *PS* for women is wider as for man, as apparent from the standard deviations (Std) shown in Table 6. This might be attributed to two aspects. It may point to some degree of estimation error, since the estimation of IATEs is a much harder problem compared to the estimation of average or group average effects. While Table 6 documents this showing for both men and women the highest average standard errors for *PS* vs. *NP*, this cannot explain the wider distribution for women compared to men. The remaining explanation is therefore that it points to considerable effect heterogeneity in this programme and therefore high potential for a more beneficial allocation of training programmes.

An approach to describe those populations of individuals benefiting most and least from ALMP participation is presented in Table 7. For this we show the dependence of the effects on characteristics by k-means++ clustering (compare Arthur and Vassilvitskii (2007)). By jointly using the IATEs of participation in one of the programmes relative to non-participation, five clusters are formed. Especially, those clusters are built by jointly sorting IATEs in increasing order to find clusters, which represent the group of individuals benefiting most or least. The fifth cluster represents the most affected individuals, i.e., those with the highest treatment effects. In the first cluster, the least benefiting observations are grouped.

Table 7: Descriptive statistics of clusters based on k-means clustering, IATEs

Cluster	Women		Men	
	Least beneficial	Most beneficial	Least beneficial	Most beneficial
Share of observations (in %)	13	27	13	12
JT vs. NP	3	37	27	68
RIM vs. NP	33	46	14	39
PS vs. NP	8	49	7	55
Personal characteristics				
Foreigner	0.20	0.25	0.26	0.22
Days in regular employment (previous 5 years)	265	84	704	201
Days since last employment	1798	2244	453	1758
No vocational / academic degree	0.49	0.65	0.47	0.47
Vocational degree	0.47	0.31	0.49	0.42
Academic degree	0.03	0.02	0.03	0.09
Education - no schooling diploma	0.15	0.23	0.12	0.11
Education - secondary school	0.40	0.45	0.50	0.39
Education - general certificate of secondary education	0.33	0.21	0.27	0.23
Education - advanced technical college entrance qualification	0.03	0.03	0.04	0.08
Education - high school	0.07	0.05	0.07	0.15
Marital status - unmarried	0.27	0.22	0.39	0.50
Marital status - married	0.31	0.39	0.37	0.28
Job centre characteristics				
Client-staff ratio in job centres	164	159	161	163
Sanction intensity in job centres due to violations of duties (in percent)	0.45	0.62	0.58	0.53
Sanction intensity in job centres due to failure in reporting (in percent)	0.63	0.79	0.75	0.72
Regional characteristics				
District unemployment rate	11.3	9.6	9.8	10.5
District unemployment rate of welfare recipients	8.2	6.7	6.8	7.6
Region (west=0, east=1)	0.36	0.16	0.26	0.26

Notes: k-means++ clustering is used (Arthur and Vassilvitskii (2007)) with five clusters. Reported are clusters 1 (least beneficial) and 5 (most beneficial), while the clusters 2-4 are reported in the full results in Tables 11 (men) and 12 (women), which can be found in Appendix C.2. Average effects for the most and least benefiting populations for participating in one of the programmes compared to *non-participation* can be found in the top of the table. Outcome is the cumulative days in regular employment in 36 months after start of treatment.

The means of the treatment effects by the clusters are reported in the first lines of Table 7. This is especially interesting to see if those populations of most and least benefiting individuals differ in certain characteristics. Table 7 provides the results for the "first" (least beneficial) and "last" (most beneficial) clusters, while the full results with all five clusters can be found in Tables 15 and 16, Appendix C.2. We find substantial differential characteristics for most and least benefiting individuals.

While women from the eastern part of Germany are more present in the least benefiting population, for men there is no such difference. For classical job history characteristics, the picture for men and women is more uniform. Those with worse previous labour market success, like the days since the last regular employment or the cumulated days in regular employment in the last five years, benefit more in comparison with those with a better record. Differential effects are found for job centre related characteristics. For women, a lower client-staff ratio and higher shares of sanctions are observed in the most benefiting population, whilst for men this is observed in the least benefiting population. This discrepancy is also evident with regard to local labour market conditions. While most benefiting women are rather in areas with better labour market conditions, i.e., lower share of unemployed in general and of welfare recipients in a district, this is reversed for men. Observing personal characteristics, we find a higher share of foreigners, those without academic or vocational degree and lower educational achievements in the group of most benefiting for women, but in the least benefiting group for men. Further, unmarried women are rather in the least benefiting group, while unmarried men are more present in the most benefiting group. This is similar to the findings of Achatz and Trappmann (2011), who showed that having children impedes women's labour market participation but promotes men's (as marriage highly correlates with parenthood).

In conclusion of Table 7, we can draw three general indications. First, the populations of most and least benefiting populations are different for men and women. Second, women residing in areas with better local labour market conditions are in the group that benefits most. Lastly, good a priori risks are rather in the group that benefit least from participating in the labour market programmes.

5.3 Placebo analysis

The credibility of empirical results depends on the validity of the underlying assumptions. While the unconfoundedness assumption for the training and job-search programmes investigated with such extensive, administrative data is very likely to be fulfilled in our particular setting, it is not directly testable. An indirect approach to assess the validity of the CIA is to conduct a placebo analysis, as described by Imbens and Wooldridge (2009) for example.

Table 8: Placebo effects for future programmes on cumulative days in regular employment

	Men					Women				
N	118.703	10.106	7.120	5.927	8.670	108.057	8.404	6.038	4.200	5.243
	NP	JT	RIM	PS	IFT	NP	JT	RIM	PS	IFT
Cumulated Days in employment in one year after pseudo-treatment (outcome)										
NP	23.3					11.3				
	(0.5)					(0.4)				
JT	**1.1**	24.4				**1.1**	12.5			
	(1.3)	(1.2)				**(1.1)**	(1.0)			
RIM	**0.8**	**-0.3**	24.1			**0.9**	**-0.2**	12.2		
	(1.4)	**(1.7)**	(1.3)			**(1.1)**	**(1.5)**	(1.1)		
PS	**2.1**	**1.1**	**1.3**	25.4		**2.3**	**1.1**	**1.4**	13.6	
	(1.8)	**(2.1)**	**(2.2)**	(1.8)		**(1.6)**	**(1.8)**	**(1.9)**	(1.5)	
IFT	**14.9*****	**13.8*****	**14.1*****	**12.8*****	38.2	**9.0*****	**7.9*****	**8.2*****	**6.8*****	20.4
	(1.6)	**(1.9)**	**(2.0)**	**(2.3)**	(1.5)	**(1.5)**	**(1.7)**	**(1.8)**	**(2.1)**	(1.4)

Notes: Outcomes are measured in days in regular employment. ATEs in bold font; potential outcomes on the main diagonals. Standard errors are in parentheses. *** indicate that the p-value of a two-sided significance test is below 1%. The programmes are labelled as NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*, IFT: i*n-firm training*.

To be more concrete, we take those individuals of our original sample which were also unemployed two years before the treatment is allocated, i.e., by the end of 2007, and measure the outcome as cumulative days in employment in one year after this pseudo-treatment date.[14]

[14] We cannot use the cumulative days in employment for three years, as this is partly in our true treatment phase. Moreover, we cannot go further into the past, since we do not observe many of the covariates that are related to the benefit system otherwise. The set of covariates is slightly smaller now, as we cannot construct all the covariates back two years before the treatment. Still, the most crucial variables are captured in our pseudo-analysis database, and if we do not reject the null

For this, we constructed a new database with most of the covariates used in the main analysis dated back to the end of 2007. The participation in the job-search or training programmes in 2010 should not have an influence on the outcome measured prior to this. Therefore, if we observe all confounding characteristics, the pseudo treatment effect should be zero. Not rejecting this placebo null hypothesis does not imply that the CIA is valid but gives some evidence that the CIA is plausible in this case, while if we reject this test there might be some unobserved confounding.

Table 8 presents the results for all four initial programmes and *non-participation,* investigated in the placebo analysis. Besides Treatment 4, the *IFT*, we cannot reject the null hypothesis of a zero effect for all comparisons. For *IFT* we have to reject all tests. Conceptually, this is not unexpected. While for the allocation of *JT*, *RIM*, and *PS* it is very clear that the job centres' caseworkers can decide upon (non-)allocation, for the *IFT*, which takes place at a potentially private company, it is not solely the decision of the caseworker, but also of the company, which might have completely different objectives and information. Therefore, we decided not to investigate *IFT*, while this placebo test convinced us, and hopefully the readers, that for the other treatments the CIA is credible.[15]

6 Improving the allocation of the programmes

Section 5 provided a list of differential effects associated to specific groups of unemployed. This raises two questions with regard to the observed allocation mechanism by the respective caseworkers. 1.) How well did the caseworkers allocate the programmes to the unemployed? 2.) Can we improve on their assignment? In the following, we show how different hypothetical programme allocations ("black-box") would have worked (Section 6.1). Since

hypothesis with a smaller set of covariates, having more is likely to make the unconfoundedness assumption even more plausible.

[15] However, our arguments do not necessarily invalidate the findings of studies that estimated the treatment effects of *IFT* (e.g., Kopf (2013)), as the identification potentially can be credible using other approaches.

most of those black-box allocations are difficult to understand, we propose simple, transparent rules (Section 6.2). They are easy to understand and to apply and already allow to reap substantial improvements. For this we use a random subset, men and women combined in the original shares in the population, of 10,000 observations.[16] This is due to the fact that in practice ALMP allocations are not separately done for men and women and to get one single rule. In order not to lose the substantial differential effectiveness with regard to gender as discussed before, we add a variable for gender for the following allocations.

6.1 Hypothetical programme allocation

We start by looking at various different hypothetical allocations and compare those to the observed allocation. For this exercise, individuals with their estimated IATEs are allocated in a way to maximise the population average number of days in regular employment. This is conducted by allocating those with the highest potential outcomes to the respective programmes, according to given rules or restrictions. The first column of Table 9, Panel A, shows the restrictions that are imposed for the respective simulation. First, we investigate the allocation observed in the data. 7.20%, 5.09%, and 3.95% of all unemployed are allocated to *JT*, *RIM*, and *PS*, respectively. This results in an average of 171.25 days in regular employment within 36 months after the treatment. We take this as the benchmark value. The first simulated allocation is a purely randomized allocation, for which the resulting average days in employment are equally high as for the caseworkers' allocation. The fact that the observed allocation is only about as good as a random allocation leaves us with some room to improve the overall efficiency (see e.g., Lechner and Smith (2007)).

[16] Since this is a 10,000 observations random subset of the used data, in which we have a 20% random subset of all non-participants, it does not represent the shares of job-search and training programme allocated to the whole means-tested benefits population. To account for this fact, we calculate a "gain for switchers", which is not related to the population, but to those who are reallocated by the algorithms.

The next simulation is maximising the total benefits for every unemployed without restrictions.[17] In this scenario, only 0.09% of individuals remain untreated, while 10.21%, 22.79%, and 66.91% are assigned to *JT*, *RIM*, and *PS*, respectively. This leads to the maximum achievable average outcome of 222 days in employment.

Table 9: Overall effects of simulated hypothetical programme allocations

	Share in different programmes (in %) JT	RIM	PS	Cum. # of days in employment in 36 months after start of treatment	Gain for switchers (in %)
Panel A: Hypothetical programme allocations					
Observed	7.20	5.09	3.95	171.25	-
Random	7.26	5.06	3.84	171.26	+ 0.00
Policy simulation					
- No constraint	10.21	22.79	66.91	222.39	+ 31.27
- No constraint, only significant	10.13	14.96	51.03	208.58	+ 35.54
- Constrained, preference to largest gain	7.20	5.09	3.95	177.35	+ 12.51
- Constrained, sequential optimisation	7.20	5.09	3.95	178.16	+ 14.22
- Constrained, preference to days since last employment	7.20	5.09	3.95	172.03	+ 1.54
Panel B: Decision Trees					
- Constrained, 2 level	6.58	4.40	3.82	172.48	+ 2.40
- Constrained, 3 level	7.35	4.87	3.85	174.03	+ 5.42
- Constrained, 4 level	7.33	4.93	3.72	174.40	+ 6.12

Notes: Share in non-participation can be calculated as 100% - Share JT / RIM / PS. In the “Observed” allocation the outcome is the realised mean of cumulated days in employment in 36 months after start of treatment. In all the other scenarios some individuals are hypothetically switched from the actual to another treatment status. The “gain for switchers” reflects the gains in percent for those actually switching the treatment status, thus can be higher for the same absolute gain if less people are reallocated. The “Constrained” allocations take the shares as in the “Observed” allocation as given to simulate a budget constraint. In Panel B this can deviate since constraints are binding only in the training set. *n* level refers to the number of levels in the decision tree, i.e., 4 level (or depth 4) can have at most 16 “leaves”.

For reallocating only those with IATEs statistically significantly different from zero (this additional constraint is imposed to minimise the dependence on some estimates just being positive/negative because of estimation error), we find about 61% to switch the treatment status and 39% would not have benefitted significantly from any other programme (non-

[17] Starting from the observed allocation, we reallocate everyone with higher IATE in another than the observed programme/non-participation. This results in 95.49% of individuals who were switched to another programme/non-participation.

)participation. This results in an average outcome of 209, which is an increase of about 37 days more in employment on average, and for the population of switchers an average gain of 36% (last column). According to this, most unemployed individuals should be participating in one of the training and private placement service programmes if the goal is to improve chances on the labour market of as many long-term unemployed as possible. Obviously, job centres cannot send a major part of unemployed to such programmes, as those are usually costly. Unfortunately, we do not have any information on costs of the programmes, which would be needed for a cost-benefit analysis. To take the budget constraint of job centres into account, the following hypothetical programme allocations are restricted to have the same share of participants as observed in the data, so that we can talk about gains at the same costs. Bear in mind that average gains cannot be very high, since in any case about 84% of the population remain non-participants.

Three allocation scenarios with budget constraints are presented. In the first, priority is given to those individuals with the largest gains from participating in a certain programme or *non-participation*. The programmes and *non-participation* are filled by those with the largest gains until the budget constraints for the programmes or *non-participation* are reached. Here, the average gain would be about 6 days compared to the observed scenario, with an average gain for the switchers of 12%. The second allocation is reshuffling the participants to achieve a higher overall efficiency, which leads to the maximum achievable average outcome under budget constraint with an average of 178 days in regular employment. In a more social approach, preferring those individuals to participate in one of the programmes, which are in unemployment for the longest time (*days since last employment*) the average days in employment with 172 and a gain of below 1 day on average is marginal, but still higher compared to the observed allocation.[18] In Appendix C.4 additional results are presented, with

[18] In this setup, we only consider individuals who have been in regular employment at least once in the past.

Table 17 showing more types of allocation rules and Tables 18 and 19 presenting separate hypothetical allocations for women and men.

In conclusion, gains from different allocation schemes could be large, which is also true if holding the training capacity constant. Since such types of "black-box" allocations cannot be implemented in a transparent way in the job centres' counselling process they might not be desirable from a political point of view. Further, those mechanisms might be subject to ethical or societal concerns (Whittlestone, Nyrup, Alexandrova, Dihal, and Cave (2019), Reddy, Allan, Coghlan, and Cooper (2020)). This might lead to caseworkers not trusting those allocations and therefore not following such untransparent rules. Section 6.2 is proposing simple, transparent rules, which are easily understandable and applicable. Further, since those rules only use few characteristics, it is easier to decide if allocating according to them is socially and ethically acceptable.

6.2 Policy Tree

For the purpose of providing easy rules for allocation of unemployed to the job-search and training programmes we follow the approach of Zhou, Athey, and Wager (2018) and use shallow decision trees of depth 2 (4 strata), 3 (8 strata), and 4 (16 strata) with slight modifications of their algorithm.[19]

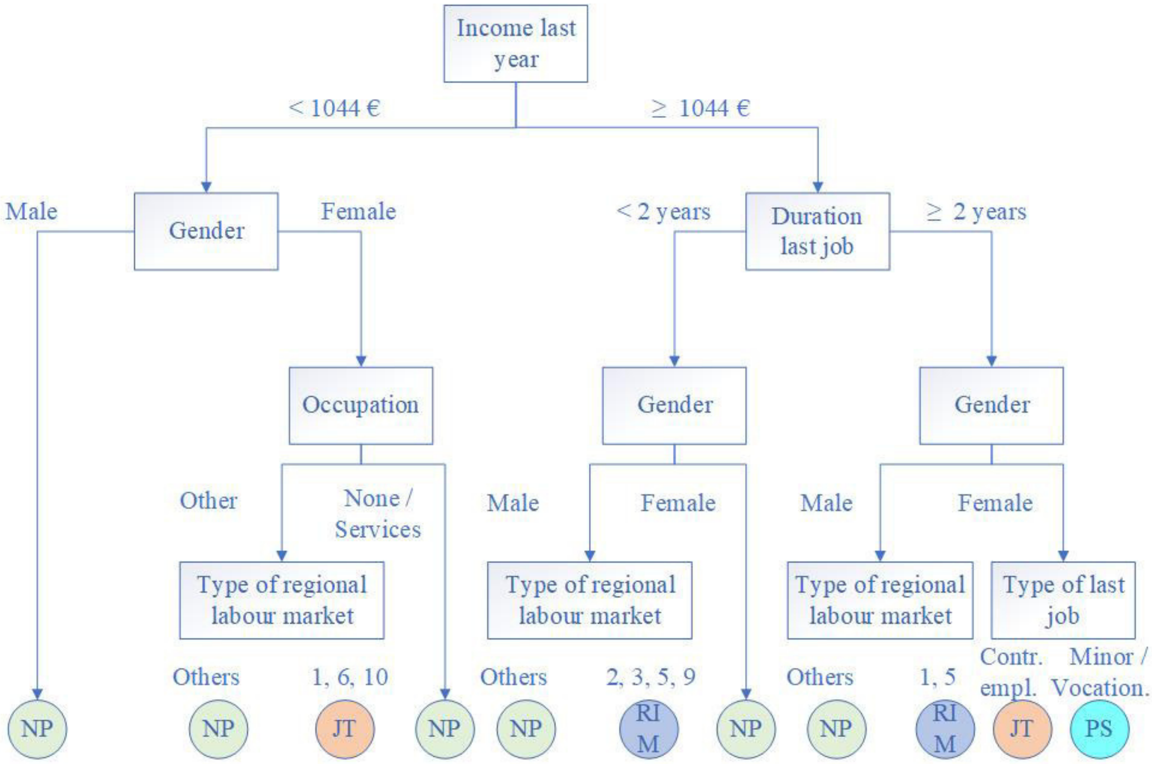
Panel B of Table 9 is summarising how well those easy implementation rules work. Having a very easy rule with depth 2 gains is limited to about 1 day. Increasing the complexity to decision trees of depth 3 and 4 results in average outcomes of about 174, implying gains of about 3 days in average. Figure 7 depicts such a depth 4 allocation. At every split-point, a certain caseworker compares the characteristics of the unemployed to the splits to be made. In a first step, one verifies if the unemployed earned more or less than € 1,044 in the last year from

[19] For details on the implementation, the interested reader refers to Appendix D. Computational restrictions do not allow for depth 5 or larger. Also, at least depth 2 (4 strata) is needed to allocate 3 treatments + non-participation.

income relevant for social security. If the individual is below and male, he would not be allocated to a programme, while for a woman the occupation and the type of the regional labour market plays a role, etc.

A smaller tree with depth 3 can be found in Appendix C.5, Figure 16. Here, gender, days in regular employment in the last five years, type and length of last job as well as educational achievements are used for allocation. Further, separate decision trees for men and women are presented in Appendix C.5 for depth 3 (Figure 17) and depth 4 (Figures 18 and 19).

Figure 7: Assignment rule of shallow decision tree (depth 4)



Notes: Types of regional labour markets are: 1: Cities west, average labour market situation (LMS), high GDP, high rate of long term unemployed; 2: Cities west, above average LMS, high GDP; 3: Cities west, below average LMS, very high rate of long-term unemployed; 4: Cities, mainly east, bad LMS, very high rate of long-term unemployed; 5: Predominantly urban, west, average LMS, high rate of long-term unemployed; 6: rural, west, average LMS; 7: Predominantly urban, west and east, below average LMS; 8: rural, west, good LMS, high seasonal dynamic; 9: rural, west, very good LMS, seasonal dynamic, very low rate of long-term unemployed; 10: rural, west, very good LMS, low average rate of long-term unemployed; 11: predominantly rural, east, bad LMS, low GDP; 12: predominantly rural, east, very bad LMS, very low GDP, high average rate of long-term unemployed. NP stands for *non-participation*, JT *job-training*, RIM *reducing impediments*, and PS *placement services*.

In general, we would like to point out four things about this allocation in Figure 7. First, as already detailed in the previous sections, gender plays a prominent role for this allocation.

Men would not be allocated to the *PS*, which is the most beneficial programme for them, but for women the gains seem to be stronger. Second, with past income, duration and type of last job, gender and the type of the regional labour market only 5 characteristics are used, making this a very transparent allocation scheme. Third, the presented decision tree rule strongly favours individuals living in West Germany and in regions with good labour market conditions. This might optimise the gains from the programmes but could also lead to a more diverging east-west gap. Lastly, the exact budget constraint is restricting the algorithm, as it must not only optimise the allocation, but subject to restricting the sample to a certain maximum of observations allowed in the treatment allocation relevant leaves.[20]

7 Discussion

In Germany, the above-investigated schemes for activation and integration were introduced in 2009 with the goal of creating a programme that can be flexibly designed to address the needs of different types of participants. Hence, they should foster the integration of many different groups of unemployed people and should be effective for people with considerable employment impediments. Our results on the distribution of IATEs show that for most individuals the three different programmes are effective and thus address participants' employment impediments. A greater flexibility in the programme design is the most important difference between the schemes for activation and integration and the former programmes that they replaced. Therefore, comparing our results with those of studies analysing the former programmes may highlight the relevance of a flexible ALMP design in supporting welfare recipients' labour market integration.

