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Unobservable, but Unimportant? The Influence of Personality Traits (and Other Usually Unobserved Variables) for the Estimation of Treatment Effects

Marco Caliendo* Robert Mahlstedt[†] Oscar A. Mitnik[‡]

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Abstract

A large and highly used number of treatment effects estimators rely on the unconfound-edness assumption ("selection on observables") which is fundamentally non testable. When evaluating the effects of labor market policies, researchers need to observe both variables that affect treatment participation and labor market outcomes. Even though many countries now offer access to (very) informative administrative data concerns about the validity of the unconfoundedness assumption remain. The main concern is that the observable characteristics of the individuals may not be enough to properly address potential selection bias. This is especially relevant in light of the research about the influence of personality traits on economic outcomes. We exploit a unique dataset that contains a rich set of administrative information of individuals entering unemployment in Germany, as well as several usually not observed characteristics like personality traits, attitudes, expectations, and job search behavior. This allows us to empirically assess how estimators based on the unconfoundedness assumption perform when alternatively including or not these usually not observed variables. Our results suggest that these variables, which appear as relevant for the participation probabilities, do not matter for the estimation of effects of the programs evaluated.

Keywords: Matching, Unconfoundedness, Unobervables, Selection Bias, Heterogeneity, Personality Traits, Active Labor Market Policy

JEL codes: C14, J18, D03, D04

^{*}University of Potsdam, IZA Bonn, DIW Berlin, IAB Nuremberg; e-mail: caliendo@empwifo.uni-potsdam.de. Corresponding address: University of Potsdam, Chair of Empirical Economics, August-Bebel-Str. 89, 14482 Potsdam, Germany. Tel: +49 331 977 3225. Fax: +49 331 977 3210.

[†]IZA Bonn, University of Potsdam; e-mail: mahlstedt@iza.org.

[‡]Federal Deposit Insurance Corporation, IZA Bonn; e-mail: oscar@mitnik.net.

1 Introduction

Evaluating the *causal* effects(s) on outcomes of an intervention or treatment(s) has become the key empirical objective in many areas of Economics, Statistics, and other fields like Sociology, Political Science, Epidemiology, and Medicine. If an experiment is properly conducted, where units (e.g. individuals) are randomly assigned to the alternative treatment levels, the average causal effect of any given treatment level compared to another can be obtained by just comparing the average outcomes across the treatment levels.

However, if the assignment to treatment is nonexperimental assumptions are needed to identify the treatment effects of interest. One of the most popular approaches is based on the assumption referred alternatively as unconfoundedness, exogeneity, ignorability, or selection on observables (Imbens and Wooldridge, 2009). In a binary setting where units are either treated or used as comparisons (controls), the assumption, in its various forms, is essentially that adjusting treated and control individuals for differences in *observed* covariates (pre-treatment characteristics and/or outcomes) is enough to eliminate any biases in the comparison between treated and control groups. In other words, the assumption implies that after controlling for differences in observed covariates between the two groups, any remaining differences are as if they had been generated by random assignment to the groups.

The unconfoundedness assumption is fundamentally not testable, and a leading critique of estimators based on this assumption is that, in many cases, it is not realistic. When evaluating the effects of labor market policies, researchers need to observe both variables that affect treatment participation and labor market outcomes. The development of the literature with respect to this is two-sided. On the one hand, many countries now offer access to (very) informative administrative data - including detailed information on the labor market history of individuals – increasing the likelihood that the identifying assumption is met. On the other hand we have seen an upsurge of literature showing the influence of "new" variables such as personality traits and preferences for economic outcomes. As these variables might be important on many dimensions, like the job search behavior, the selection into programs or the overall labor market performance, concerns about the validity of the unconfoundedness assumption are strengthened. The main concern is that there are other not-observed characteristics ("unobservables"), which explain to what group the individuals belong, and the differences in average outcomes. If that is the case, then estimators based on the unconfoundedness assumption become biased, either underestimating or overestimating the causal effects of the treatment. This paper exploits a unique dataset that contains a rich set of administrative information of individuals entering unemployment in Germany, as well as several usually not observed characteristics like personality traits, attitudes, expectations, and job search behavior. This allow us to empirically assess how estimators based on the unconfoundedness assumption perform when alternatively including or not these usually not observed variables.

Our focus is on a family of estimators that rely on comparing treated and control individuals based on the propensity score, the probability of receiving treatment, as a way of reducing a multi-dimensional problem to a one-dimensional problem (Rubin, 1974). Most of the technical details regarding the properties and features of estimators based on the propensity score are at this point well understood, but the key issue of contention that remains is about the validity of the "unconfoundedness" assumption needed to justify the use of propensity score-based estimators. Intuitively propensity score-based estimators are based on comparing individuals with similar scores. The key is that even if individuals in the two treatment arms have similar values of their estimated propensity scores (and thus in the observable characteristics used to estimate the propensity score), they could still differ in other characteristics not observed by the researcher. A typical example for participants in a training program: individuals who volunteer (or are selected) to be treated might be more motivated than those individuals not treated; or maybe the treated individuals have different cognitive and non-cognitive skills from those of the non treated individuals (for many examples of this sort see Heckman, LaLonde, and Smith, 1999). In these kinds of situations it is not possible to claim that selection into a treatment is only based on observed characteristics, unless they include motivation or non-cognitive skills, and thus any estimator of the average treatment effect will be typically biased. The size and direction of the bias will depend on the source of the bias and its relation to the outcome. For example, if trainees are more motivated than individuals not treated, it is likely that the bias will be upwards, meaning that the method will overestimate the actual effect of the training program (because even without training the more motivated individuals are expected to have better outcomes).

Even though the concern about the role of "unobservables" is very sensible, there is surprisingly little research on the actual consequences in applied work, when using propensity score-based estimators, of not observing all the variables that explain selection into a particular treatment. In a sense it should not be so surprising: if variables are not observed, then it is difficult to assess the effect of not having information on those variables. But, on the other hand, even "sensitivity" analyses, where the results when including different sets of observed characteristics

¹Even though these characteristics are many times referred as "unobservables" in the literature, we will refer to them as "usually unobserved".

are compared, are many times not performed, even though they are a readily available option. This paper relates to the prior literature dealing with the sensitivity of unconfoundedness-based estimators. Imbens (2003), Altonji, Elder, and Taber (2005) and Ichino, Mealli, and Nannicini (2008) have proposed methods to assess the sensitivity of unconfoundedness-based estimators to the presence of unobservable variables. With methodological differences in their approaches, these studies try to assess how big should the effect of hypothetical not observed variables be to invalidate the results obtained from applying propensity score-based estimators in different situations. Oster (2013) relates Altonji, Elder, and Taber (2005) to coefficient movements when adding controls in linear models. Lechner and Wunsch (2013) explore, using a German dataset, how sensitive are matching estimators to the inclusion of a variety of usually observable (but rich) characteristics, and find that those rich characteristics can remove selection bias.