For such a comparison, two studies can be considered. Firstly, Bernhard and Wolff (2008) studied welfare recipients who were assigned to private placement services. Even though their

[20] Results for the less restricted scenarios can be found in Appendix C.4, Table 13.

outcome somewhat differs from ours, our results on PS can be made comparable to theirs. The calculation is based on the ATETs displayed in Table 3 and implies an average monthly effect on the regular employment rate of 4.2 percentage points for men and 5.9 percentage points for women.[21] Bernhard and Wolff (2008) display ATETs on regular employment rate of three age groups aged at least 25 years for men and women that tend to be lower than ours, for some of the age groups the effects are near zero. They rarely found effects higher than three percentage points except for West German women aged 50 to 57 years; the effects for the latter group are most of the time of an order of magnitude of five percentage points and hence similar to our overall ATET of *PS* for women. Secondly, the study of Kopf (2013) studied effects of different types of classroom training programmes in 2005 that are - to some extent but not completely - comparable to *JT* and *RIM*.[22] Application training is one of the programmes that is now part of *JT*. Our effects for *JT* are clearly higher than the mostly negative application training effect estimates found by Kopf (2013). In the same way, effects for aptitude tests and skill training, for both men and women, tend to be lower than our average effects for *JT* and *RIM*. However, by the end of her observation window, they are of a similar order of magnitude. In summary, it appears that participation in the more recent, more flexible SAI tends to lead to higher effects compared to the previous programmes.[23]

Besides the general effectiveness of the investigated programmes, we documented several differential effects, especially for women. We find evidence that the effects of *RIM* tend to increase with the age of women and that married women profit more from *PS* than other women.

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[21] Those numbers are calculated as an average monthly effect on the employment rate for the ATET of PS by dividing the effect in days by the total number of days of the three years, for which the effect was estimated.

[22] Carrying out the same exercise as for PS with our results of Table 3 on JT, we find an effect on the average monthly employment rate of 3.2 percentage points for men and 2.2 percentage points for women. The corresponding numbers for RIM are 3.1 and 3.2 percentage points.

[23] Note though that in Kopf (2013), the effect estimates are not available for different age groups and her sample members are aged 15 to 57 years, while the individuals in our sample at the sampling date are 25 to 54 years old. Moreover, both the studies of Bernhard and Wolff (2008) and Kopf (2013) studied a different observation window than we did. Hence, the differences between their and our ATETs are likely to not only reflect differences in programme design. Other factors that influence the ATETs like differences in the composition of the participant samples and different economic conditions may also play a role in explaining those differences.

Moreover, women living in West Germany and in districts with low unemployment rates benefit more from *JT* and *PS* than women living in East Germany and in districts with high unemployment rates. The fact that those women with the highest potential to raise their employment rate are found among elderly women, married women and women in the West, a region that was characterised by more conservative attitudes towards childcare (Boelmann, Raute, and Schönberg (2020)) and scarcer provision of external childcare (Rosenfeld, Trappe, and Gornick (2004)), might be related to their (rather low) labour market attachment. In addition, the result that the programme effects increase with the sanction rates could be in line with such an interpretation. People with a relatively weak attachment to the labour market are likely to search less intensely for work than others. Though, that group might increase their search intensity during and after programme participation considerably to avoid the threat of benefit sanctions.

A favourable circumstance for the relatively higher employment effects among women could originate from the labour demand side. Although labour demand increased overall by 4.4% in Germany between 2010 and 2013, some sectors like healthcare and hospitality had an above average increase.[24] In our sample (as can be seen in Appendix A), women more often have been working in such occupations. Thus, an improvement in employability by the programme participation might more easily translate into a rise of their employment chances. These considerations are in line with findings on the German workfare programme called One-Euro Jobs, which were more effective in sectors with high labour demand (Harrer and Stockinger (2021)). Especially, private placement services might have better contact to firms in specific sectors. It is noticeable, that women's last occupations, especially those women allocated to *PS*, were more often in sectors of trade and business management. In contrast, men more likely worked in sectors of manufacturing as well as security and logistics.

[24] Source: DataWareHouse of the Statistics Department of the German Federal Employment Agency.

In accordance with this, our proposed transparent allocations in form of policy trees especially emphasises the importance of treating different genders appropriately, which may hint to gender differences in the reasons of unemployment with women having more interruptions in their employment careers due to care responsibilities and men confronting lacking job opportunities in the labour market segments they predominantly work in. Thus, it might help closing the gender employment gap in Germany if the counselling process of the job were to focus more on the individual needs of long-term unemployed women.

8 Conclusions

Our study analyses the effects of three different active labour market programmes for long-term unemployed, namely *job-training* (*JT*), *reducing impediments* (*RIM*) and *placement services* (*PS*). In this study, we focus on unemployed welfare recipients in Germany, a group of persons in particular need for active support in their labour market integration. We analysed participation effects on cumulated days in regular employment three years after programme start.

The estimation results for *JT*, *RIM* and *PS* show almost no lock-in effects. These programmes are generally effective for men and women in raising their cumulated days in regular employment in the first three years after treatment start, and also in the third of these three years. Hence, the effects are long lasting. The most beneficial average treatment effects were found for *PS*. The investigated job-search and training programmes are not only beneficial for the unemployed on average, but also for a major part of the individuals in our sample. For men, we find almost no evidence of effect heterogeneity, while for women we do find heterogeneous effects. In general, our findings show that individuals benefiting most from participation are characterised by an adverse labour market history. Moreover, for men and women and for all three programmes analysed, the distribution of the IATEs show that the employment effects are positive for the overwhelming majority of participants. This is what one would expect from a programme that can be flexibly adapted to the needs of the participants.

While we cannot provide a cost-benefit analysis due to missing information on costs, we found that if costs did not play a role, the means-tested benefit recipient population would benefit from more job-search and training programmes, as most individuals would realise positive effects. Since costs are of course a restriction in practice, we implemented a strict budget constraint holding the number of programme participants constant and allocating individuals in certain optimised ways. Our analysis of simulated programme allocations based on the IATEs showed that the observed and a random allocation would lead to almost the same average effect on the number of days in employment in the 36 months after programme start. Allocating individuals, without constraints, to maximize overall gains could raise the average programme effect by more than 30%. A feasible allocation, i.e., keeping the number of participants in each programme fixed, the black-box algorithm, allocates programmes in a way to increase the employment effect by 14% for those reallocated.

On a methodological note, we found the MCF to be suitable for our comprehensive analysis of the German job-search and training programmes. There are also several topics for further research. It would be especially interesting to know whether patterns found for those job-search and training programmes can be observed in more recent data. Despite investigating and analysing the proposed allocation rules with regard to which characteristics matter for a beneficial allocation of job-search and training programmes for means-tested benefit recipients, we show the feasibility and potential of such transparent and of black-box rules. This might set the stage for politics and society to discuss whether and in what form such data-driven mechanisms should be used in practice and whether they are socially acceptable.

References

Achatz, J., & Trappmann, M. (2011). Arbeitsmarktvermittelte Abgänge aus der Grundsicherung: Der Einfluss von personen- und haushaltsgebundenen Arbeitsmarktbarrieren. *IAB Discussion Paper 2/2011*.

Arthur, D., & Vassilvitskii, S. (2007). *k-means++: The Advantages of Careful Seeding.* Society for Industrial and Applied Mathematics, Philadelphia, PA, USA.

Athey, S. (2018). The Impact of Machine Learning on Economics. In S. Athey, A. Agrawal, J. Gans, & A. Goldfarb (Hrsg.), *The economics of artificial intelligence: An agenda.* University of Chicago Press.

Athey, S., & Imbens, G. (2016). Recursive Partitioning for Heterogeneous Effect. *Proceedings of the National Academy of Sciences, 113*(27), 7353-7360.

Athey, S., & Imbens, G. (2017). The State of Applied Econometrics - Causality and Policy Evaluation. *Journal of Economic Perspectives, 31*(2), 3-32.

Athey, S., & Imbens, G. (2019). Machine Learning Methods Economists Should Know About. *arXiv:1903.10075*.

Athey, S., Tibshirani, J., & Wager, S. (2019). Generalized random forests. *Annals of Statistics, 47*(2), 1179-1203.

Bergemann, A., & van den Berg, G. (2008). Active Labour Market Policy Effects for Women in Europe - A Survey. *Annales d'Economie et de Statistique, 91/92*, 385-408.

Bernhard, S., & Kopf, E. (2014). Courses or individual counselling: does job search assistance work? *Applied Economics, 27*(46), 3261-3273.

Bernhard, S., & Wolff, J. (2008). Contracting out placement services in Germany: Is assignment to private providers effective for needy job-seekers? *IAB-Discussion Paper 5/2008. Nuremberg: Insitute for Employment Research (IAB)*.

Bertrand, M., Crépon, B., Marguerie, A., & Premand, P. (2017). *Contemporaneous and Post-Program Impacts of a Public Works Program: Evidence from Côte d'Ivoire.* World Bank.

Beste, J., & Trappmann, M. (2016). Erwerbsbedingte Abgänge aus der Grundsicherung: Der Abbau von Hemmnissen macht's möglich. *IAB-Kurzbericht 21/2016*.

Blank, R. (1989). Analyzing the Length of Welfare Spells. *Journal of Public Economics*(39), 245-273.

Blazquez, M., Herrarte, A., & Saez, F. (2019). Training and job search assistance programmes in Spain: The case of long-term unemployed. *Journal of Policy Modeling, 41*(2), 316-335.

Boelmann, B., Raute, A., & Schönberg, U. (2020). Wind of Change? Cultural Determinants of Maternal Labor Supply. *IAB-Discussion Paper, 30*.

Bork, L., Moller, S., & Pedersen, T. (2020). A New Index of Housing Sentiment. *Management Science, 66*(4), 1563-1583.

Borup, D., & Schütte, E. C. (2020). In Search of a Job: Forecasting Employment Growth Using Google Trends. *Journal of Business and Economic Statistics*, 1-15.

Borup, D., Christensen, B., Mühlbach, N., & Nielsen, M. (2020). Targeting predictors in random forest regression. *arXiv:2004.01411v4*, 1-35.

Breiman, L. (2001). Random Forests. *Machine Learning, 45*, 5-32.

Caliendo, M., & Schmidl, R. (2016). Youth unemployment and active labor market policies in Europe. *IZA Journal of Labor Policy, 5*(1), 1-30.

Caliendo, M., Mahlstedt, R., & Mitnik, O. (2017). Unobservable, but unimportant? The relevance of usually unoberved variables for evaluation of labor market policies. *Labour Economics, 46*, 14-25.

Card, D., Kluve, J., & Weber, A. (2010). Active labour market policy evaluations: a meta-analysis. *The Economic Journal, 120*, F452-F477.

Card, D., Kluve, J., & Weber, A. (2018). What works? A meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association, 16*(3), 894-931.

Carpentier, S., Neels, K., & Van den Bosch, K. (2014). How Do Exit Rates from Social Assistance Benefit in Belgium Vary with Individual and Local Agency Characteristics? *Safety Nets and Benefit Dependence (Research in Labor Economics, Vol. 39)*, 151-187.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *Econometrics Journal, 21*(1), C1-C68.

Cockx, B., Lechner, M., & Bollens, J. (2019). Priority to unemployed immigrants? A causal machine learning evaluation of training in Belgium. *arXiv: 1912.12864*.

Davis, J., & Heller, S. (2017). Using causal forests to predict treatment heterogeneity: An application to summer jobs. *American Economic Review: Papers & Proceedings, 107*(5), 546-550.

Davis, J., & Heller, S. (2020). Rethinking the Benefits of Youth Employment Programs: The Heterogeneous Effects of Summer Jobs. *The Review of Economics and Statistics, 102*(4), 664-677.

Dengler, K. (2019). Effectiveness of Active Labour Market Programmes on the Job Quality of Welfare Recipients in Germany. *Journal of Social Policy, 48*(4), 807-838.

Gerfin, M., & Lechner, M. (2002). A microeconometric evaluation of the active labour market policy in Switzerland. *The Economic Journal, 112*(482), 854-893.

Goller, D., Lechner, M., Moczall, A., & Wolff, J. (2020). Does the Estimation of the Propensity Score by Machine Learning Improve Matching Estimation? The Case of Germany's Programmes for Long Term Unemployed. *Labour Economics, 65*, 101855.

Harrer, T., & Stockinger, B. (2021). First step and last resort: One-Euro-Jobs after the reform. *Journal of Social Policy*, 1-23. doi:10.1017/S0047279421000313.

Harrer, T., Moczall, A., & Wolff, J. (2020). Free, free, set them free? Are programmes effective that allow job centres considerable freedom to choose the exact design? *International Journal of Social Welfare, 29*, 154-167.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning - Data mining, inference, and prediction.* 2nd. ed. New York: Springer.

Heckman, J., Ichimura, H., Smith, A., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica, 66*(5), 1017-1098.

Heckmann, J., Lalonde, R., & Smith, J. (1999). The economics and econometrics of active labor market programmes. *in Ashenfelter, O. and Card, D. (Eds), Handbook of Labor Economics, Elsevier, Amsterdam*, 1865-2097.

Hohmeyer, K. (2012). Effectiveness of One-Euro-Jobs: Do programme characteristics matter? *Applied Economics, 44*(34), 4469-4484.

Hohmeyer, K., & Lietzmann, T. (2020). Persistence of Welfare Receipt and Unemployment in Germany: Determinants and Duration Dependence. *Journal of Social Policy, 49*(2), 299-322.

Holland, P. (1986). Statistics and causal inference. *Journal of the American Statistical Association*.

Imbens, G. (2000). The role of the propensity score in estimating dose-response functions. *Biometrika, 87*(3), 706-710.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature, 47*(1), 5-86.

Kluve, J. (2010). The effectiveness of European active labor market programs. *Labour economics*, 904-918.

Knaus, M. (2020). Double Machine Learning based Program Evaluation under Unconfoundedness. *arXiv:2003.03191*.

Knaus, M., Lechner, M., & Strittmatter, A. (2020). Heterogeneous Employment Effects of Job Search Programmes: A Machine Learning Approach. *Journal of Human Resources, 0718-9615R1. https://doi.org/10.3368/jhr.57.2.0718-9615R1*.

Knaus, M., Lechner, M., & Strittmatter, A. (2021). Machine Learning Estimation of Heterogeneous Causal Effects: Empirical Monte Carlo Evidence. *The Econometrics Journal, 24*(1), 134-161.

Kopf, E. (2013). Short training for welfare recipients in Germany: which types work? *International Journal of Manpower, 34*(5), 486-516.

Kotchoni, R., Leroux, M., & Stevanovic, D. (2019). Macroeconomic forecast accurary in a data-rich environment. *Journal of Applied Econometrics, 34*(7), 1050-1072.

Lechner, M. (2001). Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption. In M. Lechner, M. Lechner, & F. Pfeiffer (Hrsg.), *Econometric Evaluation of Active Labour Market Policies* (S. 43-58). Heidelberg: Physica.

Lechner, M. (2018). Modified Causal Forests for Estimating Heterogeneous Causal Effects. *arXiv:1812.09487v2*.

Lechner, M., & Smith, J. (2007). What is the value added by caseworkers? *Labour Economics, 14*(2), 135-151.

Lechner, M., & Wunsch, C. (2009). Are Training Programs More Effective When Unemployment Is High? *Journal of Labor Economics, 27*(4), 653-692.

Lechner, M., & Wunsch, C. (2013). Sensitivity of matching-based program evaluations to the availability of control variables. *Labour Economics, 21*, 111-121.

Lorentzen, T., & Dahl, E. (2005). Active labour market programmes in Norway: are they helpful for social assistance recipients? *Journal of European Social Policy, 15*(1), 27-45.

Martin, J. P., & Grubb, D. (2001). What works for whom: a review of OECD countries' experiences with active labour market policies. *Swedish Economic Policy Review, 8*(2), 9-56.

Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. *Journal of the American Medical Informatics Association, 27*(3), 491-497.

Rosenfeld, R. A., Trappe, H., & Gornick, J. C. (2004). Gender and Work in Germany: Before and After Reunification. *Annual Review of Sociology, 30*(1), 103-124.

Rubin, D. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology, 66*(5), 688-701.

Sianesi, B. (2004). An Evaluation of the Swedish System of Active Labour Programmes in the 1990s. *The Review of Economics and Statistics, 86*(1), 133-166.

Wager, S., & Athey, S. (2018). Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. *Journal of the American Statistical Association, 113*(523), 1228-1242.

Whittlestone, J., Nyrup, R., Alexandrova, A., Dihal, K., & Cave, S. (2019). *Ethical and societal implications of algorithms, data, and artificial intelligence: a roadmap for research.* London: Nuffield Foundation.

Zhou, Z., Athey, S., & Wager, S. (2018). Offline Multi-Action Policy Learning: Generalization and Optimization. *arXiv:1810.04778*.

Appendices

Appendix A: Full descriptive statistics

Appendix A.1 Men

Table 10: Summary of covariates, ***men***

Variable	Men			
	Job-training	Reducing impediments	Placement services	Non-participants
Panel A: Sociodemographic characteristics				
Age at sampling date (in years)	38.28	37.74	39.03	39.70
	(8.66)	(8.36)	(39.03)	(8.57)
Region (west=0, east=1)	0.29	0.26	0.14	0.35
Foreigner	0.20	0.21	0.29	0.20
Nationality - Germany	0.80	0.79	0.71	0.80
Nationality - EU (w/o Germany, w/o former YUG)	0.03	0.04	0.05	0.03
Nationality - Europe rest (w/o former YUG)	0.02	0.02	0.03	0.02
Nationality - Turkey	0.07	0.07	0.11	0.07
Nationality - former Soviet Union (without EU members)	0.02	0.02	0.02	0.02
Nationality - other countries	0.05	0.06	0.08	0.05
Continent - Germany	0.80	0.79	0.71	0.80
Continent - Europe	0.15	0.15	0.21	0.14
Continent - Africa	0.02	0.02	0.03	0.02
Continent - America	0.00	0.00	0.00	0.00
Continent - Asia / Oceania	0.03	0.03	0.04	0.04
Continent - stateless / unknown	0.00	0.00	0.00	0.00
Education - no schooling diploma	0.12	0.13	0.14	0.14
Education - secondary school	0.49	0.51	0.48	0.48
Education - general certificate of secondary education	0.25	0.25	0.21	0.26
Education - advanced technical college entrance qualification	0.04	0.04	0.05	0.04
Education - high school	0.08	0.07	0.12	0.08
Education - missing values	0.01	0.01	0.01	0.01
No vocational / academic degree	0.49	0.51	0.54	0.50
Vocational degree	0.47	0.46	0.41	0.46
Academic degree	0.04	0.03	0.05	0.04
Vocational degree - missing values	0.00	0.00	0.00	0.00
Family status - single	0.51	0.51	0.45	0.48
Family status - married	0.26	0.26	0.32	0.27
Family status - no longer married	0.15	0.15	0.17	0.17
Family status - cohabitation	0.08	0.09	0.07	0.08
Marital status - unmarried	0.51	0.51	0.45	0.48
Marital status - married	0.26	0.26	0.32	0.27
Marital status - widowed	0.00	0.00	0.00	0.00
Marital status - divorced	0.10	0.09	0.10	0.11
Marital status - separated	0.05	0.05	0.06	0.06
Marital status - cohabitation	0.08	0.09	0.07	0.08
BG type - single	0.62	0.61	0.58	0.61
BG type - single with adult aged <25 years	0.00	0.00	0.00	0.00
BG type - single with children aged <18 years	0.02	0.01	0.01	0.02
BG type - single with children aged <18 years and adult aged <25 years	0.00	0.00	0.00	0.00

BG type - couple w/o children	0.08	0.08	0.08	0.09
BG type - couple w/o children, but with adult aged <25 years	0.02	0.02	0.02	0.02
BG type - couple with children aged <18 years	0.22	0.24	0.27	0.22
BG type - couple with children aged <18 years and adult aged <25 years	0.03	0.03	0.03	0.03
BG type - other	0.01	0.01	0.00	0.01
Pregnancy - neither sample member nor partner	0.98	0.98	0.98	0.98
Pregnancy - sample member	0.00	0.00	0.00	0.00
Pregnancy - partner	0.02	0.02	0.02	0.02
Pregnancy - missing value sample member	0.00	0.00	0.00	0.00
Pregnancy - missing value partner	0.00	0.00	0.00	0.00
Partner living in HH (1=yes)	0.34	0.36	0.39	0.35
Child in HH (1=yes)	0.27	0.28	0.31	0.27
Own child in HH (1=yes)	0.27	0.28	0.31	0.27
Profile of unemployed - Market	0.04	0.03	0.07	0.03
Profile of unemployed - Activation	0.03	0.02	0.05	0.02
Profile of unemployed - Support	0.23	0.25	0.29	0.21
Profile of unemployed - Development	0.38	0.41	0.37	0.38
Profile of unemployed - Stabilisation	0.07	0.07	0.05	0.08
Profile of unemployed - Assistance	0.15	0.14	0.11	0.21
Profile of unemployed - integrated, but dependent on help	0.03	0.03	0.03	0.02
Profile of unemployed - not specified	0.03	0.02	0.02	0.02
Profile of unemployed - missing	0.04	0.02	0.02	0.01
Profile of unemployed - assignment not required	0.01	0.01	0.01	0.01
Panel B: Labour market history				
Cumul. days in unemployment in the last year	254.80 (112.75)	262.46 (105.58)	265.59 (103.94)	277.17 (101.81)
Cumul. days in unemployment in the last year - 1 month	0.05	0.03	0.02	0.02
Cumul. days in unemployment in the last year - >1-2 months	0.04	0.03	0.03	0.02
Cumul. days in unemployment in the last year - >2-3 months	0.05	0.04	0.04	0.04
Cumul. days in unemployment in the last year - >3-6 months	0.14	0.15	0.15	0.14
Cumul. days in unemployment in the last year - >6-9 months	0.19	0.19	0.20	0.17
Cumul. days in unemployment in the last year - >9-12 months	0.54	0.56	0.56	0.62
Cumul. days in unemployment in the last 2 years	438.66 (213.68)	451.96 (202.48)	456.77 (202.70)	488.99 (202.01)
Cumul. days in unemployment in the last 5 years	977.01 (496.19)	1,001.77 (470.91)	992.66 (481.31)	1,081.21 (479.48)
Cumul. days in unemployment in the last 5 years - 0-6 months	0.06	0.04	0.04	0.04
Cumul. days in unemployment in the last 5 years - >6-12 months	0.07	0.06	0.07	0.05
Cumul. days in unemployment in the last 5 years - >12-24 months	0.20	0.20	0.21	0.17
Cumul. days in unemployment in the last 5 years - >24-36 months	0.23	0.25	0.24	0.23
Cumul. days in unemployment in the last 5 years - >36-48 months	0.24	0.24	0.24	0.25
Cumul. days in unemployment in the last 5 years - >48 months	0.20	0.20	0.20	0.26
Cumul. days in job search in the last 1 year	310.75 (97.34)	322.24 (83.82)	324.06 (80.33)	328.24 (76.55)

Cumul. days in job search in the last 2 years	566.90	588.28	588.14	608.77
	(210.70)	(189.95)	(188.79)	(178.63)
Cumul. days in job search in the last 5 years	1,285.18	1,329.59	1,295.50	1,374.14
	(531.51)	(492.01)	(504.48)	(480.72)
Cumul. days in UB II in the last 1 year	288.75	303.13	302.30	318.32
	(119.52)	(105.56)	(104.19)	(91.27)
Cumul. days in UB II in the last 1 year - 1 month	0.07	0.04	0.03	0.02
Cumul. days in UB II in the last 1 year - >1-2 months	0.04	0.03	0.03	0.02
Cumul. days in UB II in the last 1 year - >2-6 months	0.09	0.09	0.10	0.08
Cumul. days in UB II in the last 1 year - >6-9 months	0.08	0.08	0.09	0.07
Cumul. days in UB II in the last 1 year - >9-12 months	0.72	0.76	0.75	0.81
Cumul. days in UB II in the last 2 years	534.42	558.00	550.75	593.15
	(252.86)	(232.95)	(232.95)	(210.63)
Cumul. days in UB II in the last 5 years	1,196.07	1,243.57	1,204.96	1,312.36
	(623.13)	(587.76)	(595.77)	(561.15)
Cumul. days in UB II in the last 5 years - 0-6 months	0.10	0.07	0.07	0.05
Cumul. days in UB II in the last 5 years - >6-12 months	0.06	0.06	0.07	0.05
Cumul. days in UB II in the last 5 years - >12-24 months	0.11	0.11	0.11	0.10
Cumul. days in UB II in the last 5 years - >24-36 months	0.12	0.12	0.12	0.11
Cumul. days in UB II in the last 5 years - >36-48 months	0.14	0.15	0.15	0.15
Cumul. days in UB II in the last 5 years - >48 months	0.48	0.50	0.47	0.55
Experience in UB I (1=yes)	0.05	0.05	0.05	0.04
Cumul. days in UB I in the last 1 year	34.11	34.24	36.33	23.82
	(82.44)	(81.55)	(83.26)	(68.58)
Cumul. days in UB I in the last 2 years	56.38	57.51	63.86	44.03
	(114.19)	(114.73)	(120.22)	(102.70)
Cumul. days in UB I in the last 5 years	121.36	122.91	136.87	106.14
	(177.53)	(178.32)	(183.50)	(170.44)
Days since last employment	1,527.86	1,488.66	1,383.71	1,821.92
	(1,612.28)	(1,590.92)	(1,579.42)	(1,774.76)
Cumul. days in regular employment in the last year	23.61	22.51	26.90	17.34
	(61.02)	(58.58)	(62.00)	(51.81)
Cumul. days in regular employment in the last 5 years	285.30	282.00	319.94	224.59
	(403.41)	(394.55)	(402.39)	(357.51)
Cumul. days in contributory employment in the last year	27.43	25.96	29.91	21.14
	(65.40)	(62.58)	(64.85)	(56.85)
Cumul. days in contributory employment in the last 2 years	93.99	94.10	102.34	72.49
	(150.86)	(149.32)	(149.35)	(132.90)
Cumul. days in contributory employment in the last 5 years	288.55	286.83	325.36	236.24
	(391.30)	(382.41)	(394.45)	(350.93)
Cumul. days in vocational training in the last year	1.04	0.77	0.80	0.61
	(14.59)	(11.61)	(12.11)	(10.89)
Cumul. days in vocational training in the last 2 years	4.09	3.73	3.33	2.53
	(41.14)	(37.29)	(37.47)	(31.73)
Cumul. days in vocational training in the last 5 years	24.03	23.62	18.07	15.41
	(131.68)	(129.31)	(114.27)	(104.50)
Cumul. days in minor employment in the last year	41.79	39.81	56.67	48.65
	(98.21)	(95.02)	(112.20)	(106.00)
Cumul. days in minor employment in the last 2 years	79.41	75.16	102.13	89.29
	(174.81)	(167.62)	(194.78)	(186.59)
	175.01	165.53	213.57	187.71

Cumul. days in minor employment in the last 5 years	(342.86)	(328.61)	(375.57)	(361.53)
Cumul. days in bridging allowance in the last 5 years	1.42	1.57	1.62	1.55
	(15.35)	(16.16)	(16.47)	(16.11)
Cumul. days in One-Euro-Jobs in the last year	16.80	18.73	12.89	15.54
	(53.03)	(55.86)	(46.48)	(50.28)
Cumul. days in One-Euro-Jobs in the last 2 years	36.54	41.30	29.87	36.09
	(90.85)	(96.88)	(81.77)	(90.74)
Cumul. days in One-Euro-Jobs in the last 5 years	91.42	101.30	75.91	91.08
	(173.52)	(180.90)	(152.56)	(172.43)
Cumul. days in subsidised public employment in the last year	2.35	2.55	1.84	2.90
	(20.47)	(20.78)	(17.25)	(22.47)
Cumul. days in subsidised public employment in the last 2 years	6.04	6.87	4.48	7.42
	(36.83)	(38.42)	(31.48)	(41.23)
Cumul. days in subsidised public employment in the last 5 years	14.91	16.69	11.74	17.16
	(61.00)	(65.02)	(56.35)	(68.18)
Cumul. days in subsidised employment in the last year	2.24	1.73	1.86	1.39
	(17.23)	(15.21)	(14.84)	(13.19)
Cumul. days in subsidised employment in the last 5 years	12.59	12.63	12.27	10.47
	(46.70)	(48.99)	(45.72)	(44.16)
Experience in further vocational training (1=yes)	0.35	0.37	0.32	0.33
Cumul. days in further vocational training in the last 1 year	8.05	6.73	9.11	7.16
	(33.80)	(30.39)	(36.65)	(32.08)
Cumul. days in further vocational training in the last 5 years	30.64	30.52	31.27	26.69
	(94.77)	(95.67)	(96.59)	(89.53)
Experience in in-firm SAI (1=yes)	0.05	0.05	0.04	0.04
Cumul. days in in-firm SAI in the last year	0.52	0.52	0.48	0.43
	(3.12)	(3.02)	(3.07)	(2.86)
Cumul. days in in-firm SAI in the last 2 years	0.52	0.52	0.48	0.43
	(3.12)	(3.02)	(3.07)	(2.86)
Experience in classroom SAI (1=yes)	0.11	0.14	0.11	0.07
Cumul. days in classroom SAI in the last year	3.85	5.74	6.38	3.04
	(18.90)	(21.52)	(26.53)	(17.37)
Cumul. days in classroom SAI in the last 2 years	3.85	5.74	6.38	3.04
	(18.90)	(21.52)	(26.53)	(17.37)
Experience in *job-training* (*JT*) (1=yes)	0.07	0.05	0.04	0.03
Experience in *reducing impediments* (*RIM*) (1=yes)	0.02	0.07	0.02	0.02
Cumul. days in SAI in the last year	4.35	6.21	6.82	3.46
	(19.06)	(21.50)	(26.68)	(17.55)
Cumul. days in SAI in the last 2 years	4.35	6.21	6.82	3.46
	(19.06)	(21.50)	(26.68)	(17.55)
Experience in in-firm training (1=yes)	0.23	0.23	0.19	0.20
Cumul. days in in-firm training in the last year	0.55	0.54	0.50	0.45
	(3.26)	(3.26)	(3.21)	(3.02)
Cumul. days in in-firm training in the last 5 years	3.25	3.46	2.77	2.89
	(10.67)	(11.03)	(10.15)	(10.21)
Experience in classroom training (1=yes)	0.57	0.64	0.57	0.49
Cumul. days in classroom training in the last year	6.29	9.33	9.59	4.81
	(22.07)	(25.94)	(30.30)	(20.09)
Cumul. days in classroom training in last 5 years	17.42	23.72	19.96	13.33
	(34.73)	(42.19)	(44.90)	(31.41)
Ever received mild sanction (1=yes)	0.16	0.16	0.14	0.17
Cumul. days in mild sanctions in the last year	6.89	6.62	5.96	7.66
	(27.42)	(26.25)	(25.49)	(29.41)
Cumul. days in mild sanctions in the last year - never sanctioned	0.92	0.92	0.93	0.92
Cumul. days in mild sanctions in the last year - once (3 months)	0.06	0.06	0.06	0.06
Cumul. days in mild sanctions in the last year - more than once	0.02	0.02	0.01	0.02

Ever received strong sanction (1=yes)	0.23	0.24	0.21	0.21
Cumul. days in strong sanctions in the last year	8.80 (29.42)	9.20 (29.63)	8.25 (28.03)	7.49 (27.05)
Cumul. days in strong sanctions in the last year - never sanctioned	0.89	0.88	0.90	0.91
Cumul. days in strong sanctions in the last year - once (3 months)	0.09	0.10	0.09	0.08
Cumul. days in strong sanctions in the last year - more than once	0.02	0.02	0.02	0.01
Panel C: Last job characteristics				
Type of last job - contributory employment	0.62	0.63	0.59	0.59
Type of last job - minor employment	0.32	0.31	0.37	0.36
Type of last job - vocational training	0.03	0.02	0.02	0.02
Type of last job - no last job	0.03	0.03	0.02	0.03
Last occupation - agriculture, forestry, gardening	0.05	0.04	0.05	0.05
Last occupation - manufacturing	0.13	0.13	0.10	0.12
Last occupation - manufacturing engineering	0.08	0.08	0.08	0.08
Last occupation - construction	0.20	0.19	0.17	0.21
Last occupation - grocery, hospitality	0.08	0.08	0.09	0.08
Last occupation - healthcare	0.01	0.01	0.01	0.01
Last occupation - humanities, arts	0.01	0.01	0.02	0.02
Last occupation - trading	0.06	0.07	0.08	0.07
Last occupation - business management and organisation	0.03	0.03	0.04	0.03
Last occupation - service	0.03	0.03	0.04	0.04
Last occupation - security, logistic, transport	0.23	0.25	0.25	0.22
Last occupation - cleaning	0.03	0.04	0.04	0.04
Last occupation - no last job / missing	0.05	0.05	0.04	0.06
Last occupational level - assistant	0.39	0.42	0.38	0.36
Last occupational level - specialist	0.49	0.48	0.49	0.50
Last occupational level - expert	0.04	0.03	0.04	0.04
Last occupational level - professional	0.03	0.03	0.04	0.04
Last occupational level - no last job / missing	0.05	0.05	0.04	0.06
Last job industry - agriculture, forestry, fishing, mining, manufacturing, energy, water supply	0.11	0.10	0.09	0.10
Last job industry - construction	0.11	0.10	0.11	0.12
Last job industry - trade, car sales and maintenance	0.11	0.10	0.13	0.11
Last job industry - hospitality	0.08	0.08	0.11	0.09
Last job industry - transport and postal services, telecommunication	0.08	0.08	0.09	0.08
Last job industry - financial services, real estate, renting out property, services for companies	0.32	0.37	0.33	0.30
Last job industry - public administration, defence, social security agencies, education, health and social work	0.09	0.09	0.06	0.10
Last job industry - other services	0.06	0.06	0.06	0.07
Last job industry - no last job / missing	0.03	0.03	0.02	0.04
Last job working time - full-time	0.61	0.61	0.58	0.57
Last job working time - part-time	0.36	0.36	0.40	0.40
Last job working time - no last job	0.03	0.03	0.02	0.04
Last job duration - <1 month	0.14	0.16	0.13	0.13
Last job duration - 1 - <3 months	0.21	0.21	0.21	0.21
Last job duration - 3 - <6 months	0.19	0.19	0.19	0.19
Last job duration - 6 - <12 months	0.19	0.18	0.20	0.20
Last job duration - 12 - <24 months	0.12	0.12	0.12	0.12
Last job duration - 24 - <36 months	0.05	0.04	0.05	0.05
Last job duration - 36 - <60 months	0.04	0.03	0.04	0.04
Last job duration - 60+ months	0.04	0.04	0.05	0.04

Last job duration - no last job	0.03	0.03	0.02	0.03
Last daily real wage (in Euro)	32.11	31.16	32.59	30.87
	(41.06)	(27.26)	(30.68)	(32.96)
Panel D: Labour market status in December 2004				
Dec 2004 - unemployment insurance receipt	0.09	0.10	0.11	0.09
Dec 2004 - unemployment assistance receipt	0.35	0.35	0.32	0.37
Dec 2004 - registered unemployment	0.48	0.50	0.46	0.50
Dec 2004 - registered jobseeker not unemployed	0.13	0.14	0.12	0.12
Dec 2004 - participation in any ALMP	0.11	0.11	0.11	0.10
Dec 2004 - contributory employment	0.24	0.23	0.26	0.21
Dec 2004 - minor employment	0.08	0.08	0.09	0.08
Panel E: Household level				
HH with members aged 18-24 years (1=yes)	0.08	0.08	0.08	0.08
HH with members aged 25-34 years (1=yes)	0.44	0.47	0.42	0.38
HH with members aged 35-44 years (1=yes)	0.37	0.37	0.40	0.38
HH with members aged 45-54 years (1=yes)	0.30	0.27	0.32	0.36
HH with members aged 55-64 years (1=yes)	0.01	0.01	0.00	0.01
# of own children aged <3 years	0.11	0.13	0.13	0.10
# of own children aged 3-5 years	0.11	0.12	0.13	0.10
# of own children aged 6-9 years	0.13	0.13	0.15	0.12
# of own children aged 10-12 years	0.08	0.08	0.09	0.08
# of own children aged 13-14 years	0.05	0.04	0.06	0.05
# of own children aged 15-17 years	0.06	0.07	0.08	0.07
HH equiv. UB II income (in prices of 2010)	677.95	697.92	719.50	717.34
	(266.08)	(240.21)	(253.37)	(226.84)
HH receives income from dependent employment	0.15	0.15	0.21	0.18
HH receives income from self-employment	0.01	0.01	0.01	0.01
HH receives UB I	0.05	0.06	0.06	0.04
HH receives income from child support	0.01	0.01	0.01	0.01
HH receives income from alimony	0.00	0.00	0.00	0.00
HH receives pension or housing assistance	0.01	0.01	0.01	0.01
HH receives income from other sources	0.03	0.03	0.03	0.03
HH - no information UB II income found	0.05	0.03	0.02	0.01
Panel F: Partner characteristics				
Partner's age (in years)	12.19	12.39	13.85	12.91
	(17.83)	(17.47)	(18.26)	(18.42)
Partner's nationality - Germany	0.23	0.24	0.21	0.24
Partner's nationality - EU (w/o Germany, with former YUG)	0.02	0.02	0.03	0.02
Partner's nationality - Europe rest (w/o former YUG)	0.01	0.01	0.02	0.01
Partner's nationality - Turkey	0.04	0.04	0.06	0.04
Partner's nationality - former Soviet Union (w/o EU members)	0.01	0.02	0.02	0.01
Partner's nationality - other countries	0.03	0.03	0.05	0.03
Partner's nationality - missing	0.66	0.65	0.62	0.65
Partner's continent - Germany	0.23	0.24	0.21	0.24
Partner's continent - Europe	0.08	0.08	0.12	0.08
Partner's continent - Africa	0.01	0.01	0.02	0.01
Partner's continent - America	0.00	0.00	0.00	0.00
Partner's continent - Asia / Oceania	0.02	0.02	0.03	0.02
Partner's continent - stateless / unknown	0.00	0.00	0.00	0.00
Partner's continent - missing	0.66	0.65	0.62	0.65
Partner's education - no schooling diploma	0.08	0.07	0.11	0.08
Partner's education - secondary school	0.13	0.14	0.14	0.13
Partner's education - general certificate of secondary education	0.08	0.09	0.07	0.09
Partner's education - advanced technical college entrance qualification	0.01	0.01	0.01	0.01
Partner's education - high school	0.02	0.02	0.02	0.02

Partner's education - missing	0.69	0.68	0.65	0.68
Partner's vocational degree - no vocational / academic degree	0.21	0.22	0.27	0.21
Partner's vocational degree - vocational degree	0.11	0.12	0.09	0.12
Partner's vocational degree - academic degree	0.01	0.01	0.01	0.01
Partner's vocational degree - missing	0.67	0.66	0.63	0.66
Partner's marital status - single	0.03	0.03	0.02	0.03
Partner's marital status - married	0.24	0.24	0.30	0.25
Partner's marital status - no longer married	0.02	0.02	0.02	0.02
Partner's marital status - cohabitation	0.06	0.07	0.05	0.06
Partner's marital status - missing	0.66	0.64	0.61	0.65
Partner's disability status (1= yes)	0.01	0.01	0.01	0.01
Partner's disability status (1= missing)	0.01	0.01	0.02	0.01
Partner's last job type - contributory employment	0.13	0.14	0.14	0.14
Partner's last job type - minor employment	0.12	0.12	0.14	0.12
Partner's last job type - vocational training	0.01	0.01	0.01	0.01
Partner's last job type - no last job	0.74	0.73	0.71	0.73
Partner's last occupation - agriculture, forestry, gardening	0.01	0.01	0.01	0.01
Partner's last occupation - manufacturing	0.02	0.02	0.01	0.01
Partner's last occupation - manufacturing engineering	0.01	0.01	0.01	0.01
Partner's last occupation - construction	0.00	0.00	0.00	0.00
Partner's last occupation - grocery, hospitality	0.03	0.04	0.03	0.03
Partner's last occupation - healthcare	0.02	0.02	0.02	0.02
Partner's last occupation - humanities, arts	0.02	0.02	0.02	0.02
Partner's last occupation - trading	0.04	0.05	0.05	0.04
Partner's last occupation - business management and organisation	0.02	0.02	0.02	0.02
Partner's last occupation - service	0.01	0.01	0.01	0.01
Partner's last occupation - security, logistic, transport	0.02	0.02	0.02	0.02
Partner's last occupation - cleaning	0.03	0.03	0.04	0.04
Partner's last occupation - no last job / missing	0.79	0.77	0.77	0.77
Partner's last occupational level - assistant	0.09	0.10	0.11	0.10
Partner's last occupational level - specialist	0.11	0.12	0.11	0.11
Partner's last occupational level - expert	0.01	0.01	0.01	0.01
Partner's last occupational level - professional	0.01	0.01	0.01	0.01
Partner's last occupational level - no last job / missing	0.79	0.77	0.77	0.77
Partner's last job industry - agriculture, forestry, fishing, mining, manufacturing, energy, water supply	0.02	0.02	0.02	0.02
Partner's last job industry - construction	0.01	0.00	0.00	0.00
Partner's last job industry - trade, car sales and maintenance	0.04	0.05	0.05	0.05
Partner's last job industry - hospitality	0.03	0.04	0.04	0.03
Partner's last job industry - transport and postal services, telecommunication	0.01	0.01	0.01	0.01
Partner's last job industry - financial services, real estate, renting out property, services for companies	0.08	0.08	0.10	0.08
Partner's last job industry - public administration, defence, social security agencies, education, health and social work	0.04	0.05	0.04	0.05
Partner's last job industry - other services	0.03	0.03	0.02	0.03