Building upon this previous literature, we start our analysis by estimating several types of logit models in order determine the importance of different sets of usually unobserved variables on the selection into four types of treatments. Based on this selection models we estimate average treatment effects on the treated using using different types of propensity score matching. To evaluate the size of potential bias caused by omitting these variables, we compare estimated treatment effects of the full model, including all available covariates, to different baseline models, including only variables which are typically assumed to be available in register data. For a more profound analysis, we also examine the effect on the propensity scores, ranks, the matching quality and run a sensitivity analysis for a subgroup of high-skilled job-seekers. The paper is structured as follows. The next section gives a short summary about the identification treatment effects and potential unobserved variables. Section 3 describes the institutional background, the dataset and shows some descriptives statistics. Section 4 presents the results for the results for selection into different treatments and resulting treatment effects, while Section 5 concludes.

2 Identifying Treatment Effects - A (Very) Short Summary

We base our discussion on the well known potential outcome framework (Roy, 1951; Rubin, 1974), where we have two potential outcomes (Y^1 with treatment, Y^0 without treatment), a treatment indicator (W = 1 if individual received treatment) and a set of obervable characteristics X. We focus on the most prominent evaluation parameter, which is the average treatment effect on the treated (ATT):

$$\tau_{ATT} = E(Y^1 \mid D = 1) - E(Y^0 \mid D = 1). \tag{1}$$

The fundamental evaluation problem arises because the last term on the right hand side of

equation (1) is not observed and selection bias arises if participants and non-participants are selected groups in terms of (un)observable characteristics who would have different potential outcomes even in the absence of treatment. To correct for this selection bias, propensity score matching estimators rely on the conditional independence assumption (CIA), which states that conditional on observable characteristics (X) the counterfactual outcome is independent of treatment. In addition to the CIA, we also assume overlap which implies that there are no perfect predictors which determine participation. Additionally, as direct matching on X can become hazardous when X is of high dimension ("curse of dimensionality"), Rosenbaum and Rubin (1983) suggest using balancing scores such as the propensity score. These two assumptions

$$Y^0 \perp D|P(X)$$
 and $Pr(D=1 \mid P(X)) < 1$, for all X (2)

are sufficient for identification of the ATT based on matching. The CIA is clearly a very strong assumption and its justification depends crucially on the availability of informative data which allow to control for all relevant variables that simultaneously influence the participation decision and the outcome variable. If there are unobserved variables which affect assignment into treatment and the outcome variable simultaneously, a *hidden bias* might arise to which matching estimators are not robust (see, e.g. Rosenbaum, 2002, for an extensive discussion). To see what happens, let us assume that the participation probability is not only determined by X any longer, but also by a set of unobservable variables U. Then

$$P_{i} = P(X_{i}, U_{i}) = P(D_{i} = 1 \mid X_{i}, U_{i}) = F(\beta X_{i} + \gamma U_{i}), \tag{3}$$

where γ is the effect of U_i on the participation decision. If the study is free of hidden bias, γ will be zero and the participation probability will solely be determined by X_i . However, if there is hidden bias, two individuals with the same observed covariates X have differing chances of receiving treatment. Let us assume we have a matched pair of individuals i and j and further assume that F is the logistic distribution. The odds that individuals receive treatment are then given by $\frac{P_i}{(1-P_i)}$ and $\frac{P_j}{(1-P_i)}$, and the odds ratio is given by $\frac{P_i}{\frac{P_j}{1-P_j}} = \frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)}$. If both units have identical observed covariates – as implied by the matching procedure – the X-vector cancels out implying that $\exp[\gamma(u_i - u_j)]$. Both individuals differ in their odds of receiving treatment by a factor that involves the parameter γ and the difference in their unobserved covariates U.

2.1 Potential Unobservables when Evaluating Labour Market Policies

Now the extent to which γ and U play a role in a given empirical context is a much discussed topic. The importance of the unobserved characteristics U clearly depends on the extent of the observed characteristics. A more informative set of control variables X reduces the likelihood that γ has an effect on the participation decision. Previous studies suggest that socio-demographic and regional information as well as labour market histories of participants play an important role when evaluating treatment effects (e.g. Mueser, Troske, and Gorislavsky, 2007; Heckman, Ichimura, Smith, and Todd, 1998). Especially, the improved availability and quality of administrative data over the last years allows to investigate the effects of certain characteristics on potential treatment effects in a systematic way (e.g. Lechner and Wunsch, 2013; Huber, Lechner, and Wunsch, 2013). However, at the same time a variety of studies shows the importance of several 'new' variables, like personality traits (Nyhus and Pons, 2005), cognitive and non-cognitive skills (Heckman, Stixrud, and Urzua, 2006) or preferences and attitudes (Pannenberg, 2010; Belzil and Leonardi, 2007) for economic outcomes.

In this context several variables which are usually not observed when evaluating labour market policies, using administrative data, might be of special interest. For example, Mueller and Plug (2006) show that the so called 'Big Five' personality traits - extraversion, agreeableness, conscientiousness, neuroticism and openness - have a significant impact on earnings which appears comparable to effects commonly for cognitive abilities for the US. Similar results are found by Nyhus and Pons (2005) for the Netherlands. Moreover, several empirical studies investigate how the individual locus of control might be related to the labour market performance. Locus of control refers to a general expectation about internal versus external control of reinforcement (Rotter, 1966). People with a more external locus of control believe that much of what happens in life is beyond their control, while people with an internal locus of control see life's outcomes as dependent on their own decisions and behavior. Psychologists argue that these beliefs are central to understanding a person's motivation and the way that he or she makes decisions and sets goals. Those with an external locus of control are more likely to avoid situations in which they feel unable to cope, while those with an internal locus of control tend to set higher goals, persevere in challenging situations, and be more likely to achieve successful outcomes (Strauser, Keim, and Ketz, 2002). Several studies (e.g. Andrisani, 1977; Heineck and Anger, 2010; Semykina and Linz, 2007) find a significant effect of the locus of control on individual earnings.

Another strand of literature analyzes the effect of job search outcomes, like the use of different search channels (e.g. Holzer, 1988; Van den Berg and Van der Klaauw, 2006) or reservation wages

(e.g. Shimer and Werning, 2007; Brown, Roberts, and Taylor, 2010), on the individual labour market performance. Based on theoretical job search models (Mortensen, 1986), these variables are substantial for determine the unemployment duration and the speed at which job-seekers will be reintegrated into the labour market. Combining these different strands of literature the natural question arises whether these new variables play also a role when evaluating the effects of active labour market programs.