Partner's last job industry - no last job / missing	0.74	0.73	0.71	0.73
Partner's last job working time - full-time	0.09	0.10	0.10	0.10
Partner's last job working time - part-time	0.17	0.17	0.20	0.18
Partner's last job working time - no last job	0.74	0.73	0.71	0.73
Partner's last job duration - <1 month	0.03	0.03	0.03	0.03
Partner's last job duration - 1-<3 months	0.04	0.05	0.05	0.05
Partner's last job duration - 3 -<6 months	0.04	0.05	0.05	0.05
Partner's last job duration - 6 -<12 months	0.05	0.05	0.06	0.06
Partner's last job duration - 12-<24 months	0.04	0.04	0.04	0.04
Partner's last job duration - 24-<36 months	0.02	0.02	0.02	0.02
Partner's last job duration - 36-<60 months	0.02	0.02	0.02	0.02
Partner's last job duration - 60+ months	0.02	0.02	0.02	0.02
Partner's last job duration - no last job / missing	0.74	0.73	0.71	0.73
Partner's last daily wage (in Euro)	5.55	5.82	6.43	6.05
	(13.59)	(14.52)	(14.72)	(16.04)
Partner's cumul. days in unemployment in the last year	46.21	45.29	50.62	51.47
	(105.83)	(104.25)	(110.41)	(112.58)
Partner's cumul. days in unemployment in the last 5 years	215.30	216.78	232.63	242.83
	(439.36)	(432.42)	(448.30)	(471.53)
Partner's cumul. days in job search in the last year	71.41	73.44	81.10	81.17
	(135.45)	(136.62)	(141.84)	(143.67)
Partner's cumul. days in job search in the last 5 years	316.15	324.87	346.16	357.47
	(569.83)	(566.76)	(579.86)	(606.36)
Partner's cumul. days in UB II in the last year	102.94	110.50	120.29	112.61
	(157.44)	(160.71)	(164.00)	(162.77)
Partner's cumul. days in UB II in the last 5 years	425.53	455.29	485.31	470.71
	(690.33)	(706.39)	(711.56)	(721.03)
Partner's days since last regular employment	206.06	229.29	217.26	225.54
	(647.00)	(676.46)	(655.97)	(678.57)
Partner's cumul. days in regular employment in the last year	14.03	16.17	18.29	16.62
	(64.18)	(68.58)	(72.53)	(70.29)
Partner's cumul. days in regular employment in the last 5 years	81.26	90.38	92.95	87.45
	(296.22)	(311.29)	(308.86)	(310.39)
Partner in contributory employment at sampling date	0.04	0.04	0.05	0.05
Partner in minor employment at sampling date	0.05	0.05	0.06	0.05
Panel G: District-level information				
Unemployment rate (in %)	10.39	10.49	10.15	10.99
	(3.49)	(3.13)	(3.01)	(3.54)
Long-term unemployment rate (in %)	3.78	3.75	3.99	3.97
	(1.76)	(1.56)	(1.63)	(1.69)
Long-term unemployment stock	8,371.45	8,989.26	15,501.27	14,755.62
	(15,703.18)	(15,233.79)	(18,970.25)	(24,556.80)
Unemployment rate of welfare recipients (in %)	7.32	7.42	7.46	7.90
	(3.13)	(2.88)	(2.89)	(3.26)
District vacancy-unemployment ratio	0.08	0.09	0.10	0.08
	(0.04)	(0.05)	(0.05)	(0.04)
Panel H: Information at the job centre level				
Employees in job centre (JC)	334.49	407.95	628.75	417.02
	(330.57)	(417.74)	(452.81)	(400.36)
Share of JC employees in Market and Integration	0.43	0.43	0.45	0.42
	(0.10)	(0.10)	(0.10)	(0.08)
Share of JC employees in Benefits Administration	0.40	0.40	0.38	0.40
	(0.10)	(0.09)	(0.10)	(0.08)
Share of JC employees of female JC employees	0.68	0.68	0.66	0.68
	(0.10)	(0.10)	(0.07)	(0.09)
Share of JC employees being civil servants	0.17	0.17	0.21	0.17
	(0.08)	(0.08)	(0.08)	(0.08)
	0.23	0.23	0.24	0.22

Share of JC employees on fixed-term contract	(0.07)	(0.06)	(0.05)	(0.07)
Share of JC employees on fixed-term contract among employees in Market and Integration	0.21 (0.09)	0.22 (0.08)	0.24 (0.07)	0.21 (0.09)
Client-staff ratio	65.77 (7.11)	66.73 (6.64)	67.80 (7.20)	67.06 (7.67)
Client-staff ratio among employees in Market and Integration	158.76 (28.54)	159.58 (28.11)	155.90 (26.81)	162.41 (26.19)
JC 2009/q4 - people with at least 1 sanction / UB II recipients stock (25-54 years)	2.62 (0.93)	2.65 (0.82)	2.64 (0.79)	2.60 (0.83)
JC 2009/q4 - people with complete sanction (no UB II) / UB II recipients stock (25-54 years)	0.11 (0.12)	0.11 (0.11)	0.09 (0.10)	0.10 (0.11)
JC 2009/q4 - sanction intensity due to failure in reporting (25-54 years)	0.71 (0.26)	0.71 (0.27)	0.71 (0.23)	0.71 (0.26)
JC 2009/q4 - sanction intensity due to violations of duties (25-54 years)	0.54 (0.28)	0.54 (0.23)	0.53 (0.23)	0.51 (0.24)
JC 2009/q4 - inflow into classroom SAI / stock of UB II jobseekers (25-54 years)	1.69 (1.00)	1.79 (1.12)	1.63 (1.06)	1.30 (0.89)
JC 2009/q4 - inflow into in-firm SAI / stock of UB II jobseekers (25-54 years)	0.41 (0.20)	0.42 (0.20)	0.30 (0.23)	0.38 (0.20)
JC 2009/q4 - inflow into further vocational training / stock of UB II recipients (25-54 years)	0.51 (0.33)	0.52 (0.31)	0.35 (0.28)	0.54 (0.33)
JC 2009/q4 - inflow into wage subsidies / stock of UB II jobseekers (25-54 years)	0.24 (0.10)	0.25 (0.10)	0.21 (0.09)	0.24 (0.10)
JC 2009/q4 - inflow into One-Euro-Jobs / stock of UB II jobseekers (25-54 years)	1.11 (0.56)	1.10 (0.58)	0.95 (0.48)	1.11 (0.61)
JC type - Cities west, average labour market situation (LMS), high GDP, high rate of long term unemployed	0.10	0.10	0.48	0.12
JC type - Cities west, above average LMS, high GDP	0.06	0.05	0.06	0.04
JC type - Cities west, below average LMS, very high rate of long-term unemployed	0.17	0.15	0.14	0.22
JC type - Cities, mainly east, bad LMS, very high rate of long-term unemployed	0.06	0.11	0.03	0.09
JC type - Predominantly urban, west, average LMS, high rate of long-term unemployed	0.10	0.20	0.06	0.12
JC type - rural, west, average LMS	0.13	0.10	0.09	0.12
JC type - Predominantly urban, west and east, below average LMS	0.07	0.05	0.02	0.05
JC type - rural, west, good LMS, high seasonal dynamic	0.02	0.02	0.03	0.02
JC type - rural, west, very good LMS, seasonal dynamic, very low rate of long-term unemployed	0.03	0.02	0.02	0.02
JC type - rural, west, very good LMS, low average rate of long-term unemployed	0.08	0.08	0.03	0.06
JC type - predominantly rural, east, bad LMS, low GDP	0.10	0.09	0.03	0.10
JC type - predominantly rural, east, very bad LMS, very low GDP, high average rate of long-term unemployed	0.07	0.03	0.01	0.05

Notes: Means of the covariates. Values in parentheses are the standard deviations.

Appendix A.2 Women

Table 11: Summary of covariates, ***women***

Variable	Women			
	Job-training	Reducing impediments	Placement services	Non-participants
Panel A: Sociodemographic characteristics				
Age at sampling date (in years)	38.90	38.53	39.62	39.86
	(8.48)	(8.27)	(8.30)	(8.41)
Region (west=0, east=1)	0.31	0.28	0.16	0.33
Foreigner	0.18	0.19	0.24	0.22
Nationality - Germany	0.82	0.81	0.76	0.78
Nationality - EU (w/o Germany, w/o former YUG)	0.05	0.05	0.06	0.05
Nationality - Europe rest (w/o former YUG)	0.02	0.02	0.03	0.02
Nationality - Turkey	0.05	0.05	0.07	0.07
Nationality - former Soviet Union (without EU members)	0.03	0.03	0.03	0.03
Nationality - other countries	0.04	0.05	0.05	0.05
Continent - Germany	0.82	0.81	0.76	0.78
Continent - Europe	0.13	0.14	0.19	0.16
Continent - Africa	0.01	0.01	0.02	0.01
Continent - America	0.00	0.00	0.00	0.00
Continent - Asia / Oceania	0.03	0.03	0.03	0.04
Continent - stateless / unknown	0.00	0.00	0.00	0.00
Education - no schooling diploma	0.13	0.11	0.13	0.17
Education - secondary school	0.42	0.42	0.42	0.40
Education - general certificate of secondary education	0.31	0.33	0.27	0.30
Education - advanced technical college entrance qualification	0.03	0.04	0.05	0.03
Education - high school	0.08	0.07	0.10	0.07
Education - missing values	0.03	0.03	0.02	0.03
No vocational / academic degree	0.48	0.49	0.52	0.53
Vocational degree	0.46	0.47	0.43	0.42
Academic degree	0.04	0.04	0.05	0.04
Vocational degree - missing values	0.01	0.01	0.01	0.01
Family status - single	0.31	0.31	0.30	0.28
Family status - married	0.27	0.27	0.27	0.32
Family status - no longer married	0.34	0.34	0.37	0.33
Family status - cohabitation	0.08	0.08	0.06	0.07
Marital status - unmarried	0.31	0.31	0.30	0.28
Marital status - married	0.27	0.27	0.27	0.32
Marital status - widowed	0.02	0.01	0.01	0.02
Marital status - divorced	0.19	0.19	0.21	0.18
Marital status - separated	0.14	0.14	0.14	0.13
Marital status - cohabitation	0.08	0.08	0.06	0.07
BG type - single	0.30	0.28	0.32	0.27
BG type - single with adult aged <25 years	0.02	0.01	0.01	0.01
BG type - single with children aged <18 years	0.28	0.31	0.29	0.27
BG type - single with children aged <18 years and adult aged <25 years	0.03	0.03	0.03	0.03
BG type - couple w/o children	0.10	0.09	0.10	0.11
BG type - couple w/o children, but with adult aged <25 years	0.02	0.02	0.02	0.03
BG type - couple with children aged <18 years	0.18	0.19	0.17	0.20
BG type - couple with children aged <18 years and adult aged <25 years	0.03	0.03	0.03	0.04

BG type - other	0.03	0.04	0.04	0.04
Pregnancy - neither sample member nor partner	1.00	1.00	1.00	0.98
Pregnancy - sample member	0.00	0.00	0.00	0.02
Pregnancy - partner	0.00	0.00	0.00	0.00
Pregnancy - missing value sample member	0.00	0.00	0.00	0.00
Pregnancy - missing value partner	0.00	0.00	0.00	0.00
Partner living in HH (1=yes)	0.32	0.32	0.29	0.36
Child in HH (1=yes)	0.53	0.55	0.52	0.54
Own child in HH (1=yes)	0.53	0.55	0.52	0.54
Profile of unemployed - Market	0.03	0.02	0.05	0.02
Profile of unemployed - Activation	0.02	0.02	0.03	0.01
Profile of unemployed - Support	0.20	0.22	0.27	0.18
Profile of unemployed - Development	0.42	0.45	0.39	0.40
Profile of unemployed - Stabilisation	0.08	0.08	0.06	0.08
Profile of unemployed - Assistance	0.17	0.14	0.14	0.23
Profile of unemployed - integrated, but dependent on help	0.02	0.01	0.02	0.02
Profile of unemployed - not specified	0.02	0.02	0.02	0.02
Profile of unemployed - missing	0.03	0.02	0.01	0.01
Profile of unemployed - assignment not required	0.03	0.02	0.02	0.03
Panel B: Labour market history				
Cumul. days in unemployment in the last year	252.02 (119.31)	259.49 (111.88)	265.57 (108.79)	277.59 (106.73)
Cumul. days in unemployment in the last year - 1 month	0.06	0.04	0.03	0.02
Cumul. days in unemployment in the last year - >1-2 months	0.05	0.04	0.03	0.03
Cumul. days in unemployment in the last year - >2-3 months	0.05	0.05	0.04	0.04
Cumul. days in unemployment in the last year - >3-6 months	0.15	0.15	0.15	0.13
Cumul. days in unemployment in the last year - >6-9 months	0.15	0.16	0.18	0.15
Cumul. days in unemployment in the last year - >9-12 months	0.54	0.57	0.58	0.63
Cumul. days in unemployment in the last 2 years	441.19 (236.28)	450.95 (221.00)	466.83 (221.70)	491.66 (219.74)
Cumul. days in unemployment in the last 5 years	944.92 (541.93)	959.85 (516.84)	978.67 (520.62)	1,038.15 (523.84)
Cumul. days in unemployment in the last 5 years - 0-6 months	0.10	0.07	0.07	0.06
Cumul. days in unemployment in the last 5 years - >6-12 months	0.09	0.08	0.08	0.07
Cumul. days in unemployment in the last 5 years - >12-24 months	0.20	0.23	0.21	0.19
Cumul. days in unemployment in the last 5 years - >24-36 months	0.19	0.20	0.20	0.19
Cumul. days in unemployment in the last 5 years - >36-48 months	0.20	0.21	0.21	0.22
Cumul. days in unemployment in the last 5 years - >48 months	0.22	0.21	0.23	0.27
Cumul. days in job search in the last year	303.23 (107.27)	315.71 (94.87)	319.77 (88.48)	323.04 (86.41)
Cumul. days in job search in the last 2 years	554.79 (236.90)	576.97 (217.52)	581.59 (211.43)	597.05 (203.61)
Cumul. days in job search in the last 5 years	1,227.30 (577.52)	1,260.54 (550.21)	1,258.27 (546.96)	1,303.11 (533.31)
Cumul. days in UB II in the last year	310.40 (106.32)	321.71 (92.54)	323.03 (89.25)	332.03 (79.45)

Cumul. days in UB II in the last year - 1 month	0.05	0.03	0.02	0.01
Cumul. days in UB II in the last year - >1-2 months	0.03	0.02	0.02	0.01
Cumul. days in UB II in the last year - >2-6 months	0.07	0.07	0.07	0.06
Cumul. days in UB II in the last year - >6-9 months	0.05	0.06	0.06	0.05
Cumul. days in UB II in the last year - >9-12 months	0.80	0.83	0.83	0.87
Cumul. days in UB II in the last 2 years	589.52	610.14	607.51	632.58
	(231.79)	(209.77)	(209.67)	(187.83)
Cumul. days in UB II in the last 5 years	1,316.60	1,352.04	1,332.04	1,403.04
	(600.14)	(570.81)	(574.50)	(531.32)
Cumul. days in UB II in the last 5 years - 0-6 months	0.09	0.06	0.06	0.04
Cumul. days in UB II in the last 5 years - >6-12 months	0.04	0.05	0.05	0.04
Cumul. days in UB II in the last 5 years - >12-24 months	0.08	0.08	0.09	0.08
Cumul. days in UB II in the last 5 years - >24-36 months	0.09	0.09	0.10	0.09
Cumul. days in UB II in the last 5 years - >36-48 months	0.12	0.12	0.12	0.13
Cumul. days in UB II in the last 5 years - >48 months	0.58	0.60	0.58	0.63
Experience in UB I (1=yes)	0.05	0.04	0.04	0.03
Cumul. days in UB I in the last year	18.36	17.97	19.09	13.21
	(61.63)	(60.68)	(62.36)	(52.26)
Cumul. days in UB I in the last 2 years	31.71	31.72	35.12	25.37
	(90.09)	(90.43)	(94.68)	(82.06)
Cumul. days in UB I in the last 5 years	76.65	79.97	86.42	67.77
	(150.29)	(153.04)	(160.45)	(143.51)
Days since last employment	1,973.28	1,952.10	1,896.75	2,115.16
	(2,116.50)	(2,118.96)	(2,164.42)	(2,287.01)
Cumul. days in regular employment in the last year	17.89	16.34	19.71	12.01
	(58.44)	(53.71)	(56.83)	(45.80)
Cumul. days in regular employment in the last 5 years	174.49	169.05	196.01	137.26
	(346.47)	(335.20)	(347.01)	(298.46)
Cumul. days in contributory employment in the last year	20.43	18.90	21.77	14.46
	(61.74)	(57.28)	(59.41)	(50.17)
Cumul. days in contributory employment in the last 2 years	58.33	54.95	62.43	42.79
	(134.15)	(127.53)	(130.30)	(110.70)
Cumul. days in contributory employment in the last 5 years	176.62	168.63	196.66	141.74
	(338.42)	(325.82)	(339.41)	(292.74)
Cumul. days in vocational training in the last year	0.82	0.82	0.90	0.57
	(13.20)	(12.93)	(13.31)	(10.38)
Cumul. days in vocational training in the last 2 years	2.91	2.90	2.39	2.14
	(35.22)	(34.63)	(32.15)	(29.83)
Cumul. days in vocational training in the last 5 years	14.86	15.83	12.74	11.13
	(101.50)	(108.09)	(92.37)	(88.90)
Cumul. days in minor employment in the last year	66.65	62.50	88.05	82.89
	(124.72)	(120.95)	(139.04)	(136.94)
Cumul. days in minor employment in the last 2 years	129.72	121.73	165.15	153.37
	(229.59)	(220.20)	(251.89)	(248.13)
Cumul. days in minor employment in the last 5 years	284.96	270.29	348.13	318.90
	(471.93)	(454.65)	(504.82)	(500.52)
Cumul. days in bridging allowance in the last 5 years	0.56	0.53	0.75	0.58
	(9.83)	(9.51)	(11.55)	(9.86)
Cumul. days in One-Euro-Jobs in the last year	13.38	15.91	12.65	12.51
	(47.84)	(52.15)	(46.68)	(45.51)
	30.79	37.15	28.26	29.99

Cumul. days in One-Euro-Jobs in the last 2 years	(84.23)	(91.88)	(79.15)	(83.50)
Cumul. days in One-Euro-Jobs in the last 5 years	72.51 (152.58)	81.30 (159.03)	60.13 (134.12)	69.38 (151.64)
Cumul. days in subsidised public employment in the last year	2.05 (19.17)	2.25 (20.71)	1.64 (17.48)	2.13 (19.99)
Cumul. days in subsidised public employment in the last 2 years	5.31 (35.00)	4.98 (34.81)	3.54 (28.93)	5.17 (35.61)
Cumul. days in subsidised public employment in the last 5 years	11.72 (55.93)	10.18 (51.81)	8.07 (45.31)	11.06 (55.50)
Cumul. days in subsidised employment in the last year	1.27 (14.50)	1.04 (11.43)	1.28 (13.00)	0.82 (10.36)
Cumul. days in subsidised employment in the last 5 years	5.49 (33.59)	5.52 (32.30)	5.69 (34.38)	4.81 (31.30)
Experience in further vocational training (1=yes)	0.26	0.27	0.27	0.24
Cumul. days in further vocational training in the last year	6.69 (32.25)	6.06 (29.12)	8.61 (36.10)	5.85 (29.62)
Cumul. days in further vocational training in the last 5 years	23.77 (88.84)	24.80 (85.95)	26.51 (89.35)	21.03 (82.79)
Experience in in-firm SAI (1=yes)	0.02	0.03	0.03	0.02
Cumul. days in in-firm SAI in the last year	0.24 (2.06)	0.30 (2.35)	0.32 (2.60)	0.24 (2.21)
Cumul. days in in-firm SAI in the last 2 years	0.24 (2.06)	0.30 (2.35)	0.32 (2.60)	0.24 (2.21)
Experience in classroom SAI (1=yes)	0.11	0.14	0.09	0.06
Cumul. days in classroom SAI in the last year	4.46 (21.89)	6.15 (22.96)	5.75 (25.35)	2.84 (17.28)
Cumul. days in classroom SAI in the last 2 years	4.46 (21.89)	6.15 (22.96)	5.75 (25.35)	2.84 (17.28)
Experience in *job-training* (*JT*) (1=yes)	0.07	0.05	0.03	0.02
Experience in *reducing impediments* (*RIM*) (1=yes)	0.02	0.07	0.02	0.02
Cumul. days in SAI in the last year	4.65 (21.77)	6.40 (22.84)	6.06 (25.45)	3.07 (17.38)
Cumul. days in SAI in the last 2 years	4.65 (21.77)	6.40 (22.84)	6.06 (25.45)	3.07 (17.38)
Experience in in-firm training (1=yes)	0.13	0.14	0.11	0.11
Cumul. days in in-firm training in the last year	0.26 (2.23)	0.35 (2.83)	0.33 (2.70)	0.26 (2.37)
Cumul. days in in-firm training in the last 5 years	1.96 (9.19)	2.04 (9.01)	1.73 (8.82)	1.51 (7.78)
Experience in classroom training (1=yes)	0.50	0.56	0.47	0.40
Cumul. days in classroom training in the last year	6.75 (24.67)	9.55 (26.53)	9.02 (28.64)	4.53 (19.94)
Cumul. days in classroom training in the last 5 years	17.69 (37.71)	22.62 (40.93)	17.63 (37.65)	12.11 (30.55)
Ever received mild sanction (1=yes)	0.09	0.09	0.09	0.10
Cumul. days in mild sanctions in the last year	4.06 (21.58)	3.81 (20.53)	4.19 (21.13)	4.38 (22.42)
Cumul. days in mild sanctions in the last year - never sanctioned	0.96	0.96	0.95	0.95
Cumul. days in mild sanctions in the last year - once (3 months)	0.04	0.03	0.04	0.04
Cumul. days in mild sanctions in the last year - more than once	0.01	0.01	0.01	0.01
Ever received strong sanction (1=yes)	0.10	0.10	0.09	0.09
Cumul. days in strong sanctions in the last year	3.66 (18.87)	3.84 (18.79)	3.91 (19.14)	2.97 (16.84)
Cumul. days in strong sanctions in the last year - never sanctioned	0.95	0.95	0.95	0.96

Cumul. days in strong sanctions in the last year - once (3 months)	0.04	0.05	0.04	0.03
Cumul. days in strong sanctions in the last year - more than once	0.01	0.01	0.01	0.00
Panel C: Last job characteristics				
Type of last job - contributory employment	0.41	0.42	0.40	0.36
Type of last job - minor employment	0.47	0.47	0.52	0.51
Type of last job - vocational training	0.03	0.03	0.02	0.02
Type of last job - no last job	0.09	0.09	0.07	0.11
Last occupation - agriculture, forestry, gardening	0.04	0.03	0.04	0.04
Last occupation - manufacturing	0.05	0.04	0.04	0.05
Last occupation - manufacturing engineering	0.03	0.03	0.02	0.02
Last occupation - construction	0.01	0.01	0.01	0.01
Last occupation - grocery, hospitality	0.14	0.13	0.13	0.12
Last occupation - healthcare	0.06	0.06	0.06	0.06
Last occupation - humanities, arts	0.05	0.05	0.05	0.05
Last occupation - trading	0.15	0.16	0.18	0.14
Last occupation - business management and organisation	0.08	0.10	0.11	0.08
Last occupation - service	0.03	0.04	0.05	0.04
Last occupation - security, logistic, transport	0.09	0.08	0.07	0.07
Last occupation - cleaning	0.11	0.09	0.10	0.10
Last occupation - no last job / missing	0.17	0.17	0.15	0.22
Last occupational level - assistant	0.37	0.34	0.34	0.33
Last occupational level - specialist	0.41	0.43	0.43	0.40
Last occupational level - expert	0.03	0.03	0.04	0.03
Last occupational level - professional	0.03	0.02	0.04	0.03
Last occupational level - no last job / missing	0.17	0.17	0.15	0.22
Last job industry - agriculture, forestry, fishing, mining, manufacturing, energy, water supply	0.08	0.07	0.07	0.07
Last job industry - construction	0.01	0.01	0.01	0.01
Last job industry - trade, car sales and maintenance	0.15	0.17	0.18	0.15
Last job industry - hospitality	0.13	0.12	0.13	0.13
Last job industry - transport and postal services, telecommunication	0.04	0.04	0.04	0.03
Last job industry - financial services, real estate, renting out property, services for companies	0.26	0.27	0.28	0.25
Last job industry - public administration, defence, social security agencies, education, health and social work	0.15	0.13	0.12	0.14
Last job industry - other services	0.10	0.10	0.11	0.11
Last job industry - no last job / missing	0.17	0.17	0.15	0.22
Last job working time - full-time	0.33	0.33	0.33	0.30
Last job working time - part-time	0.58	0.58	0.60	0.60
Last job working time - no last job	0.09	0.09	0.07	0.11
Last job duration - <1 month	0.10	0.10	0.09	0.09
Last job duration - 1 - <3 months	0.16	0.18	0.17	0.16
Last job duration - 3 - <6 months	0.16	0.16	0.16	0.16
Last job duration - 6 - <12 months	0.20	0.20	0.19	0.19
Last job duration - 12 - <24 months	0.13	0.13	0.14	0.13
Last job duration - 24 - <36 months	0.06	0.06	0.07	0.06
Last job duration - 36 - <60 months	0.05	0.04	0.06	0.05
Last job duration - 60+ months	0.05	0.05	0.06	0.05
Last job duration - no last job	0.09	0.09	0.07	0.11
Last daily real wage (in Euro)	18.93	19.33	20.13	17.60
	(20.64)	(31.30)	(22.78)	(21.44)

Panel D: Labour market status in December 2004				
Dec 2004 - unemployment insurance receipt	0.06	0.07	0.07	0.06
Dec 2004 - unemployment assistance receipt	0.23	0.23	0.21	0.23
Dec 2004 - registered unemployment	0.36	0.36	0.35	0.36
Dec 2004 - registered jobseeker not unemployed	0.11	0.10	0.10	0.10
Dec 2004 - participation in any ALMP	0.07	0.07	0.08	0.06
Dec 2004 - contributory employment	0.16	0.16	0.18	0.14
Dec 2004 - minor employment	0.14	0.14	0.16	0.14
Panel E: Household level				
HH with members aged 18-24 years (1=yes)	0.11	0.11	0.10	0.13
HH with members aged 25-34 years (1=yes)	0.36	0.37	0.33	0.32
HH with members aged 35-44 years (1=yes)	0.39	0.41	0.40	0.40
HH with members aged 45-54 years (1=yes)	0.35	0.33	0.38	0.39
HH with members aged 55-64 years (1=yes)	0.02	0.02	0.02	0.03
# of own children aged <3 years	0.02	0.02	0.01	0.02
# of own children aged 3-5 years	0.20	0.19	0.16	0.18
# of own children aged 6-9 years	0.25	0.27	0.24	0.27
# of own children aged 10-12 years	0.17	0.20	0.20	0.19
# of own children aged 13-14 years	0.10	0.11	0.10	0.12
# of own children aged 15-17 years	0.14	0.14	0.14	0.16
HH equiv. UB II income (in prices of 2010)	649.11	664.22	695.43	668.09
	(255.10)	(240.89)	(238.07)	(232.37)
HH receives income from dependent employment	0.21	0.20	0.30	0.27
HH receives income from self-employment	0.01	0.01	0.01	0.01
HH receives UB I	0.04	0.04	0.04	0.03
HH receives income from child support	0.06	0.06	0.04	0.05
HH receives income from alimony	0.01	0.02	0.02	0.01
HH receives pension or housing assistance	0.02	0.02	0.01	0.02
HH receives income from other sources	0.04	0.04	0.04	0.04
HH - no information UB II income found	0.03	0.02	0.01	0.01
Panel F: Partner characteristics				
Partner's age (in years)	13.65	13.67	12.74	15.71
	(20.52)	(20.55)	(20.29)	(21.62)
Partner's nationality - Germany	0.23	0.23	0.19	0.25
Partner's nationality - EU (w/o Germany, with former YUG)	0.01	0.01	0.02	0.02
Partner's nationality - Europe rest (w/o former YUG)	0.01	0.01	0.01	0.01
Partner's nationality - Turkey	0.03	0.03	0.04	0.05
Partner's nationality - former Soviet Union (w/o EU members)	0.01	0.02	0.01	0.01
Partner's nationality - other countries	0.02	0.02	0.02	0.02
Partner's nationality - missing	0.68	0.68	0.71	0.64
Partner's continent - Germany	0.24	0.23	0.19	0.25
Partner's continent - Europe	0.06	0.06	0.08	0.08
Partner's continent - Africa	0.01	0.01	0.01	0.01
Partner's continent - America	0.00	0.00	0.00	0.00
Partner's continent - Asia / Oceania	0.02	0.02	0.02	0.02
Partner's continent - stateless / unknown	0.00	0.00	0.00	0.00
Partner's continent - missing	0.68	0.68	0.71	0.64
Partner's education - no schooling diploma	0.05	0.05	0.05	0.07
Partner's education - secondary school	0.15	0.15	0.14	0.17
Partner's education - general certificate of secondary education	0.08	0.08	0.07	0.08
Partner's education - advanced technical college entrance qualification	0.01	0.01	0.01	0.01
Partner's education - high school	0.02	0.02	0.03	0.02
Partner's education - missing	0.69	0.69	0.71	0.65

Partner's vocational degree - no vocational / academic degree	0.17	0.17	0.17	0.20
Partner's vocational degree - vocational degree	0.14	0.14	0.11	0.14
Partner's vocational degree - academic degree	0.01	0.01	0.01	0.01
Partner's vocational degree - missing	0.68	0.68	0.71	0.64
Partner's marital status - single	0.02	0.02	0.01	0.02
Partner's marital status - married	0.23	0.23	0.22	0.27
Partner's marital status - no longer married	0.01	0.01	0.01	0.01
Partner's marital status - cohabitation	0.06	0.06	0.05	0.06
Partner's marital status - missing	0.68	0.68	0.71	0.64
Partner's disability status (1= yes)	0.01	0.01	0.01	0.02
Partner's disability status (1= missing)	0.00	0.00	0.00	0.00
Partner's last job type - contributory employment	0.21	0.21	0.19	0.23
Partner's last job type - minor employment	0.09	0.09	0.09	0.11
Partner's last job type - vocational training	0.00	0.00	0.00	0.00
Partner's last job type - no last job	0.69	0.69	0.72	0.66
Partner's last occupation - agriculture, forestry, gardening	0.02	0.02	0.01	0.02
Partner's last occupation - manufacturing	0.04	0.04	0.03	0.04
Partner's last occupation - manufacturing engineering	0.03	0.02	0.02	0.03
Partner's last occupation - construction	0.07	0.07	0.05	0.07
Partner's last occupation - grocery, hospitality	0.03	0.03	0.03	0.03
Partner's last occupation - healthcare	0.00	0.00	0.00	0.00
Partner's last occupation - humanities, arts	0.00	0.00	0.00	0.00
Partner's last occupation - trading	0.02	0.02	0.02	0.02
Partner's last occupation - business management and organisation	0.01	0.01	0.01	0.01
Partner's last occupation - service	0.01	0.01	0.01	0.01
Partner's last occupation - security, logistic, transport	0.07	0.08	0.08	0.08
Partner's last occupation - cleaning	0.01	0.01	0.01	0.01
Partner's last occupation - no last job / missing	0.70	0.70	0.72	0.66
Partner's last occupational level - assistant	0.12	0.11	0.11	0.13
Partner's last occupational level - specialist	0.16	0.16	0.14	0.18
Partner's last occupational level - expert	0.01	0.01	0.01	0.01
Partner's last occupational level - professional	0.01	0.01	0.01	0.01
Partner's last occupational level - no last job / missing	0.70	0.70	0.72	0.66
Partner's last job industry - agriculture, forestry, fishing, mining, manufacturing, energy, water supply	0.04	0.03	0.03	0.04
Partner's last job industry - construction	0.04	0.04	0.03	0.04
Partner's last job industry - trade, car sales and maintenance	0.04	0.04	0.04	0.04
Partner's last job industry - hospitality	0.03	0.03	0.03	0.03
Partner's last job industry - transport and postal services, telecommunication	0.03	0.04	0.04	0.04
Partner's last job industry - financial services, real estate, renting out property, services for companies	0.09	0.09	0.08	0.10
Partner's last job industry - public administration, defence, social security agencies, education, health and social work	0.03	0.03	0.02	0.03
Partner's last job industry - other services	0.02	0.02	0.02	0.02

Partner's last job industry - no last job / missing	0.69	0.69	0.72	0.66
Partner's last job working time - full-time	0.20	0.19	0.17	0.21
Partner's last job working time - part-time	0.11	0.11	0.11	0.13
Partner's last job working time - no last job	0.69	0.69	0.72	0.66
Partner's last job duration - <1 month	0.03	0.03	0.03	0.03
Partner's last job duration - 1-<3 months	0.05	0.06	0.05	0.06
Partner's last job duration - 3 -<6 months	0.05	0.06	0.05	0.06
Partner's last job duration - 6 -<12 months	0.06	0.06	0.05	0.07
Partner's last job duration - 12-<24 months	0.04	0.04	0.04	0.05
Partner's last job duration - 24-<36 months	0.02	0.02	0.02	0.02
Partner's last job duration - 36-<60 months	0.02	0.02	0.02	0.02
Partner's last job duration - 60+ months	0.02	0.03	0.02	0.03
Partner's last job duration - no last job / missing	0.69	0.69	0.72	0.66
Partner's last daily wage (in Euro)	10.65	10.42	9.61	11.72
	(22.08)	(21.63)	(22.87)	(26.03)
Partner's cumul. days in unemployment in the last year	58.90	57.57	55.44	66.62
	(117.56)	(116.80)	(115.77)	(124.52)
Partner's cumul. days in unemployment in the last 5 years	279.47	274.63	265.78	325.35
	(508.51)	(504.21)	(508.23)	(544.66)
Partner's cumul. days in job search in the last year	95.45	95.81	89.26	108.90
	(153.97)	(154.59)	(150.82)	(160.63)
Partner's cumul. days in job search in the last 5 years	415.16	417.81	381.86	479.31
	(676.82)	(678.85)	(657.37)	(710.20)
Partner's cumul. days in UB II in the last year	98.35	100.20	95.01	115.97
	(155.99)	(157.22)	(154.92)	(164.28)
Partner's cumul. days in UB II in the last 5 years	423.58	429.07	392.51	494.45
	(701.36)	(702.79)	(681.94)	(735.45)
Partner's days since last regular employment	269.94	265.87	247.78	320.91
	(717.15)	(709.22)	(674.94)	(778.54)
Partner's cumul. days in regular employment in the last year	21.59	22.54	18.64	22.74
	(76.89)	(78.79)	(71.44)	(79.12)
Partner's cumul. days in regular employment in the last 5 years	130.03	134.56	115.92	134.47
	(359.61)	(371.04)	(342.83)	(363.88)
Partner in contributory employment at sampling date	0.06	0.06	0.05	0.06
Partner in minor employment at sampling date	0.04	0.05	0.04	0.05
Panel G: District-level information				
Unemployment rate (in %)	10.35	10.44	10.19	10.79
	(3.50)	(3.26)	(3.07)	(3.56)
Long-term unemployment rate (in %)	3.73	3.73	4.00	3.89
	(1.75)	(1.61)	(1.65)	(1.72)
Long-term unemployment stock	7,476.41	8,421.65	15,364.40	13,517.08
	(14,024.04)	(14,693.48)	(18,602.57)	(23,215.80)
Unemployment rate of welfare recipients (in %)	7.26	7.37	7.50	7.71
	(3.11)	(2.97)	(2.92)	(3.28)
District vacancy-unemployment ratio	0.08	0.09	0.10	0.08
	(0.05)	(0.05)	(0.05)	(0.04)
Panel H: Information at the job centre level				
Employees in job centre (JC)	321.19	379.58	626.56	400.14
	(322.15)	(379.49)	(462.92)	(389.11)
Share of JC employees in Market and Integration	0.42	0.43	0.44	0.42
	(0.10)	(0.11)	(0.09)	(0.08)
Share of JC employees in Benefits Administration	0.40	0.40	0.39	0.41
	(0.09)	(0.10)	(0.09)	(0.08)
Share of JC employees of female JC employees	0.69	0.68	0.67	0.68
	(0.10)	(0.10)	(0.07)	(0.09)
Share of JC employees being civil servants	0.16	0.17	0.20	0.17
	(0.08)	(0.08)	(0.08)	(0.08)
	0.23	0.23	0.24	0.22

Share of JC employees on fixed-term contract	(0.07)	(0.06)	(0.06)	(0.07)
Share of JC employees on fixed-term contract among employees in Market and Integration	0.21 (0.09)	0.22 (0.08)	0.25 (0.08)	0.21 (0.09)
Client-staff ratio	65.51 (7.26)	(66.80) (6.91)	(67.77) (7.14)	66.86 (7.64)
Client-staff ratio among employees in Market and Integration	159.60 (27.80)	159.82 (29.39)	157.69 (26.29)	162.13 (26.69)
JC 2009/q4 - people with at least 1 sanction / UB II recipients stock (25-54 years)	2.63 (0.95)	2.65 (0.82)	2.65 (0.83)	2.62 (0.85)
JC 2009/q4 - people with complete sanction (no UB II) / UB II recipients stock (25-54 years)	0.12 (0.12)	0.11 (0.11)	0.09 (0.11)	0.11 (0.12)
JC 2009/q4 - sanction intensity due to failure in reporting (25-54 years)	0.71 (0.27)	0.72 (0.27)	0.72 (0.24)	0.71 (0.26)
JC 2009/q4 - sanction intensity due to violations of duties (25-54 years)	0.55 (0.28)	0.55 (0.23)	0.53 (0.23)	0.52 (0.25)
JC 2009/q4 - inflow into classroom SAI / stock of UB II jobseekers (25-54 years)	1.70 (0.98)	1.80 (1.14)	1.61 (1.05)	1.32 (0.90)
JC 2009/q4 - inflow into in-firm SAI / stock of UB II jobseekers (25-54 years)	0.42 (0.19)	0.42 (0.20)	0.32 (0.25)	0.38 (0.20)
JC 2009/q4 - inflow into further vocational training / stock of UB II recipients (25-54 years)	0.51 (0.33)	0.51 (0.30)	0.34 (0.30)	0.53 (0.33)
JC 2009/q4 - inflow into wage subsidies / stock of UB II jobseekers (25-54 years)	0.25 (0.11)	0.25 (0.09)	0.21 (0.10)	0.24 (0.10)
JC 2009/q4 - inflow into One-Euro-Jobs / stock of UB II jobseekers (25-54 years)	1.11 (0.57)	1.06 (0.58)	0.92 (0.47)	1.11 (0.61)
JC type - Cities west, average labour market situation (LMS), high GDP, high rate of long term unemployed	0.09	0.11	0.46	0.11
JC type - Cities west, above average LMS, high GDP	0.06	0.05	0.05	0.04
JC type - Cities west, below average LMS, very high rate of long-term unemployed	0.15	0.14	0.12	0.21
JC type - Cities, mainly east, bad LMS, very high rate of long-term unemployed	0.07	0.11	0.04	0.08
JC type - Predominantly urban, west, average LMS, high rate of long-term unemployed	0.11	0.18	0.06	0.12
JC type - rural, west, average LMS	0.13	0.08	0.10	0.13
JC type - Predominantly urban, west and east, below average LMS	0.07	0.05	0.02	0.05
JC type - rural, west, good LMS, high seasonal dynamic	0.03	0.02	0.05	0.02
JC type - rural, west, very good LMS, seasonal dynamic, very low rate of long-term unemployed	0.03	0.02	0.02	0.03
JC type - rural, west, very good LMS, low average rate of long-term unemployed	0.08	0.11	0.03	0.07
JC type - predominantly rural, east, bad LMS, low GDP	0.11	0.10	0.05	0.10
JC type - predominantly rural, east, very bad LMS, very low GDP, high average rate of long-term unemployed	0.08	0.04	0.02	0.05

Notes: Means of the covariates. Values in parentheses are the standard deviations.

Appendix B: Wald tests

Appendix B.1 Women

*Table 12: Wald tests for heterogeneity, **women***

Heterogeneity Variable (Z)	JT vs. NP	RIM vs. NP	PS vs. NP	RIM vs. JT	PS vs. JT	PS vs. RIM
Region (west =0, east=1)	1	42	<1	31	12	3
# of own children age <3years	67	9	13	23	46	50
# of own children age 3-5 years	22	68	84	24	33	79
# of own children age 6-9 years	14	75	93	74	90	93
# of own children age 10-12 years	33	69	46	93	40	56
# of own children age 13-14 years	36	56	15	62	16	73
# of own children age 15-17 years	42	41	18	74	37	47
Family status	3	73	1	44	3	18
Household-type	88	16	59	42	92	63
Profile of unemployed	69	46	73	56	71	39
Type of regional labour market	<1	41	2	57	18	78
Nationality	48	27	<1	80	15	13
Educational achievement	14	24	6	31	81	37
Vocational degree	20	33	24	37	81	57
Days in regular employment, last 5 years	99	83	70	97	66	41
Days since last employment	19	99	23	98	71	63
Job centre-employees / unemployed-ratio	8	63	5	79	6	11
Intensity of One-Euro-Job assignment in jc	3	35	13	63	18	24
Intensity of MAG assignment in jc	<1	41	1	81	3	20
Intensity of MAT assignment in jc	36	48	4	79	16	79
Sanction-intensity in jc (due to violations of duties)	<1	96	2	54	1	48
Sanction-intensity in jc (due to failure in reporting)	11	53	9	79	19	59
Age	93	46	13	41	31	13
Days in regular employment last 1 year	81	87	39	78	28	27
Days in regular employment last 2 year	92	83	48	88	44	30
District unemployment rate of welfare recipients	2	58	37	67	6	37
District unemployment rate	<1	67	<1	71	2	37
Share of non- to tenured employed in jc	57	99	<1	96	1	2

Notes: p-values in percent. NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. jc= job centre. Green cells highlight test results that are statistically significant.