[Insert Tables 1 about here]

Table 1 gives an overview about covariates of interest in our study. First of all, we divide the variables in five categories: socio-demographic variables, labour market history, personality traits, job search and employment outlook and additional characteristics. The first category includes, beside typical socio-demographic variables, like age, gender, marital status, educational level, health status etc, also control variables for the month of entry into unemployment, the time between the entry and the interview and regional information. The second block, the labour market history, can be divided into the short-term and long-term history. The short-term history summarizes information up to two years before beginning of the current unemployment spell, while the long-term history involves information for the last 10 years. Additionally, we define three groups of variables containing information on usually unobserved variables. First, the personality traits contain the "Big Five" factors of personality openness, conscientiousness, extraversion and neuroticism (agreeableness is not included here) (see Digman, 1990, for an overview) and the locus of control. Second, the job search and employment outlook variables contain information on the individual reservation wage, the search intensity, search channels, as well as expectations about future employment prospects and program participation. Third, the additional characteristics include variables like the number of good friends outside the family, problems with child care, father's education and individual life satisfaction. The idea of our study is to investigate the influence of each group of covariates on treatment effects and to show how matching estimators react to absence these groups. In order to do so, we compare three different models. The basic model only includes only the socio-demographics, which are assumed to be usually available when evaluating the active labour market policies. The standard model additionally includes the labour market history which is available when using administrative data, while the extended model combines these register data with detailed survey information.

3 Institutional Background, Data and Descriptives

3.1 Institutional Background

Germany has a long tradition in the provision of labor market policies for unemployed and we can draw on a large set of potential programs. Beside ALMP participation in general, we investigate the effect on three programs in detail – short-term training, long-term training and wage subsidies – as these represent different re-integration strategies (for different types of unemployed individuals). Short-term training measures introduced in 1998 have a maximum duration of eight weeks. The courses can either serve as test of the participant's occupation specific aptitude, or aim to improve the general employability. For example, the courses teach the unemployed how to apply effectively for a new job or the behavior in job interviews. Short-term training programmes are designed to improve the unemployed's human capital, e.g., through the provision of computer or language classes and to attain additional information on the participant's abilities and willingness to work. Some of the courses impart knowledge on starting a business to founders of start-ups, while others are concerned with the special needs of certain rather hard-to-place job-seekers. About one third of the short-term training programs carried out within companies (practical training) while the other two thirds take place in classrooms. Courses are conducted full- or part-time and last from two days up to eight weeks, while an individual's time spent in short-term training programs is limited to twelve weeks in total. While in a training program the unemployed can not earn additional wages, however he continues receiving unemployment benefits and costs arising from participation like those for transport or child care are also covered by the LEA. During the course, participants are still registered as job-seeking but not as unemployed (see Wolff and Jozwiak, 2007).

Long-term training measures have been a well established part of the German labour market policy for many decades. While the duration of short-term training measures is limited to twelve weeks, further vocational training programmes can last from three months up to three years. A caseworker could assign an unemployed individual to a specific course, which was aimed at improving his occupational skills, and thereby facilitate reintegration into the labour market. Previous studies find positive effects only in the very long-run (e.g. Fitzenberger, Osikominu, and Völter, 2008; Lechner, Miquel, and Wunsch, 2011) or even partly negative effects on employment (e.g. Lechner and Wunsch, 2008). With the reforms at the beginning of the century, the German government reduced the importance of long and expensive measures, such that the usage of (long) vocational training programmes went down. From 2003 onwards the caseworker no longer chooses a specific course for the unemployed but hands out a training voucher to the job-seeker

who is then allowed to find an appropriate training programme for himself (see Bernhard and Kruppe, 2012).

Wage subsidies are one of the oldest instruments to integrate unemployed individuals into the labour market. The aim of the subsidy is to reduce the labour costs for the firm, potentially bridging any deficiencies in worker's productivity. Wage subsidies (or temporary employment with a wage subsidy) can also be used as a screening advice, lowering uncertainty and creating hopefully stable employer-employee relationships. Whether or not an unemployed is supported with a targeted wage subsidy is a decision that is made by her caseworker. Beyond that the caseworker determines further properties of the subsidy (restricted by the legal framework and guidelines of the LEA): up to 50 percent of the monthly wage can be covered by the subsidy for at most 12 months. Extensions are possible if the wage subsidy aims at the integration of older or handicapped workers. Employers of subsidized workers agree to employ workers who are younger than 50 years for a follow-up period after the subsidy ended. This follow-up period is usually as long as the period of subsidization itself. In case the worker is dismissed for reasons that are not attributable to him the employer has to return a part of the subsidy. Wage subsidies are criticized because of potential substitution/displacement effects and deadweight losses. Previous research shows relatively large favorable effects on employment prospects of hard-to-place workers (e.g. Bernhard and Wolff, 2008; Jaenichen and Stephan, 2011).

3.2 The IZA Evaluation Dataset

This study uses the IZA Evaluation Dataset M, which was created by IZA with financial support of the Deutsche Post Foundation. The IZA Evaluation Dataset M combines survey information and administrative data on individuals who entered unemployment between June 2007 and May 2008 in Germany (see Caliendo, Falk, Kaiser, Schneider, Uhlendorff, van den Berg, and Zimmermann, 2011). The dataset contains a 9% random sample, from the monthly unemployment inflows of approximately 206,000 individuals identified in the administrative records, which are selected for interview. From this gross sample of individuals aged between 16 and 54 years, representative samples of about 1,450 individuals are interviewed each month so that after one year twelve monthly cohorts were gathered. The first wave of interviews takes place shortly after the entry into unemployment. Besides the extensive set of individual-level characteristics and labour market outcomes, the individuals are asked a variety of non-standard questions about search behavior, social networks, psychological factors, cognitive and non-cognitive skills, subjective assessments on future outcomes, and attitudes.

For all individuals who agreed, these survey data were then matched to administrative information from the *Integrated Employment Biographies* (IEB) as provided by the Institute for Employment Research (IAB) and consists of a random sample of unemployment entries between 2001 and 2008.² The IEB are administrative data and consist of different sources, e.g., employment history, benefit recipient history, training participant history and job search history and therefore contains detailed information on employment subject to social security contributions, unemployment and participation in active labour market policy including wages and transfer payments. The data additionally include a broad range of socio-economic characteristic including education, family status and health restrictions. The data do not contain information about the working hours and periods in self-employment, working as a civil servant, or spent in inactivity. Altogether, this amounts to a total of 15,274 realized interviews with an time lag from seven to fourteen weeks between the unemployment registration and the interview.

For the purpose of the study, we restrict our estimation sample to all individuals who are still unemployment and do not participate in any ALMP program when the interview takes place. Furthermore, we include only respondents who state that they are actively searching for a new employment. We end up with an estimation sample of 6,861 individuals, including 3,092 participants in any ALMP program within a period of 12 months after the entry into unemployment. Of these participants 1,607 participate in short-term training, 694 in long-term training and 501 receive a wage subsidy.