Appendix B.2 Men

*Table 13: Wald tests for heterogeneity, **men***

Heterogeneity Variable (Z)	JT vs. NP	RIM vs. NP	PS vs. NP	RIM vs. JT	PS vs. JT	PS vs. RIM
Region (west =0, east=1)	38	66	93	80	68	84
# of own children age <3years	42	94	63	59	31	58
# of own children age 3-5 years	92	99	46	98	67	60
# of own children age 6-9 years	97	71	69	88	85	83
# of own children age 10-12 years	99	82	52	86	64	41
# of own children age 13-14 years	87	97	55	99	53	63
# of own children age 15-17 years	86	87	72	98	81	88
Family status	16	58	59	95	38	34
Household-type	79	90	87	96	66	88
Profile of unemployed	67	22	42	35	66	89
Type of regional labour market	72	98	99	99	88	95
Nationality	87	54	51	78	54	67
Educational achievement	2	61	95	32	69	78
Vocational degree	1	18	60	10	45	43
Days in regular employment, last 5 years	94	85	65	86	88	98
Days since last employment	9	18	88	98	99	99
Job centre-employees / unemployed-ratio	79	99	99	99	97	99
Intensity of One-Euro-Job assignment in jc	93	99	98	99	96	99
Intensity of MAG assignment in jc	35	99	99	93	72	99
Intensity of MAT assignment in jc	42	93	99	99	71	98
Sanction-intensity in jc (due to violations of duties)	35	99	99	96	92	99
Sanction-intensity in jc (due to failure in reporting)	51	99	97	98	61	99
Age	98	86	93	99	82	85
Days in regular employment in the last year	95	78	4	98	50	80
Days in regular employment in the last 2 year	99	91	38	98	90	76
District unemployment rate of welfare recipients	34	99	99	87	70	97
District unemployment rate	31	99	99	95	81	99
Share of non- to tenured employed in jc	23	99	99	88	60	99

Notes: p-values in percent. NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. jc= job centre. Green cells highlight test results that are statistically significant.

Appendix C: Additional Results

Appendix C.1: Treatment effects by subpopulation

Table 14: Treatment effects in all four treatment specific subpopulations

Treatment effect	Subpopulation (observed in…) NP	JT	RIM	PS	ATE
Panel A.1: Women, in months 25 – 36 after treatment starts					
JT vs. NP	11.3 (2.7)	11.4 (2.8)	**12.4 (2.8)**	12.0 (3.3)	11.3 (2.7)
RIM vs. NP	15.3 (3.2)	15.1 (3.4)	**15.5 (3.3)**	11.9 (3.7)	15.2 (3.2)
PS vs. NP	17.6 (3.8)	17.3 (4.0)	16.6 (3.9)	**19.3 (4.1)**	17.5 (3.8)
RIM vs. JT	**4.0 (4.0)**	3.7 (4.1)	3.2 (4.1)	-0.1 (4.7)	3.9 (4.0)
PS vs. JT	6.3 (4.5)	5.9 (4.7)	4.2 (4.6)	**7.3 (5.0)**	6.2 (4.5)
PS vs. RIM	2.3 (4.8)	2.2 (5.0)	1.1 (4.9)	**7.4 (5.3)**	2.3 (4.8)
Panel A.2 Women, in the 36 months after treatment starts					
JT vs. NP	25.7 (5.6)	23.6 (5.9)	**26.7 (5.9)**	21.9 (8.0)	25.7 (5.6)
RIM vs. NP	**36.9 (6.8)**	35.4 (7.2)	34.7 (6.9)	33.5 (8.6)	36.8 (6.7)
PS vs. NP	54.0 (8.7)	55.6 (9.6)	54.1 (9.2)	**64.1 (9.1)**	54.1 (8.7)
RIM vs. JT	11.2 (8.3)	**11.8 (8.7)**	8.0 (8.5)	11.6 (11.0)	11.2 (8.3)
PS vs. JT	28.3 (10.0)	32.0 (10.8)	27.4 (10.5)	**42.2 (11.3)**	28.5 (10.0)
PS vs. RIM	17.1 (10.7)	20.2 (11.5)	19.4 (11.1)	**30.6 (11.8)**	17.3 (10.7)
Panel B.1 Men, in months 25 – 36 after treatment starts					
JT vs. NP	12.7 (2.5)	13.1 (2.7)	12.8 (2.7)	**14.3 (4.0)**	12.7 (2.5)
RIM vs. NP	15.7 (3.0)	15.8 (3.3)	15.8 (3.2)	**17.3 (5.6)**	15.7 (3.0)
PS vs. NP	18.0 (3.7)	19.0 (4.1)	18.5 (4.1)	**20.2 (3.6)**	18.0 (3.7)
RIM vs. JT	3.0 (3.6)	2.7 (4.0)	3.0 (3.9)	**3.0 (6.5)**	3.0 (3.6)
PS vs. JT	5.2 (4.2)	5.8 (4.7)	5.7 (4.7)	**5.9 (4.9)**	5.3 (4.2)
PS vs. RIM	2.3 (4.5)	**3.2 (5.0)**	2.7 (4.9)	2.9 (6.3)	2.3 (4.5)
Panel B.2 Men, in the 36 months after treatment starts					
JT vs. NP	**36.4 (5.4)**	35.0 (6.2)	36.2 (6.1)	32.5 (8.0)	36.3 (5.4)
RIM vs. NP	34.6 (6.2)	33.5 (7.0)	34.1 (6.8)	**35.1 (9.4)**	34.6 (6.3)
PS vs. NP	45.1 (7.8)	43.2 (8.7)	43.3 (8.6)	**46.7 (7.6)**	45.1 (7.8)
RIM vs. JT	-1.8 (7.8)	-1.6 (8.6)	-2.1 (8.4)	**2.6 (11.6)**	-1.7 (7.8)
PS vs. JT	8.7 (9.1)	8.2 (10.0)	7.1 (10.0)	**14.2 (10.2)**	8.8 (9.0)
PS vs. RIM	10.5 (9.6)	9.8 (10.6)	9.2 (10.4)	**11.7 (11.3)**	10.5 (9.6)

Notes: Treatment effects on the specific treatment specific subpopulations. Most beneficial group in bold. A well selected group into treatment receives a high ATET. For comparison the group which, if well selected, should have the highest ATET is marked in grey. ATE estimates for comparison in the last column. NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*

Appendix C.2: Descriptive statistics of clusters, full tables

*Table 15: Descriptive statistics of clusters based on k-means clustering, **men**, full table*

Cluster	Least beneficial	2	3	4	Most beneficial
Share of observations (in %)	13	30	23	22	12
JT vs. NP	27	29	31	40	68
RIM vs. NP	14	23	41	53	39
PS vs. NP	7	53	35	61	55
Region (west=0, east=1)	0.26	0.44	0.36	0.26	0.26
Foreigner	0.26	0.11	0.22	0.26	0.22
Days in regular employment (last 5 years)	704	156	203	135	201
Days since last employment	453	2413	1663	1775	1758
Client-staff ratio in job centres	161	159	164	163	163
Sanction intensity in job centres due to violations of duties (in percent)	0.58	0.50	0.51	0.50	0.53
Sanction intensity in job centres due to failure in reporting (in percent)	0.75	0.71	0.72	0.70	0.72
District unemployment rate	9.76	11.36	11.05	10.87	10.52
District unemployment rate of welfare recipients	6.77	8.14	7.95	7.93	7.59
No vocational / academic degree	0.47	0.41	0.56	0.60	0.47
Vocational degree	0.49	0.56	0.41	0.37	0.42
Academic degree	0.03	0.03	0.02	0.03	0.09
Education - No schooling diploma	0.12	0.11	0.17	0.16	0.11
Education - Secondary school	0.50	0.47	0.51	0.50	0.39
Education - General certificate of secondary education	0.27	0.31	0.24	0.21	0.23
Education - Advanced technical college entrance qualification	0.04	0.03	0.03	0.04	0.08
Education - High school	0.07	0.07	0.06	0.07	0.15
Nationality - Germany	0.74	0.89	0.78	0.74	0.78
Nationality - European Union	0.05	0.02	0.03	0.05	0.04
Nationality - Rest of Europe	0.05	0.01	0.02	0.03	0.03
Nationality - Turkey	0.10	0.04	0.09	0.09	0.08
Nationality - Former Soviet Union	0.02	0.01	0.02	0.02	0.02
Nationality - Rest of the world	0.06	0.03	0.05	0.07	0.06
Marital status - unmarried	0.39	0.53	0.45	0.51	0.50
Marital status – married	0.37	0.19	0.30	0.26	0.28
Marital status – widowed	0.00	0.00	0.00	0.00	0.00
Marital status – divorced	0.09	0.15	0.08	0.09	0.08
Marital status – separated	0.05	0.06	0.05	0.06	0.05
Marital status – cohabitation	0.10	0.06	0.11	0.07	0.08
Household – single; no children	0.48	0.72	0.54	0.62	0.59
Household – single; adult children	0.00	0.00	0.00	0.00	0.00
Household – single; child. aged below 18	0.01	0.02	0.02	0.02	0.01
Household – single; adult and child. <18	0.00	0.00	0.00	0.00	0.00
Household – couple; no children	0.10	0.08	0.11	0.09	0.10
Household – couple; adult children	0.02	0.02	0.02	0.02	0.01
Household – couple; child. aged below 18	0.35	0.13	0.26	0.21	0.26
Household – couple; adult and child. < 18	0.04	0.03	0.04	0.03	0.02
Household – other type	0.01	0.01	0.01	0.01	0.01

Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. jc= job centre.

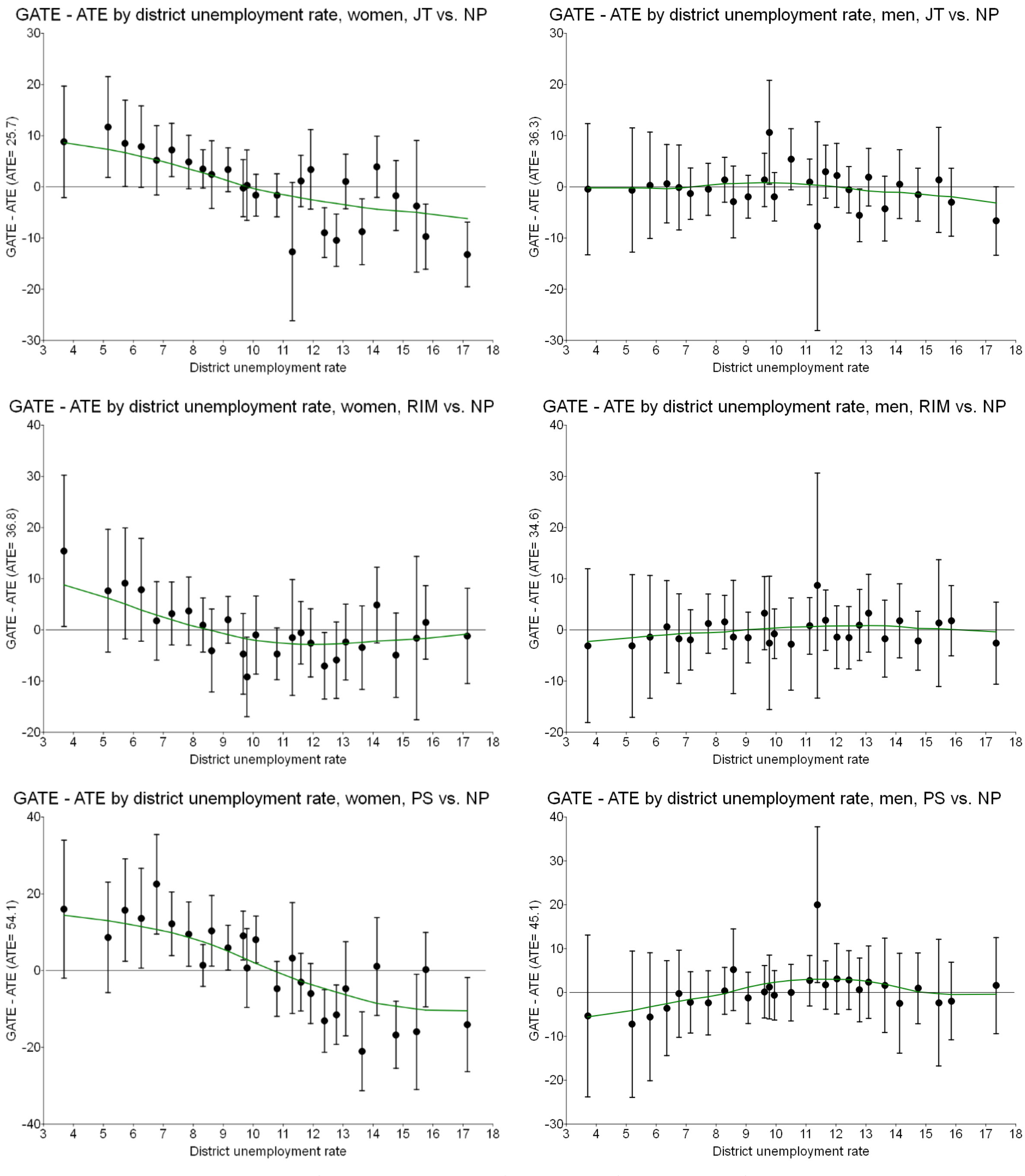
*Table 16: Descriptive statistics of clusters based on k-means clustering, **women**, full table*

Cluster	Least beneficial	2	3	4	Most beneficial
Share of observations (in %)	13	25	18	17	27
JT vs. NP	3	18	29	33	37
RIM vs. NP	33	37	14	47	46
PS vs. NP	8	28	52	91	49
Region (west=0, east=1)	0.36	0.70	0.26	0.07	0.16
Foreigner	0.20	0.12	0.22	0.29	0.25
Days in regular employment (last 5 years)	265	68	174	229	84
Days since last employment	1798	2610	1655	1794	2244
Client-staff ratio in job centres	164	165	162	159	159
Sanction intensity in job centres due to violations of duties (in percent)	0.45	0.42	0.48	0.62	0.62
Sanction intensity in job centres due to failure in reporting (in percent)	0.63	0.66	0.69	0.76	0.79
District unemployment rate	11.33	13.09	10.88	8.58	9.57
District unemployment rate of welfare recipients	8.21	9.58	7.89	5.78	6.69
No vocational / academic degree	0.49	0.38	0.47	0.61	0.65
Vocational degree	0.47	0.57	0.45	0.34	0.31
Academic degree	0.03	0.04	0.07	0.03	0.02
Education - No schooling diploma	0.15	0.12	0.11	0.18	0.23
Education - Secondary school	0.40	0.36	0.32	0.47	0.45
Education - General certificate of secondary education	0.33	0.42	0.35	0.21	0.21
Education - Advanced technical college entrance qualification	0.03	0.03	0.06	0.03	0.03
Education - High school	0.07	0.07	0.12	0.06	0.05
Nationality - Germany	0.80	0.88	0.78	0.71	0.75
Nationality - European Union	0.05	0.03	0.05	0.07	0.05
Nationality - Rest of Europe	0.02	0.01	0.02	0.04	0.02
Nationality - Turkey	0.06	0.03	0.06	0.10	0.09
Nationality - Former Soviet Union	0.02	0.02	0.04	0.03	0.03
Nationality - Rest of the world	0.05	0.03	0.06	0.06	0.06
Marital status - unmarried	0.27	0.37	0.38	0.17	0.22
Marital status – married	0.31	0.17	0.21	0.50	0.39
Marital status – widowed	0.01	0.02	0.01	0.01	0.02
Marital status – divorced	0.20	0.23	0.17	0.15	0.17
Marital status – separated	0.12	0.13	0.17	0.11	0.13
Marital status – cohabitation	0.09	0.08	0.07	0.06	0.07
Household – single; no children	0.26	0.38	0.34	0.18	0.22
Household – single; adult children	0.01	0.02	0.01	0.01	0.01
Household – single; child. aged below 18	0.27	0.31	0.34	0.18	0.26
Household – single; adult and child. <18	0.03	0.04	0.03	0.02	0.03
Household – couple; no children	0.14	0.08	0.06	0.17	0.11
Household – couple; adult children	0.04	0.02	0.01	0.04	0.03
Household – couple; child. aged below 18	0.18	0.09	0.16	0.30	0.25
Household – couple; adult and child. <18	0.04	0.02	0.02	0.07	0.06
Household – other type	0.03	0.05	0.03	0.03	0.03

Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. jc= job centre.

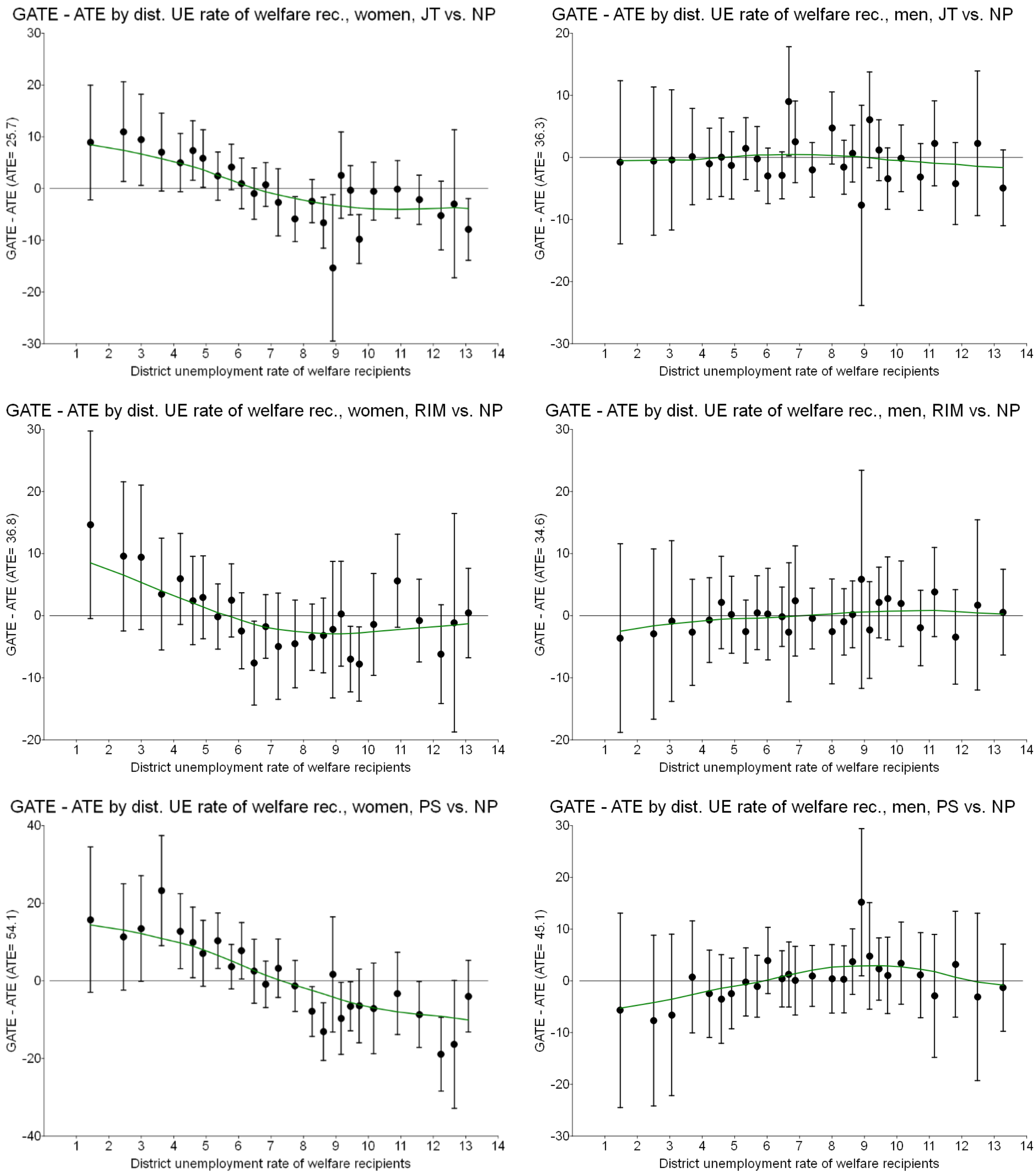
Appendix C.3: Group average level

Figure 8: District unemployment rate



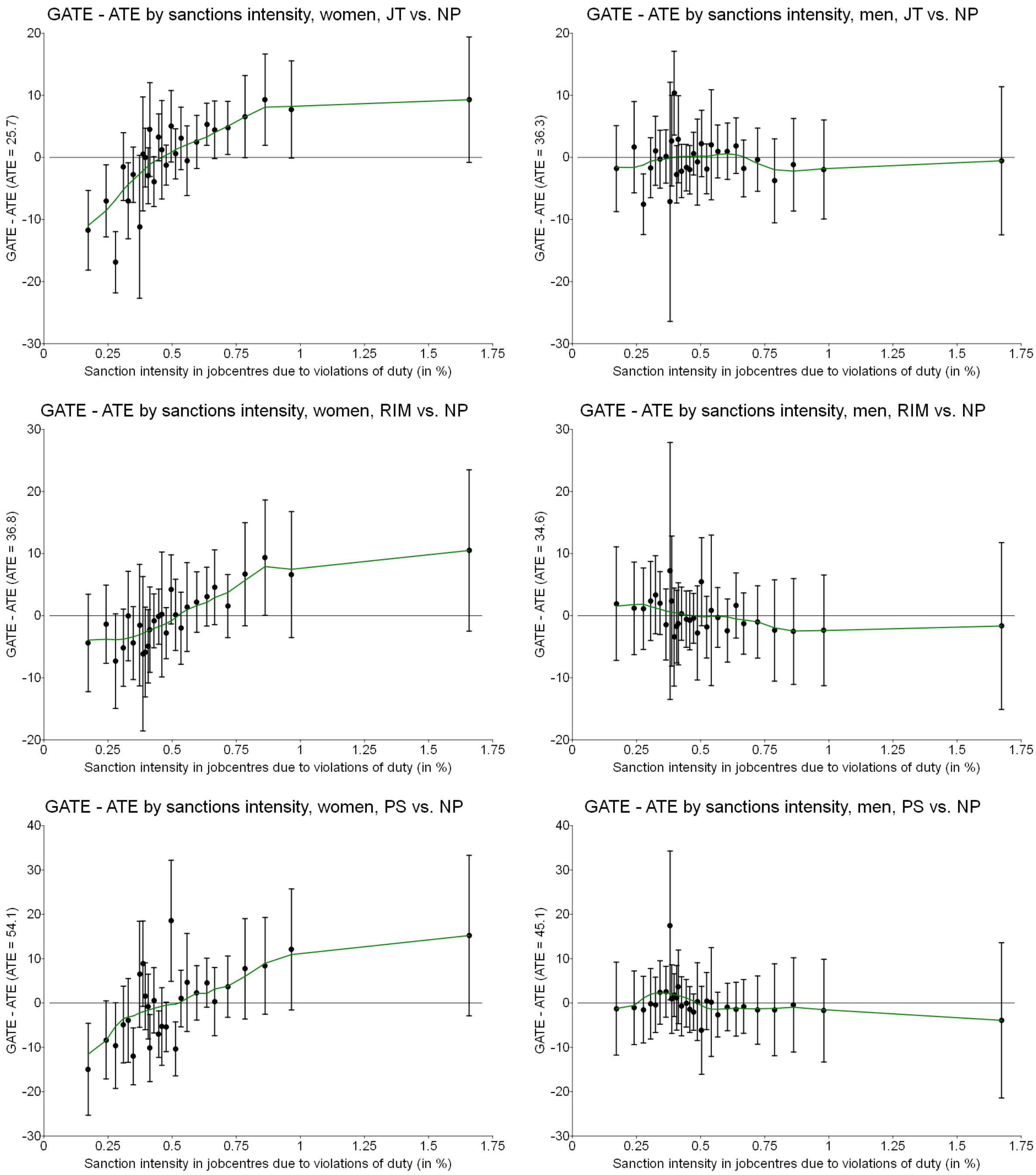
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 9: District unemployment rate of welfare recipients



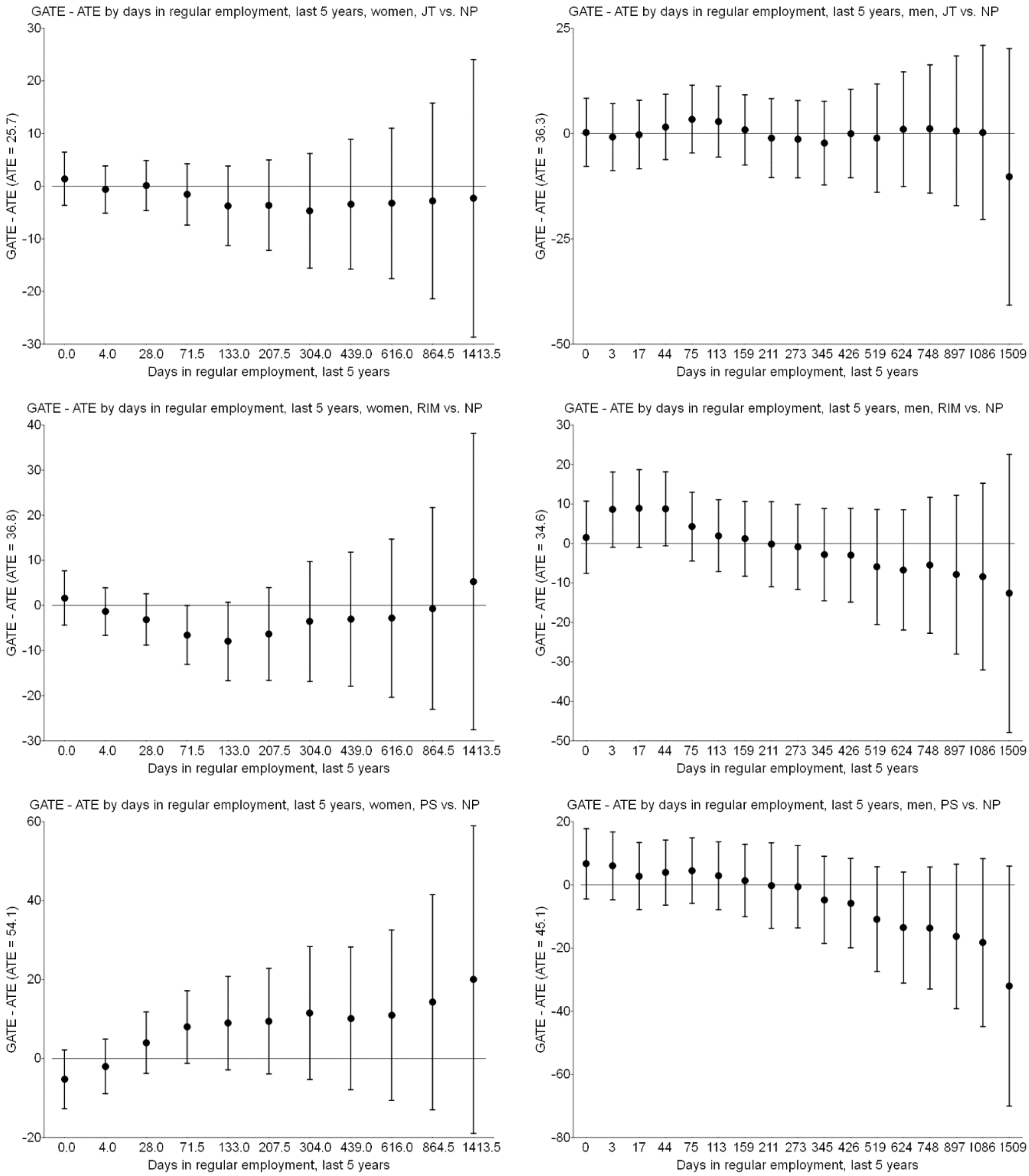
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 10: Sanction intensity (violation of duties) in job centre



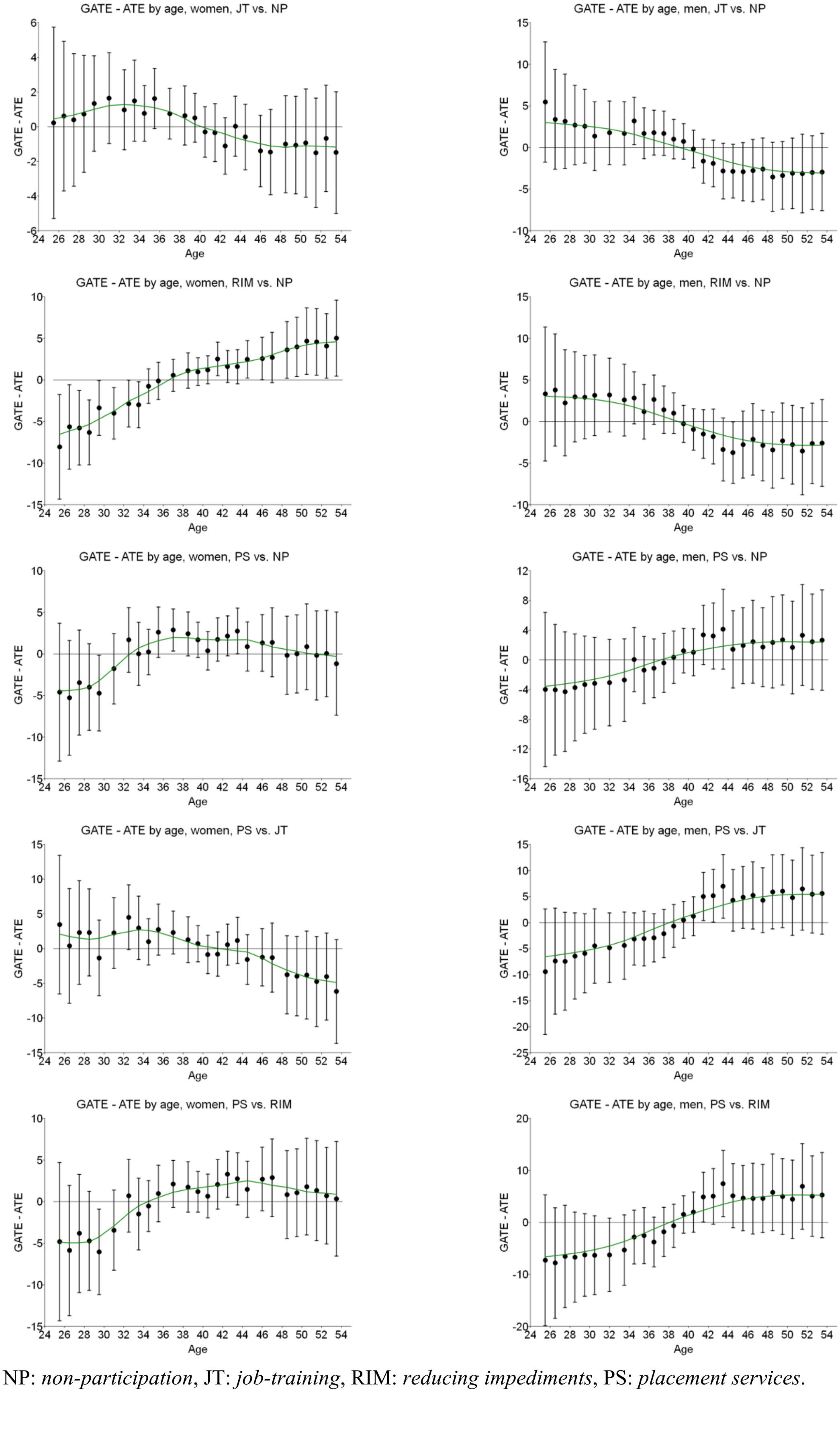
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 11: Cumulative days in regular employment, last five years



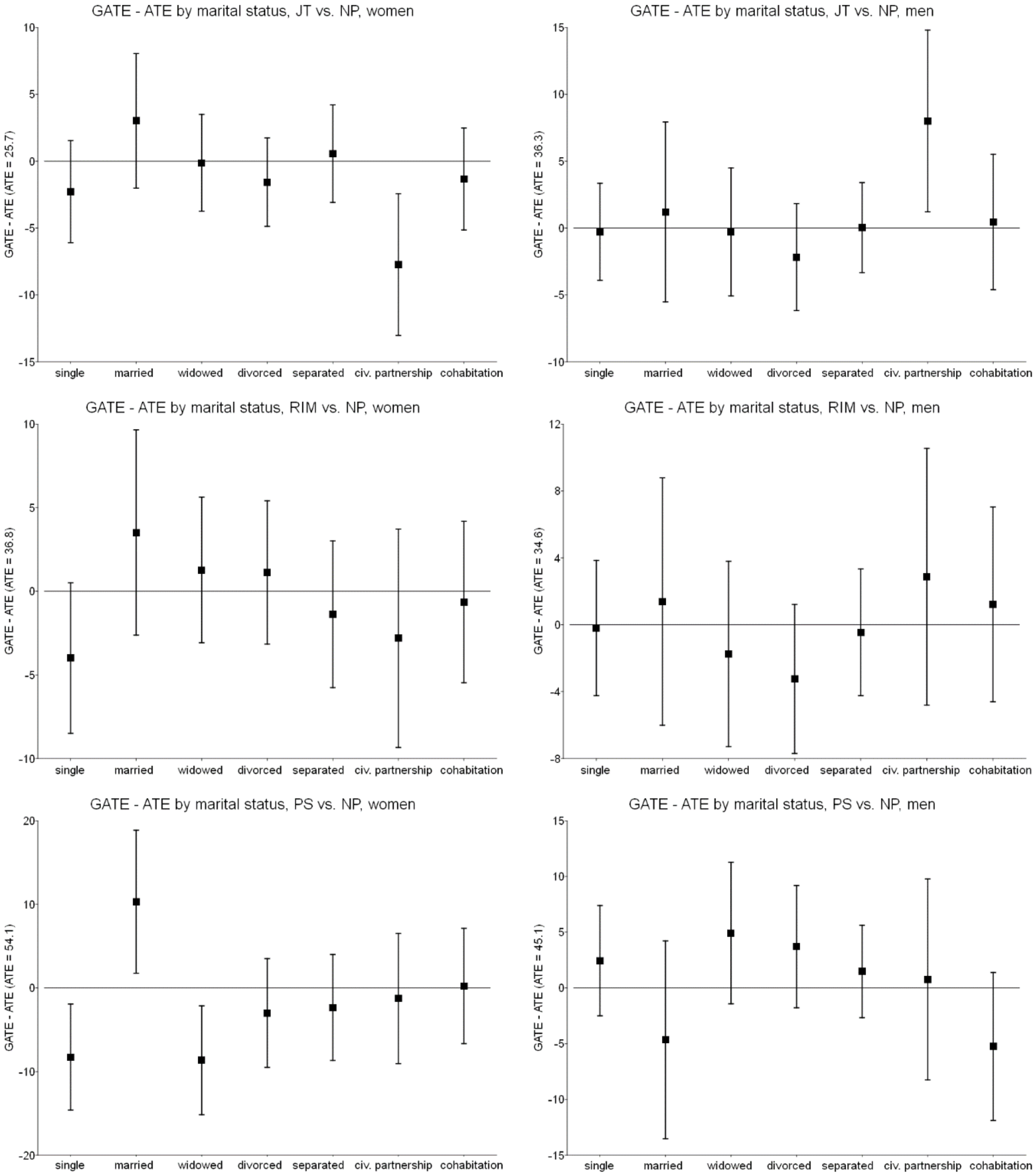
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 12: Age



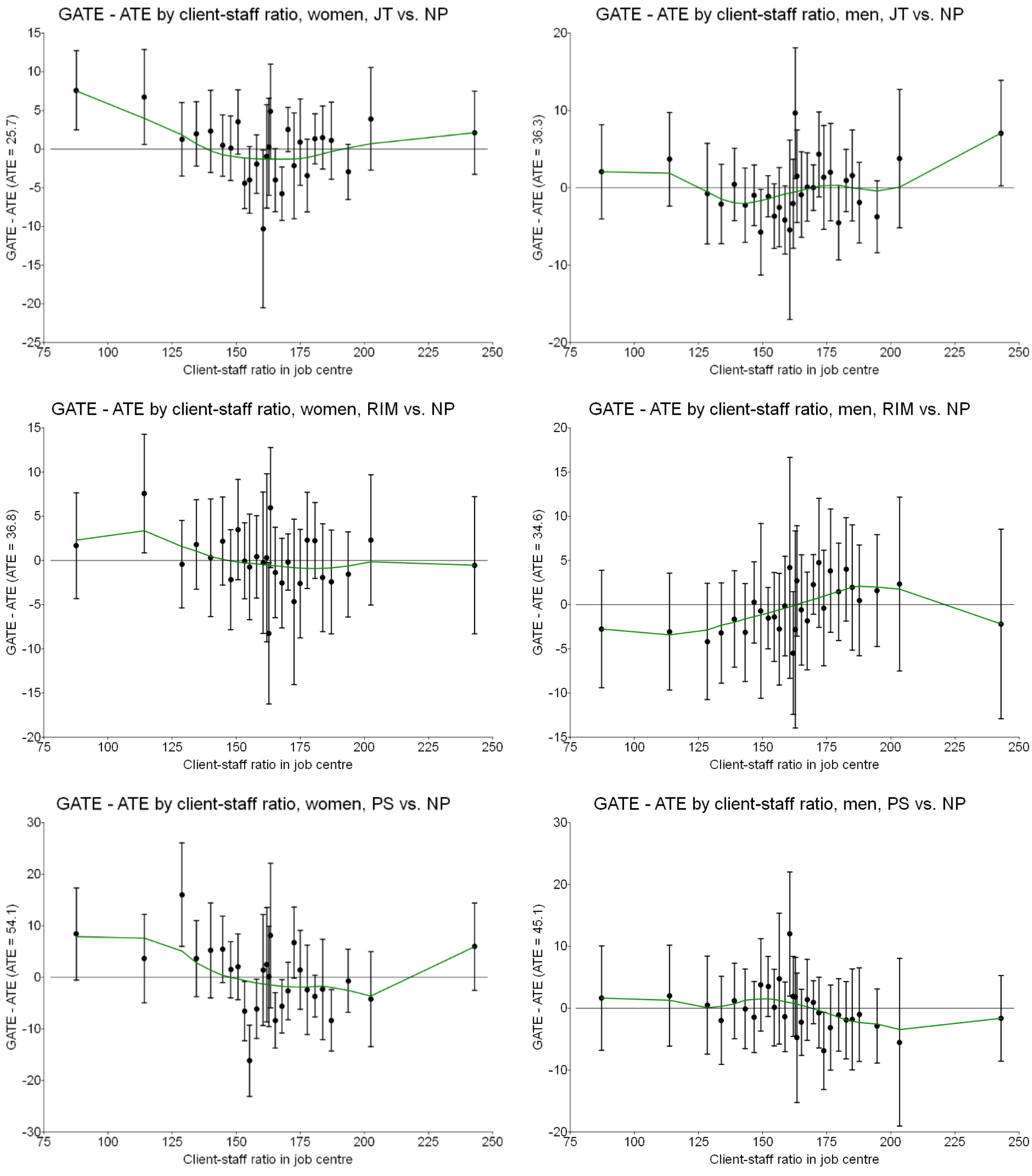
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 13: Family status



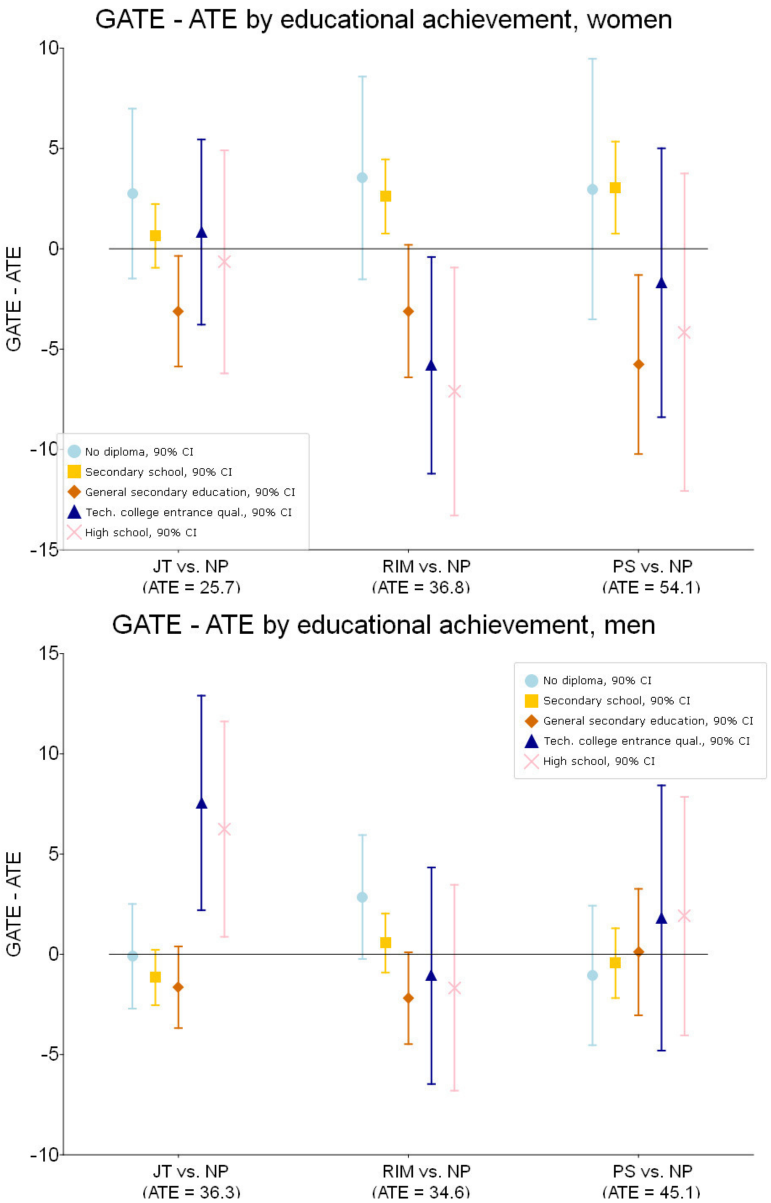
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 14: Job centre client-staff ratio



Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 15: Educational achievement



Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Appendix C.4: Hypothetical programme allocation

Table 17: Overall effects of simulated hypothetical programme allocations, full table

	Share in different programmes (in %) JT	RIM	PS	Cum. # of days in employment	Gain for switchers (in %)
Observed	7.20	5.09	3.95	171.25	-
Random	7.26	5.06	3.84	171.26	+ 0.00
		Direct Policy Simulation			
- No constraint	10.21	22.79	66.91	222.39	+ 31.27
- No constraint, only significant	10.13	14.96	51.03	208.58	+ 35.54
- Constrained, highest variance	7.20	5.09	3.95	175.93	+ 9.60
- Constrained, preference to largest gain	7.20	5.09	3.95	177.35	+ 12.51
- Constrained, lowest non-participation PO	7.20	5.09	3.95	171.37	+ 0.23
- Constrained, sequential optimisation	7.20	5.09	3.95	178.16	+ 14.22
- Constrained, preference to days since last employment	7.20	5.09	3.95	172.03	+ 1.54
- Constrained, preference to highest effect relative to non-participation	7.20	5.09	3.95	175.79	+ 9.27
		Policy Trees			
		Level 2			
- Unconstrainted	0.00	16.91	83.09	217.46	+ 28.26
- Constrained to equal total number of treated	0.00	0.00	16.25	176.13	+ 9.51
- Constrained	6.58	4.40	3.82	172.25	+ 2.40
		Level 3			
- Unconstrainted	0.28	14.98	84.74	217.64	+ 28.37
- Constrained to equal total number of treated	0.00	0.00	16.17	176.73	+ 10.67
- Constrained	7.35	4.87	3.85	174.03	+ 5.42
		Level 4			
- Unconstrainted	0.22	16.34	83.44	217.86	+ 28.50
- Constrained to equal total number of treated	0.54	0.00	15.72	177.07	+ 11.33
- Constrained	7.33	4.93	3.72	174.40	+ 6.12

Notes: JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. PO = potential outcome.