3.3 Some Descriptives

We observe every job-seeker, entering unemployment between June 2007 and May 2008, for a period of 30 months. To evaluate the influence of usually unobserved variables on the treatment effects we focus on employment probabilities after 12, 24 and 30 months, as well as the time spend in employment and the cumulated earnings within the full observation period. Table 2 shows the observed differences between non-participants and the different types of participants. For all participants, we observe significantly lower employment probabilities after 12 months which tend to vanish over time. For recipients of a wage subsidy, the raw employment probabilities are even substantially higher after 24 and 30 months. However, the overall time spend in employment within 30 months after the entry is significantly lower for participants, irrespective of the type of treatment. The cumulated earnings are also lower for participants in any ALMP, short-term

²This study is based on a weakly anonymized sample of the Integrated Employment Biographies by the IAB (V.901). The data can be accessed at the Research Data Center of the Federal Employment Agency at the Institute for Employment Research (FDZ).

training and long-term training, but higher for recipients of wage subsidies.

[Insert Tables 2 about here]

Table 3 shows differences with respect to the socio-demographic variables and the labour market history, the baseline control variables. ALMP participants in general are more likely to be female, older and have more children than non-participants. Moreover, participants are generally better educated, we observe a higher share with an upper secondary school and an university degree, spend more time in employment in the past (short- and long-term) and are more likely to live in West-Germany. Considering the three programs of interest in general the pattern is very similar. However, we observe some deviations. For example, participants in long-term training had a significantly higher income before the beginning of the unemployment, while among recipients of wage subsidies, there is a significantly lower share of individuals with health restrictions or disabilities and a higher share of people from East-Germany.

[Insert Tables 3 and 4 about here]

The main focus of the analysis lies on the usually unobserved variables presented in Table 4. For the personality traits we observe some significant differences between participants and non-participants. ALMP participants in general are less open, have a lower extraversion and a more external locus of control (means that they believe their life depends more on faith and luck than on their own effort). Participants in short-term training have a lower extraversion, are more neurotic and also have a more external locus of control, while participants in long-term training have lower extraversion but there are no significant differences with respect to the other personality traits. Recipients of wage subsidies report that they are more conscientious but no other significant differences. Furthermore, there are strong differences in terms of the job search and outlook variables. All groups of participants have lower reservation wages (the difference is not significant for participants in long-term training), send on average more job applications and make use of more search channels. Unsurprisingly, participants are more likely to expect some sort of treatment when entering unemployment, while the expected probability to find a job within the next 6 months is lower participants in (short- and long-term) training but higher for recipients of wage subsidies. Finally, there are some differences as related to the additional characteristics. In general, all participants report a lower life satisfaction and a lower likelihood that their father has an A-level qualification, while participants in long-term training are also more likely to have some problems with child care.

4 Empirical Results

4.1 Estimation Strategy

Our objective is to study in a systematic way the consequences of including, or not, a set of usually not observed variables in an evaluation of the effects of a training program for recently unemployed individuals on employment probabilities, the time spend in employment and cumulated earnings. Following the presentation of the ATT in Section 2 we report our matching estimates based on inverse probability weights and kernel matching. Before applying kernel matching, assumptions have to be made considering the choice of the kernel function and the bandwidth parameter h. In contrast to the choice of the bandwidth parameter h where a trade-off between a small variance and an unbiased estimate of the true density function arises (see the discussion in Caliendo and Kopeinig, 2008), the choice of the kernel type appears to be relatively less important in practice. We test the sensitivity of our results with respect to different bandwidth choices.

[Insert Table 5 about here]

To evaluate the effect of the unobservables in a systematic way, we start with replicating 'standard' specifications for the baseline results and subsequently include the three groups of usually unobserved variables. The 'standard' specifications include socio-demographic characteristics and the individual labour market history. Table 5 shows the different specifications. We start by including only socio-demographics (Base 1), as well as both, socio-demographics and the labour market history (Base 2). These two baseline specifications allows us to identify the estimated ATT assuming that the CIA from condition (2) holds for two different sets of covariates X. Additionally to these usually observed variables, we subsequently include the personality traits, the job search and employment outlook variables into our analysis. Finally, our full specification includes the socio-demographics, the labour market history and all usually unobserved variables. Therefore, we identify the ATT assuming that the CIA holds for the usually observed covariates X and the usually unobserved covariates U.

4.2 Relevance for Score Estimation

We start the analysis by estimating the propensity score, the probability of belonging to a training group, for each training using a logit model, as is standard in the literature. Tables 6 to 9 present the average marginal effects from propensity score models for ALMP participation

in general and short-term training, long-term training and wage subsidies in particular, with all tables depicting the specifications from Table 5. The first model only uses socio-demographic characteristics, family characteristics and variables related to unemployment entry and local economic conditions at unemployment entry. The second model additionally includes labour market history-related variables, which are consistently found to be key drivers of selection into training in the literature (e.g. Dolton and Smith, 2011). The third to fifth model subsequently include the personality traits, job search variables and additional characteristics, while the last model uses all available covariates.

The estimation results show that (except for short-term training) older job-seeker's are more likely to participate while a positive effect of being female disappears once we control 'unobservables', especially the job search and employment outlook variables. For all programs holds that the short-term labour market history seems to have a strong influence on the selection into the treatment, while the long-term history seems to be less important. Furthermore, several of the usually unobserved variables have a significant impact on the participation probabilities. For example, extraversion has a negative impact on the probability of participating in any ALMP, especially in long-term training, while an external locus of control increases the probability in short-term training. However, none of the personality traits has a significant impact on the receipt of wage subsidies.

The job search and outlook variables have a very strong impact irrespective of the program under consideration. Job-seeker's who put more effort on their job search, in terms of number of applications and search channels, are also more likely to participate in ALMP's and reservation wages have a negative significant effect for all programs, expect for long-term training. Moreover, the effect of the subjective probability of receiving the treatment is quite large, about 15 percentage points for ALMP participation in general, consistent with the individuals possessing private information which is not captured with other variables.³ In the same way, a high expected probability of finding a job in the next 6 months decreases the probability of long-term training participation in 6.5 percentage points. As a reference, the overall participation probability is 15.6 percentage points. Within the group of the additional characteristics, only a higher life satisfaction has a negative significant impact on the participation probabilities.

[Insert Tables 6 to 9 about here]

Overall, the differences, with respect to the marginal effects between the specific models, tend

³However, this does not hold for recipients of wage subsidies. This might be caused by the fact that the receipt of a wage subsidy is related to the beginning of a new employment and respondents do not consider this as a 'typical treatment'.

to be relatively small, while the percentage of observations correctly predicted between model 1 and model 6 increases between 4.7 percentage points for wage subsidies and 9.5 percentage points for long-term training. However, about half of the increasing hitrate can be explained by the labour market history, while the other half can be attributed to usually unobserved variables. Furthermore, Table 10 shows three different measures of fit for the previous six models. First, the McFadden (1974) R^2 is defined as the 'likelihood ratio index' of the estimated model and a model with all but the intercept constraint equal to zero. Second, the R^2 of McKelvey and Zavoina (1975) corresponds to the regression variation divided by the total variation in the latent index function model, where the calculations are based on predicting the continuous latent variable underlying the observed binary variable. Finally, the R^2 of Efron (1978) is the sum of squared model residuals divided by the total variability in the dependent variable. It is equal to the squared correlation between the predicted values and the actual values.

[Insert Table 10 about here]

For example, considering McKelvey and Zavoina's R2, the base specification 1, including only socio-demographics, achieves only between 22% (any ALMP) and 40% (wage subsidies) of the goodness of fit of the full model, including all variables, while additionally including the labour market history increases it up to 49% (long-term training) to 80% (wage subsidies). With respect to the usually unobserved variables, personality traits and additional characteristics have only little impact on the goodness of fit, while the job search and employment outlook variables have the largest impact on the R^2 . The effect varies between 15.6 percentage points for wage subsidies and 46.8 percentage points for long-term training. The overall pattern looks very similar for McFadden's and Efrons's R^2 while the absolute values tend to be lower. The results suggest that the baseline variables are mostly qualified to predict the selection into wage subsidies, while the job search and outlook variables especially increase the goodness of fit for long-term training.

4.3 Consequences for Score, Ranks and Matching Quality

Figure 1 shows the propensity score distribution for the two baseline specifications and the full specification for each treatment separated for participants and non-participants. Unsurprisingly, including additional control variables reduces the concentration of the propensity scores around the mean and shifts more probability mass to the tails of the distribution. As expected, this increases the probability to have a lower propensity score for non-participants and increases the probability to have a propensity score for participants, which means that the additional control

variables rises the predictive efficiency of the estimated models. With respect to the different types of treatment, the effect seems to be lower for wage subsidies than for short- and longterm training. Comparing the baseline specification 1 and the full specification for short-term training the propensity score increases for 61.2% of the participants, with a mean change of 1.5 percentage points, and 39.3% of the non-participants, with a mean change of -3.6 percentage points. The individual rank within the propensity score distribution increases for 58.4% of the participants and only 46.9% of the non-participants. Additionally including the labour market history into the base specification has only little impact the previous results. The propensity score increases for 59.4% of the participants, with a mean change of 1.9 percentage points, and 42.9% of the non-participants, with a mean change of -0.8 percentage points, while the individual rank increases for 56.9% of the participants and 47.8% of the non-participants. For wage subsidies, the overall pattern looks very similar. Switching from the base specification 1 to the full specification raises the propensity score for 61.2% of the participants (mean change: 4.5 percentage points) and 38.6% of the non-participants (mean change: -0.6 percentage points). The individual rank increases for 65.1% of the participants and 49.2% of the non-participants. Using specification 2 as the baseline, the propensity score increases for 62.3% (mean change: 1.5 percentage points) and 44.4% of the non-participants (mean change: -0.2 percentage points), while the rank increases for 60.7% of the participants and 51.3% of the non-participants.

[Insert Figures 1 and 2 about here]

Figure 2 shows the distribution of the propensity score differences between participants and matched non-participants when including all variables for each decile of the propensity score distribution in the base specification 2.4 For participation in any ALMP there are relatively small differences between participants and matched non-participants which seems to be constant over the full distribution. However, for the training measures and wage subsidies the overall level of the differences is lower, with the lowest for wage subsidies, and increase with respect to the propensity score in the base specification, with strongest rise for long-term training. Table 11 provides several correlation measures between the baseline specifications and the full specification for full sample, as well as separated by treatment status. The propensity score and rank correlation between base and full specification is the highest for wage subsidies and the lowest for long-term training, which indicates that the usually unobserved variables has the highest impact on the selection into long-term training and the lowest on that into wage subsidies. For the latter, the usually unobserved variables provide only few information which are

⁴Results are based on epanechnikov kernel propensity score matching with bandwidth 0.06.

not captured by the socio-demographics and the labour market history. Moreover, we compare the propensity score distribution of both base specifications with that of the full specification. For example, the paired t-test shows no distributional differences for the full sample, but significant variations when comparing treated and non-treated individuals separately irrespective of the treatment under consideration. With respect to the rank distribution, the Friedman test shows no differences for the full sample when investigating the selection into any ALMP, but highly significant differences when comparing participants and non-participants separately, as well as for any other program.

[Insert Table 11 about here]

Finally, we also compare the mean standardized bias, as an indicator to assess the distance in marginal distribution of the covariates, for the specific groups of control variables within each specification. Rosenbaum and Rubin (1983) define the standardized bias for the variables x as:

$$SB = \frac{100(\bar{x}_c - \bar{x}_t)}{\sqrt{(s_c^2 + s_t^2)/2}},\tag{4}$$

with \bar{x}_c being the mean of the control group, \bar{x}_t the mean of the treatment group, s_c^2 the variance of the control group and s_t^2 the variance of the treatment group. Afterwards, we build the mean for each group of covariates separately and over all variables. The first column shows the mean standardized bias without matching on any variable, the second column with matching only on socio-demographics, the third column with matching on socio-demographics and the labour market history and the last column with matching on all variables.

[Insert Table 12 about here]

First of all, it can be seen that we reduce the overall bias down to 1.9 to 3.7, which is usually seen as a sufficient level in empirical studies. Regarding the different groups of covariates, we find the largest bias with respect to the job search and employment outlook variables for all treatments, however these can be reduced by our matching procedure including the usually unobserved variables.

4.4 Consequences for Treatment Effects

Table 13 shows the average treatment effects on the treated as the difference in mean outcomes between participants and matched non-participants using epanechnikov kernel propensity score matching with bandwidth 0.06 (the estimation results for different matching estimators can be

found in the Appendix. The different specifications are defined as in Table 5. The outcomes of interest are the employment probabilities at several points in time (12 months and 30 months after the entry into unemployment), the overall time spend in employment within 30 months and the cumulated earnings within 30 months. Shortly summarizing the estimated effects of the different programs, we find a negative effect of all treatments on the employment probability after 12 months, while the negative effect gets smaller over time and we even find a positive and significant effect for wage subsidies after 30 months. Moreover, there is a negative effect of all treatments on the overall time spend in employment within 30 months, with the most unfavorable effect of long-term training. Regarding cumulated earnings within 30 months, there is a positive effect of wage subsidies, while all other programs reduces participants earnings. However, we are more interested in comparing the estimated treatment effects from our baseline specifications 1 and 2 with the treatment effect within the full model (specification 6). In general, the effect of including the usually unobserved variables is relatively small, however, depending on the program and the outcome of interest, we find some differences.