Table 18: Overall effects of simulated hypothetical programme allocations, women, full table

	Share in different programmes (in %) JT	RIM	PS	Cum. # of days in employment	Gain for switchers (in %)
Observed	6.67	4.86	3.43	145.89	-
Random	6.68	4.86	3.23	145.71	- 0.46
		Direct Policy Simulation			
- No constraint	8.79	10.09	81.09	196.74	+ 36.30
- No constraint, only significant	9.96	11.16	62.88	187.89	+ 40.76
- Constrained, highest variance	6.67	4.86	3.43	148.94	+ 7.86
- Constrained, preference to largest gain	6.67	4.86	3.43	150.47	+ 11.86
- Constrained, lowest non-participation PO	6.67	4.86	3.43	146.49	+ 1.46
- Constrained, sequential optimisation	6.67	4.86	3.43	151.05	+ 13.32
- Constrained, preference to days since last employment	6.67	4.86	3.43	146.85	+ 2.41
- Constrained, preference to highest effect relative to non-participation	6.67	4.86	3.43	148.95	+ 7.85
		Policy Tree			
		Level 2			
- Unconstrainted	0.00	0.66	99.34	193.81	+ 34.90
- Constrained to equal total number of treated	0.00	0.00	14.94	150.41	+ 13.40
- Constrained	6.88	4.81	3.02	145.63	+ 1.20
		Level 3			
- Unconstrainted	0.00	0.53	99.47	193.83	+ 34.92
- Constrained to equal total number of treated	0.00	0.00	14.87	151.14	+ 15.25
- Constrained	6.70	4.79	3.24	146.92	+ 4.47
		Level 4			
- Unconstrainted	1.54	1.34	97.12	193.88	+ 34.96
- Constrained to equal total number of treated	0.00	0.00	15.03	151.42	+ 15.95
- Constrained	6.88	4.83	3.19	147.55	+ 6.08

Notes: JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. PO = potential outcome.

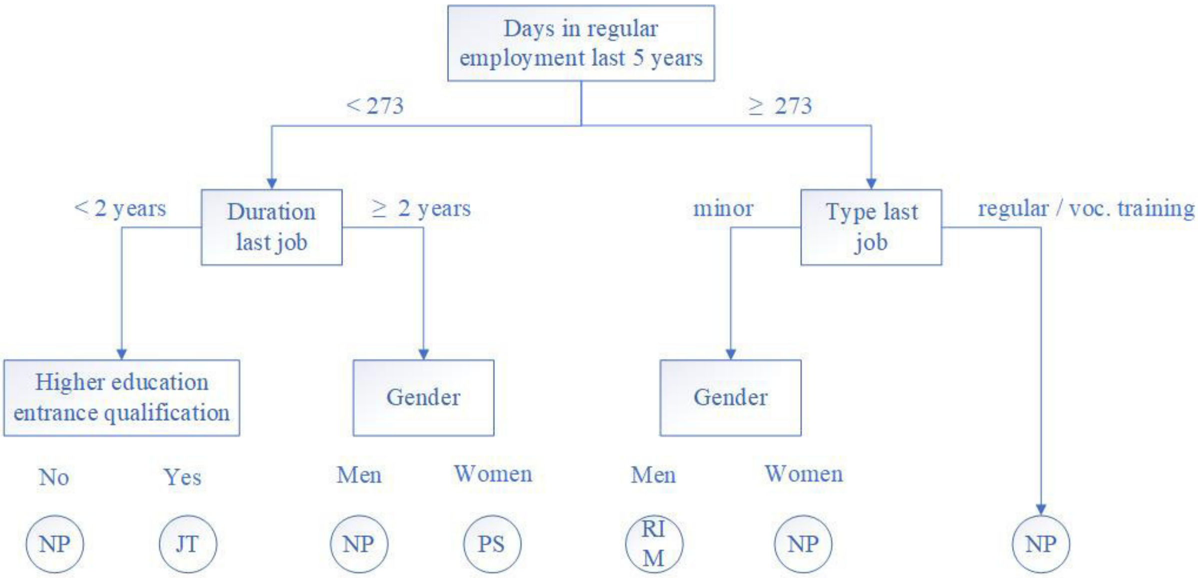
Table 19: Overall effects of simulated hypothetical programme allocations, men, full table

	Share in different programmes (in %) JT	RIM	PS	Cum. # of days in employment	Gain for switchers (in %)
Observed	7.64	5.29	4.39	192.35	-
Random	7.57	5.31	4.18	192.36	+ 0.01
		Direct Policy Simulation			
- No constraint	11.38	33.36	55.12	243.72	+ 28.10
- No constraint, only significant	10.27	18.13	41.16	225.80	+ 32.44
- Constrained, highest variance	7.64	5.29	4.39	197.91	+ 9.61
- Constrained, preference to largest gain	7.64	5.29	4.39	199.41	+ 12.16
- Constrained, lowest non-participation PO	7.64	5.29	4.39	191.88	- 0.76
- Constrained, sequential optimisation	7.64	5.29	4.39	200.26	+ 13.67
- Constrained, preference to days since last employment	7.64	5.29	4.39	193.00	+ 1.08
- Constrained, preference to highest effect relative to non-participation	7.64	5.29	4.39	197.89	+ 9.51
		Policy Tree			
		Level 2			
- Unconstrainted	0.00	30.94	69.06	234.63	+ 23.57
- Constrained to equal total number of treated	0.00	0.00	17.46	194.77	+ 5.34
- Constrained	6.98	5.49	3.80	192.40	+ 1.21
		Level 3			
- Unconstrainted	5.45	20.32	74.23	237.02	+ 24.89
- Constrained to equal total number of treated	0.43	0.00	16.99	196.54	+ 8.41
- Constrained	7.60	5.47	4.17	194.49	+ 4.85
		Level 4			
- Unconstrainted	5.89	31.20	62.91	237.36	+ 25.08
- Constrained to equal total number of treated	0.50	0.00	17.03	196.44	+ 8.25
- Constrained	7.60	5.44	4.28	195.04	+ 5.81

Notes: JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. PO = potential outcome.

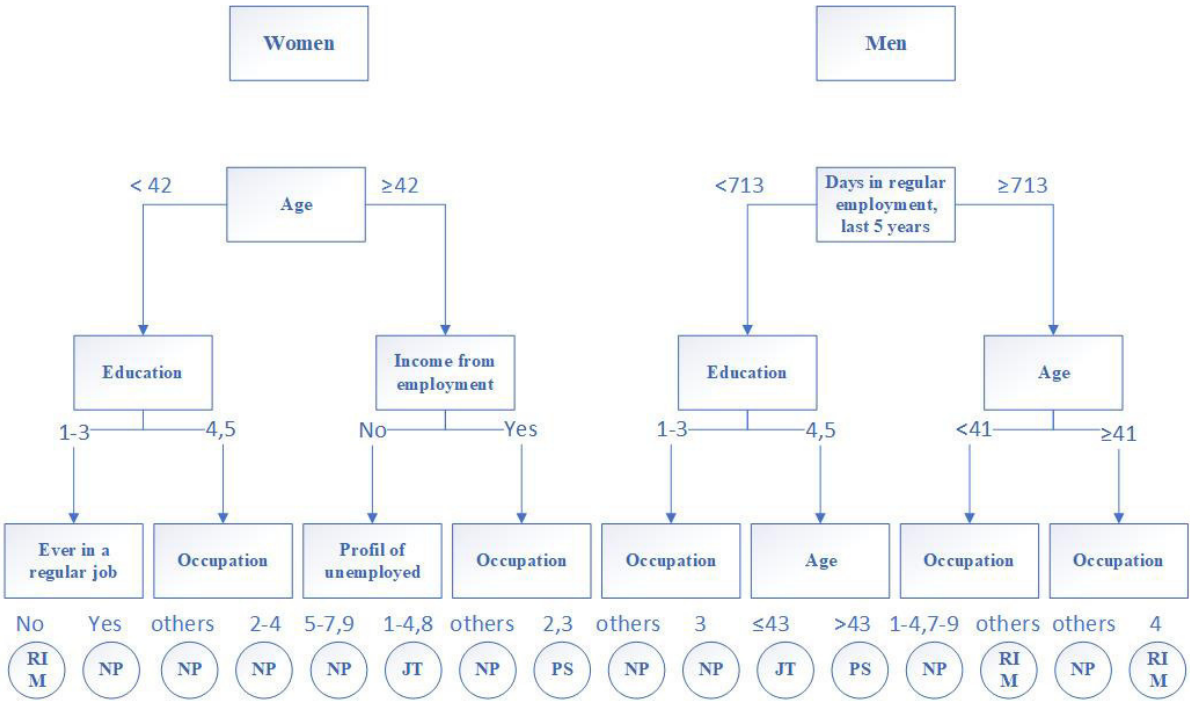
Appendix C.5: Optimal policy tree

Figure 16: Assignment rule of shallow decision tree (depth 3)



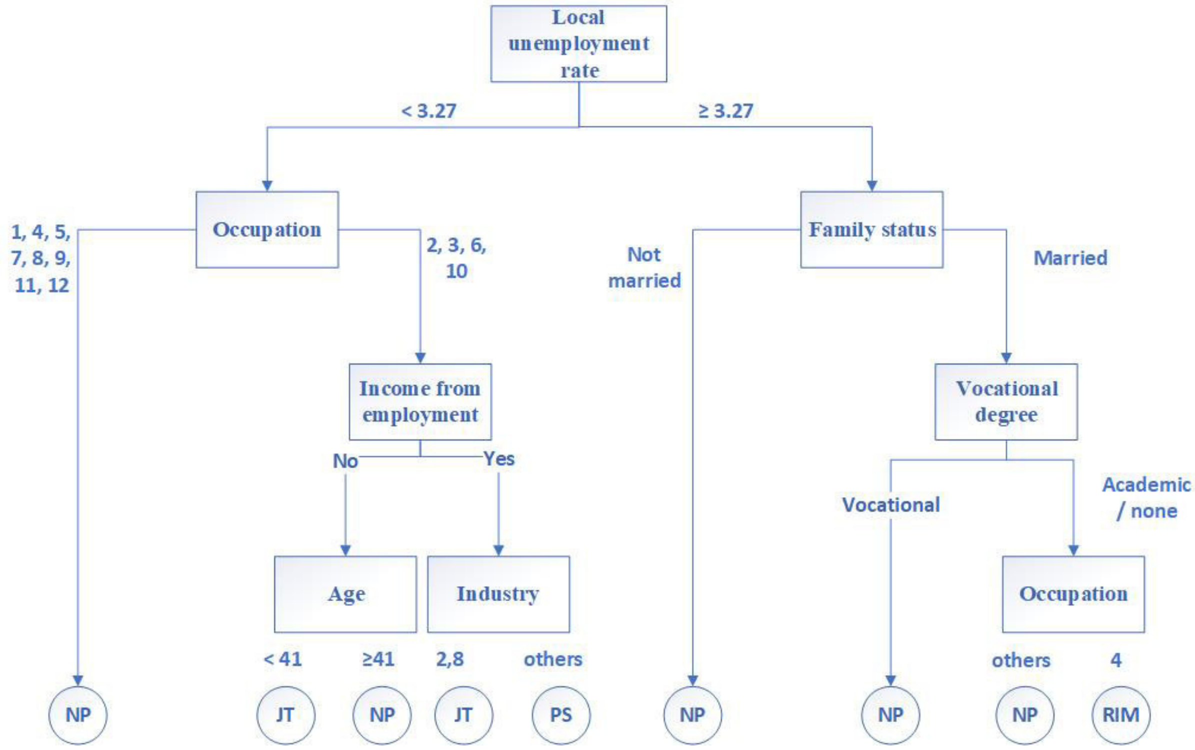
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.

Figure 17: Assignment rules of shallow decision trees (depth 3)



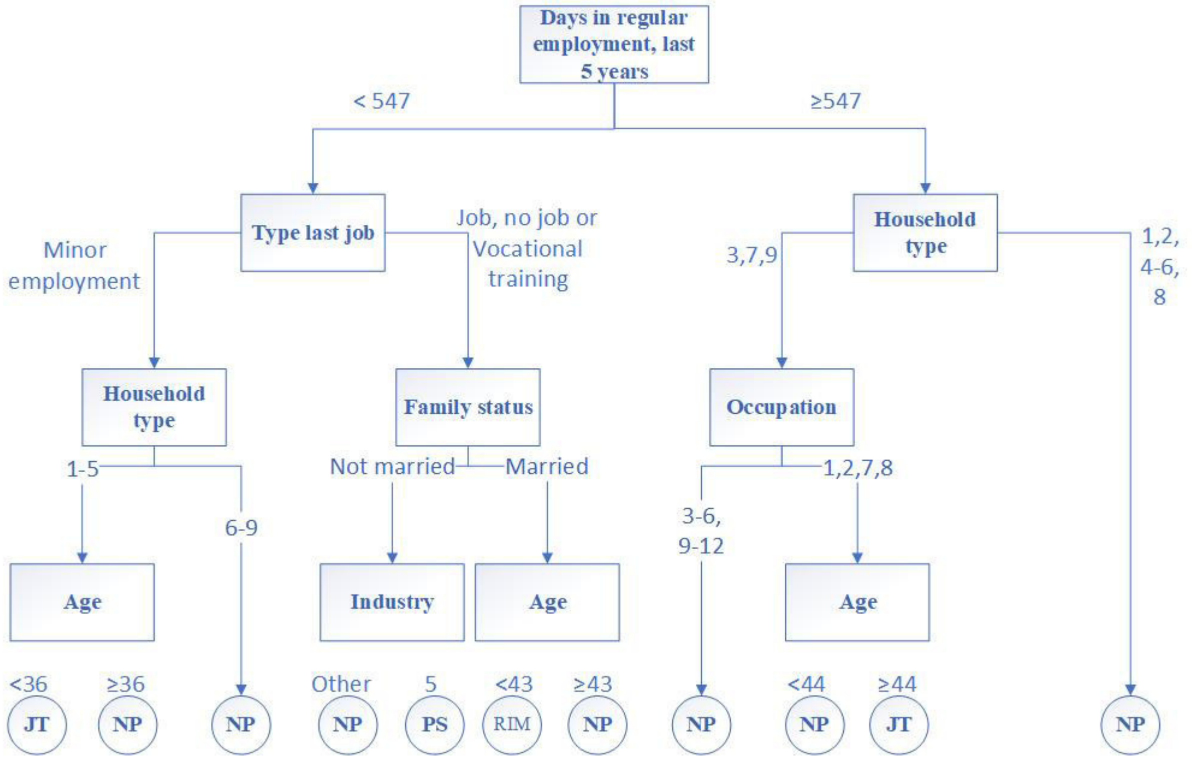
Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*.
Occupations are 1: Agriculture and forestry; 2: Manufacturing; 3: Manufacturing engineering; 4: Construction; 5: Hospitality; 6: Healthcare; 7: Humanities and arts; 8: Retail; 9: Management and organisation; 10: Services; 11: Security, traffic and logistics; 12: Cleaning. Profiles of the unemployed are defined as follows. 1: Not specified; 2: Market Profile; 3: Activation Profile; 4: Support Profile; 5: Development Profile; 6: Stabilisation Profile; 7: Assistance Profile; 8: Assignment not required; 9: Integrated, but dependent on help. Education is denoted as; 1: No degree; 2: Secondary school; 3: General certificate of secondary education; 4: Advanced technical college entrance qualification; 5: High school.

Figure 18: Assignment rules of shallow decision trees, ***women*** *(depth 4)*



Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. Occupations are 1: Agriculture and forestry; 2: Manufacturing; 3: Manufacturing engineering; 4: Construction; 5: Hospitality; 6: Healthcare; 7: Humanities and arts; 8: Retail; 9: Management and organisation; 10: Services; 11: Security, traffic and logistics; 12: Cleaning. Education is denoted as; 1: no degree; 2: Secondary school; 3: General certificate of secondary education; 4: Advanced technical college entrance qualification; 5: High school. Industry is defined by the sector of the last job. 1: No last job; 2: Agriculture, forestry, fishing; 3: Construction; 4: Trade, car sales & maintenance; 5: Transport, postal and telecommunication services; 6: Financial services and real estates; 7: Public administration; 8: Others.

*Figure 19: Assignment rules of shallow decision trees, **men** (depth 4)*



Notes: NP: *non-participation*, JT: *job-training*, RIM: *reducing impediments*, PS: *placement services*. Household types are: 1: single, no children; 2: single, adult children; 3: single, non-adult children; 4: single, adult and non-adult children; 5: couple, no children; 6: couple, adult children; 7: couple, non-adult children; 8: couple, adult and non-adult children; 9: other types. Occupations are 1: Agriculture and forestry; 2: Manufacturing; 3: Manufacturing engineering; 4: Construction; 5: Hospitality; 6: Healthcare; 7: Humanities and arts; 8: Retail; 9: Management and organisation; 10: Services; 11: Security, traffic and logistics; 12: Cleaning. Industry is defined by the sector of the last job. 1: No last job; 2: Agriculture, forestry, fishing; 3: Construction; 4: Trade, car sales & maintenance; 5: Transport, postal and telecommunication services; 6: Financial services and real estates; 7: Public administration; 8: Others.

Appendix D: Implementation of Shallow Decision Trees

This study is using the same implementation of shallow decision trees as the study of Cockx, Lechner, and Bollens (2019) and their Appendix B.4 provides the concrete algorithms, which are described in the following. The general idea goes back to Zhou, Athey, and Wager (2018) and their algorithm 2 is modified in three aspects to fit our purpose.

First, we allow for unordered categorical variables. Second, on higher levels of the tree we use a finer grid for computing possible splitting rules.[25] Third, to take budget constraints

[25] 4th level, i.e., at the top of the tree, A/8; 3rd level A/4; 2nd level A/2; and the 1st level, at the bottom of the tree, A; with A being the approximation parameter as also used in Zhou, Athey, and Wager (2018) as one single global approximation level.

with regard to training programme shares into account, constraints are enforced, to ensure overall programme shares as well as maximum individual programme shares.

Being able to work with unordered categorical variables is especially useful in cases when the number of potential splits is limited, like the underlying. A single split on a categorical variable is more informative compared to any resulting binary variable used if it is not possible to work with categorical variables. Having implemented this ensures that we do not favour any type of variable over another.

By using a finer grid at higher levels of the tree we expect to have higher precision at those splits. Since more data are available at lower levels of the tree the grid can be a bit coarser to save some computation time. In total, this adaptive way should increase precision over the one-size-fits-all approach previously proposed.

The budget constraints are implemented out of necessity due to the nature of the problem at hand. First, it is useless for policy analysis to provide allocations with arbitrary numbers of participants in the programmes. Second, while in general it would be possible to work with a monetary budget constraint, we do not know the costs of each of the programmes, just as we do not know whether the capacities for the respective programmes could be expanded at will. For these reasons, we implement the rule that at most, as many as are observed in the sample may be in the programmes after the reallocation. For more technical and implementation details, the interested reader is referred to the Appendix B.4 in Cockx, Lechner, and Bollens (2019).

Appendix E: Feature selection

In causal studies, having too few (relevant) covariates might lead to omitted variable bias. Having too many (irrelevant) covariates might lead to not controlling for the essential, confounding variables in tree-based methods.

One needs to be very careful when implementing some variable selection procedure as pre-step in causal studies to not omit variables, which are related even mildly to both, the treatment selection and the outcome. Still, e.g., Borup, Christensen, Mühlbach, and Nielsen (2020) find that excluding weak predictors before a random forest estimation improves the trees strength. In application of forest-type estimators this predictor targeting is in use, using LASSO (Kotchoni, Leroux, and Stevanovic (2019)) or Elastic Net (Borup and Schütte (2020), Bork, Møller, and Pedersen (2020)) to pre-select features. Since it is unclear in our setup which functional forms of covariates to include in a LASSO or Elastic Net and how to use this to detect all relevant confounders influencing both, the potential outcome and the treatment allocation, we chose to conduct another approach. First, we estimate an MCF on the 20% subsample and check the influence of all the variables on the estimates in form of a variable importance measure. For the final analysis on the separate 80% subsample, we only use those covariates having a positive variable importance. This is a very conservative choice, which results in a final set of about 70% of all covariates, i.e., about 140. Since there is no test to check if all the relevant confounders are included in the final set of covariates, we investigated two things. First, we checked if all the essential confounders as described and discussed in the identification section survived the selection procedure. Second, it is crucial to check if the estimates change substantially in comparison to an estimation without using a pre-feature selection procedure. In case of discrepancies in the results, this might point to omitted variables. We checked this for the main results and since results are consistent, we chose to use this computationally more attractive procedure including the pre-feature selection.