[Insert Tables 13, 14 about here]

Table 14 summarizes the differences between baseline specifications and the full specification. We find significant differences for several treatment and outcome variables when comparing base specification 1, including only socio-demographics, and the full specification. The most distinctive differences can be found when estimating the effect of any ALMP participation and short-term training on cumulated earnings, and when estimating the effect of wage subsidies on the employment probability after 30 months and the time spend in employment. However, no statistically significant differences remain when controlling also for our large set of labour market history variables.

4.5 Sensitivity Analysis: High-skilled Workers

In general, the effect of the usually unobserved variables for estimating treatment effects seems to be relatively small, at least when controlling for an extensive set of labour market history variables. However, the effect of these variables may differ with respect to the individual skill-level. Therefore, we run our previous analysis separated for job-seekers holding an university degree and those who do not.

Table 15 presents the estimated average treatment effects on the treated high-skilled workers, corresponding to Table 13. For all programs, the treatment has more deleterious effects on

all types of outcomes for high-skilled workers than for the full estimation sample. Moreover, the estimated treatment effects are more volatile with respect to the inclusion of the usually unobserved variables. Regarding employment probabilities 12 months after the entry into unemployment, we find differences between 2.1 percentage points, for long-term training, and 6.1 percentage points, for wage subsidies. Like the overall effect of the programs, the volatility of the estimated treatment effects also decreases over time. The differences are substantially smaller for the effects after 30 months. For cumulated earnings within 30 months we find differences in treatment effects varying between ≤ 228 , for long-term training, and ≤ 1155 , for any ALMP, by including all unobservables when comparing base model 2 and the full model. Disregarding the wage subsidies, where we find only a small and insignificant effect on earnings which decreases completely, relative to the initial effect in model 2, we find changes between 2.6%, for long-term training, and 15.1%, for short-term training.

When investigating the effect of each group of usually unobserved variables separately, it is remarkable that the influence of the job search and outlook variables seems to be stronger than that of the other two groups, at least for any ALMP program and short-term training. In this context, the effect of long-term training on cumulated earnings should be of special interest. When including only job search and employment outlook variables the treatment effect decreases about 41% of his initial level, but is nearly the same as without unobservables when controlling for all usually unobserved variables.

[Insert Table 15 about here]

Figure 3 shows (equivalent to Figure 2) the distribution of the propensity score differences between high-skilled participants and matched non-participants in the full specification given that individuals are in the same decile of the propensity score distribution in the baseline model 2.⁵ When comparing the propensity score differences for the full and the high-skilled sample we observe considerably higher differences for high-skilled workers which is in line with larger volatility of the treatment effects for this subgroup.

[Insert Figure 3 about here]

⁵Again, results are based on epanechnikov kernel propensity score matching with bandwidth 0.06. Estimation results for different estimators can be found in the Appendix.

5 Conclusion

[to be completed]

The aim if the study was to investigate the effect of personality traits and other usually unobserved variables on the selection into active labour market policy programs and in consequence on the estimated average treatment effects. Our results suggest that these personal and behavioral information have an substantial impact on the selection into different types of programs like training measures and wage subsidies. Especially, expectations and job search behavior influences the individual participation decision. However, when estimating the effects of ALMP programs on labour market outcomes in a second step, the overall influence of including or excluding these usually unobserved variables seems to be rather small. Our results suggests that unobserved variables have a stronger impact when evaluating the effect of wage subsidies, compared to training measures, and can be much stronger for different subgroups like high-skilled workers in our case.

The relatively small overall impact of these variables can be explained by the comprehensive baseline control variables, predominately the labour market history, which implicitly capture a large part of the "unobserved" variables. On the one hand, especially the labour market history, but also some of the socio-demographic characteristics, are a consequence of usually unobserved variables, like the personality traits, while on the other hand some of the unobservables, especially expectations and job search behavior, might be determine by the socio-demographics and previous labour market experience.

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Tables and Figures

Table 1: Overview - Control Variables

Control variables	Basic	Standard	Extended
Socio-demographic/baseline variables			
Gender, Educational level, Marital status, German citizenship,	\checkmark	\checkmark	\checkmark
Migration background, Number of children, Health problems,			
Searching for full- or part-time employment, Employment status			
of partner, Month of entry into unemployment, Time between en-			
try into unemployment and interview			
Regional information: Living in West-Germany, Local unemploy-			
ment rate			
Labour market history			,
Short-term: Information on last employment (income, full- or		\checkmark	\checkmark
part-time, reason for termination)			
Time spend in employment/unemployment/out of labour force in			
last 6 months/ 24 months Number of employers/programs/unemployment/out of labour			
force spells in last 24 months			
Long-term: Time spend in employment/ unemploy-			
ment/program/out of labour force in last 10 years			
Number employers/programs/unemployment/out of labour force			
spells in last 10 years,			
Time with last employer, Duration of last unemployment spell			
Personality traits			
Big Five: Openness, Conscientiousness, Extraversion, Neuroticism			\checkmark
Locus of control			
Job search and employment outlook			
Job search: Reservation wage, Search intensity(number of appli-			\checkmark
cations), Number of search channels used			
Expectations: Subjective (overall) probability of treatment, Ex-			
pected probability to find a job in the next 6 months			
Additional characteristics			
Number of good friends, Problems with child care, Father has			\checkmark
A-level qualification, Life satisfaction			

Table 2: Descriptive statistics: Labour market outcomes

	NP	Any	STT	LTT	WS
Regular employed					
after 12 months	0.54	0.40	0.43	0.34	0.40
after 24 months	0.53	0.51	0.54	0.53	0.67
after 30 months	0.59	0.55	0.57	0.57	0.69
Months employed within 30 months	14.54	11.54	12.48	10.96	13.25
Cumulated earnings within 30 months	26,818	21,586	22,382	21,633	29,955

Notes: Italic/bold/italic and bold numbers indicate statistically significant differences between the concerning group of participants and non-participants at the 10%/5%/1%-level based on a t-test on equal means. NP - non-participants; Any - participants in any ALMP; STT - participants in short-term training; LTT - participants in long-term training; WS - recipients of wage subsidies.

Table 3: Descriptive statistics: Socio-demographics and labour market history

	NP	Any	STT	LTT	WS
No. of observations	3769	3092	1607	694	501
Socio-demographic characteristics					
Female	0.48	0.53	0.52	0.53	0.47
Age	35.18	36.14	35.07	37.29	38.00
Married (or cohabiting)	0.38	0.41	0.39	0.42	0.41
German citizenship	0.95	0.95	0.94	0.95	0.95
West Germany	0.66	0.70	0.69	0.71	0.60
Migration background (1=yes)	0.14	0.15	0.14	0.15	0.13
Children					
No children	0.68	0.65	0.68	0.64	0.69
One child	0.19	0.19	0.19	0.20	0.18
Two (or more) children	0.13	0.15	0.13	0.16	0.13
School leaving degree					
None, special needs, other	0.02	0.02	0.03	0.02	0.03
Lower secondary school	0.28	0.32	0.34	0.27	0.30
Middle secondary school	0.41	0.44	0.46	0.43	0.46
Specialized upper secondary school	0.28	0.22	0.18	0.29	0.21
Vocational training					
None	0.09	0.10	0.09	0.08	0.07
Internal or external professional training, others	0.69	0.73	0.78	0.70	0.76
Technical college or university degree	0.22	0.17	0.13	0.22	0.17
Local UE rate at interview	0.09	0.09	0.09	0.09	0.10
Health restriction or disability	0.08	0.08	0.08	0.07	0.05
Labour market history					
Employment status before unemployment					
Employed	0.66	0.66	0.66	0.70	0.71
Subsidized employment	0.07	0.07	0.07	0.06	0.10
School, apprentice, military, etc.	0.16	0.14	0.15	0.10	0.12
Maternity leave	0.04	0.06	0.05	0.07	0.03
Other	0.08	0.07	0.07	0.07	0.04
Months employed in last 6 months	4.77	4.88	4.95	4.91	5.09
Last daily income	47.93	46.17	44.61	51.22	46.21
Last job was full-time employment	0.95	0.95	0.94	0.95	0.95
Months employed in last 2 years	15.14	15.82	16.27	15.77	16.40
No. of employers in last 2 years	1.67	1.63	1.65	1.62	1.67
Months employed in last 10 years	49.56	52.46	52.75	54.00	55.26
No. of employers in last 10 years	3.60	3.61	3.55	3.70	4.02

Notes: Italic/bold/italic and bold numbers indicate statistically significant differences between the concerning group of participants and non-participants at the 10%/5%/1%-level based on a t-test on equal means. NP - non-participants; Any - participants in any ALMP; STT - participants in short-term training; LTT - participants in long-term training; WS - recipients of wage subsidies.

Table 4: Descriptive statistics: Usually unobserved variables

	NP	Any	STT	LTT	WS
No. of observations	3769	3092	1607	694	501
Personality traits					
Openness	5.06	4.99	5.01	4.98	5.11
Conscientiousness	6.27	6.27	6.26	6.31	6.35
Extraversion	5.23	5.14	5.17	5.07	5.21
Neuroticism	3.74	3.78	3.82	3.75	3.68
Locus of control (36)	5.06	4.99	4.96	5.02	5.01
Job search and employment outlook variables		·	·		
Reservation wage (in Euro)	7.24	6.88	6.61	7.19	6.78
Number of own applications (mean)	15.07	17.02	16.49	19.46	19.12
Number of search channels	4.95	5.30	5.31	5.38	5.36
Subjective (overall) probability of treatment					
low	0.44	0.31	0.29	0.25	0.36
middle	0.25	0.26	0.27	0.19	0.25
high	0.31	0.44	0.43	0.55	0.39
Expected probability to find a job in the next 6 months			·		
improbable	0.11	0.12	0.10	0.14	0.07
probable	0.30	0.38	0.38	0.41	0.34
very probable	0.49	0.40	0.43	0.36	0.49
Additional characteristics		-			
Number of good friends outside the family	4.83	4.81	4.84	4.78	5.12
Problems with childcare (0: n/a, 1: None, 6: Very)	0.64	0.71	0.65	0.75	0.60
Father has A-level qualifications (1=yes)	0.16	0.13	0.11	0.15	0.12
Life satisfaction					
low	0.10	0.11	0.11	0.10	0.12
middle	0.35	0.38	0.38	0.38	0.40
high	0.55	0.51	0.50	0.52	0.49

Notes: Italic/bold/italic and bold numbers indicate statistically significant differences between the concerning group of participants and non-participants at the 10%/5%/1%-level based on a t-test on equal means. NP - non-participants; Any - participants in any ALMP; STT - participants in short-term training; LTT - participants in long-term training; WS - recipients of wage subsidies.

Table 5: Control variables and definition of specifications

	Specification					
Control variables	(1)	(2)	(3)	(4)	(5)	(6)
Socio-demographic variables	Yes	Yes	Yes	Yes	Yes	Yes
Short-term labour market history	No	Yes	Yes	Yes	Yes	Yes
Long-term labour market history	No	Yes	Yes	Yes	Yes	Yes
Personality traits	No	No	Yes	No	No	Yes
Job search and employment outlook	No	No	No	Yes	No	Yes
Additional characteristics	No	No	No	No	Yes	Yes

Table 6: Logit estimates - Participation in any ALMP

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Personality traits						
Openness (standardized)			004			005
Conscientiousness (standardized)			0.004			0006
Extraversion (standardized)			019***			020***
Neuroticism (standardized)			007			008
Locus of control (standardized)			013*			006
Job search and employment outlook variables			.010			.000
Ln(Reservation wage)				039**		034*
Number of own applications (mean)				0.0005**		0.0005**
Search channel(s) (Number of)				0.022***		0.0005
Subjective (overall) probability of treatment				0.022		0.022
middle						
high				0.079***		0.082***
low				074***		071***
Expected probability to find a job in the next 6 months				.011		.011
probable						
very probable				061***		056***
improbable				004		007
Additional characteristics				.001		.001
Number of good friends outside the family					0.001	0.002
Problems with child care					003	006
Father: A-level qualifications (1=yes)					016	013
Life satisfaction					.010	.010
middle						
high					044***	033**
low					0.002	004
Socio-demographic characteristics					0.002	.001
Female	0.042***	0.026^{*}	0.03**	0.013	0.028**	0.022
Age 45-55 years	0.067***	0.061**	0.053**	0.068***	0.056**	0.059**
Married (or cohabiting)	0.01	0.0001	001	002	0.002	002
Migration background (1=yes)	0.034	0.036*	0.032	0.028	0.037^*	0.025
Two (or more) children	0.037^*	0.03	0.03	0.028	0.038	0.039
(Specialized) upper secondary school	058	048	044	036	040	028
Technical college or university degree	042	042	043	034	037	034
Health restriction or disability	027	027	029	037*	029	039*
Searching for full-time employment	0.012	0.015	0.017	0.02	0.014	0.02
Partner is full-time employed	018	017	013	018	012	011
Short-term labour market history	.010	.01.	.010	.010	.012	.011
Last daily income		0004**	0004*	0002	0004**	0002
Last job was full-time employment		016	017	019	016	019
Months employed in last 6 months		015***	015***	013**	015***	013**
Months employed in last 2 years		0.007***	0.007***	0.006***	0.007***	0.006***
No. of employers in last 2 years		012	012	013*	013*	013*
No. of unemployment spells in last 2 years		026**	026**	023*	024**	023*
No. of programs in last 2 years		0.052***	0.051***	0.047***	0.051***	0.047***
Long-term labour market history		0.002	0.001	0.01.	0.001	0.01.
Months employed in last 10 years		0.0003	0.0003	0.0003	0.0003	0.0004
No. of employers in last 10 years		0.002	0.002	0.001	0.002	0.001
No. of unemployment spells in last 10 years		018***	018***	014***	018***	015***
No. of programs in last 10 years		0.011	0.011	0.008	0.01	0.007
Obs.	6861	6861	6861	6861	6861	6861
log-Likelihood	-4663.53	-4575.77	-4567.83	-4470.10	-4568.05	-4457.58
P-value joint significance personality traits			0.007	,		0.01
P-value joint significance search variables			3.001	0		0.01
P-value joint significance additional variables				Ü	0.008	0.093
P-value joint significance personality and search variables					5.000	0.055
P-value joint significance personality and additional variables						0.005
P-value joint significance all unobservables						0.005
Mean Value	0.451	0.451	0.451	0.451	0.451	0.451
Hitrate	0.551	0.582	0.58	0.609	0.585	0.614

Notes: Depicted are average marginal effects for selected control variables. In all estimations we control for additional information on sociodemographics, short- and long-term labour market history, the regional unemployment rate, the month of entry into unemployment and the time between the entry into unemployment and the interview. Full estimation results can be found in the appendix. ***/**/* indicate statistically significance at the 1%/5%/10%-level.

Table 7: Logit estimates - Participation in short-term training

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Personality traits						
Openness (standardized)			003			003
Conscientiousness (standardized)			0.001			002
Extraversion (standardized)			008			009
Neuroticism (standardized)			005			006
Locus of control (standardized)			021***			016**
Job search and employment outlook variables			.021			.010
Ln(Reservation wage)				069***		062***
Number of own applications (mean)				0.0002		0.0002
Search channel(s) (Number of)				0.0002		0.0002
Subjective (overall) probability of treatment				0.02		0.02
middle						
high				0.055***		0.058***
low				066***		063***
Expected probability to find a job in the next 6 months				000		005
probable						
very probable				035***		030**
improbable				035 025		029
Additional characteristics				025		029
Number of good friends outside the family					0.001	0.001
Problems with child care					0.001	0.001 0.0002
Father: A-level qualifications (1=yes)					025	023
Life satisfaction					025	025
middle						
high					037***	026*
low					0.006	0.0007
Socio-demographic characteristics					0.000	0.0007
Female	0.04***	0.025^{*}	0.025	0.012	0.027^{*}	0.017
Age 45-55 years	005	016	024	003	021	013
Married (or cohabiting)	0.027	0.022	0.024	0.019	0.023	0.02
Migration background (1=yes)	014	010	014	015	010	018
Two (or more) children	006	008	009	008	010	018
(Specialized) upper secondary school	109***	102***	00 <i>9</i> 095**	092**	009	008 079**
Technical college or university degree	109 043*	102 041	038	092	035	023
Health restriction or disability	045 018	041	024	027	022	023
Searching for full-time employment	018	021	024	0.002	022	0.004
Partner is full-time employed	026	003 027	022	028	003	021
Short-term labour market history	020	027	022	026	023	021
Last daily income		0005**	0005**	0003	0005**	0002
		0005 056**	0005 056**	057**	005*	057**
Last job was full-time employment		050 015***	015***	037 014**	035 016***	
Months employed in last 6 months Months employed in last 2 years		0.007***	0.007***	0.006***	0.007***	014** 0.006***
No. of employers in last 2 years		006	006	006	006	007
No. of unemployment spells in last 2 years		034***	034***	032**	033***	007 031**
No. of programs in last 2 years No. of programs in last 2 years		0.029**	0.027**	0.026**	0.028**	0.025^*
Long-term labour market history		0.029	0.027	0.020	0.026	0.025
Months employed in last 10 years		0.0004	0.0005	0.0005	0.0005	0.0006
No. of employers in last 10 years		0004	0008	001	0006	001
No. of unemployment spells in last 10 years No. of programs in last 10 years		008 0.019**	009 0.019**	006 0.015*	008 0.018**	007 $0.015*$
Obs.	5376			5376		
		5376	5376 -3134.39		5376	5376 -3065.67
log-Likelihood D value joint significance personality traits	-3208.80	-3141.05		-3074.79	-3135.22	
P-value joint significance personality traits			0.017	1 10 - 90		0.061
P-value joint significance search variables				1.19e-26	0.000	1.42e-25
P-value joint significance additional variables					0.029	0.282
P-value joint significance personality and search variables						1.25e-24
P-value joint significance personality and additional variables						0.048
P-value joint significance all unobservables Mean Value	0.299	0.299	0.299	0.299	0.299	1.23e-24 0.299
Hitrate	0.299 0.543	0.299 0.586	0.299 0.592	0.299 0.623	0.299 0.586	0.299 0.622
11101000	0.040	0.000	0.034	0.020	0.000	0.022

Notes: Depicted are average marginal effects for selected control variables. In all estimations we control for additional information on socio-demographics, short- and long-term labour market history, the regional unemployment rate, the month of entry into unemployment and the time between the entry into unemployment and the interview. Full estimation results can be found in the appendix. ***/**/* indicate statistically significance at the 1%/5%/10%-level.

Table 8: Logit Estimates - Participation in long-term training

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Personality traits						
Openness (standardized)			006			006
Conscientiousness (standardized)			0.012^{*}			0.008
Extraversion (standardized)			020***			022***
Neuroticism (standardized)			004			003
Locus of control (standardized)			001			0.003
Job search and employment outlook variables						
Ln(Reservation wage)				002		0.004
Number of own applications (mean)				0.0006^{***}		0.0006^{***}
Search channel(s) (Number of)				0.011^{***}		0.012^{***}
Subjective (overall) probability of treatment						
middle						
high				0.114^{***}		0.116^{***}
low				035***		033***
Expected probability to find a job in the next 6 months						
probable						
very probable				065***		064***
improbable				0.033		0.032
Additional characteristics						
Number of good friends outside the family					0.0007	0.001
Problems with child care					002	002
Father: A-level qualifications (1=yes)					005	007
Life satisfaction						
middle						
high					024**	014
low					011	016
Socio-demographic characteristics						
Female	0.027^{**}	0.019	0.024^{*}	0.01	0.02	0.017
Age 45-55 years	0.087^{***}	0.093^{***}	0.087^{***}	0.082***	0.092***	0.077^{***}
Married (or cohabiting)	005	014	014	016	013	017
Migration background (1=yes)	0.027	0.03	0.028	0.016	0.03	0.016
Two (or more) children	0.032^{*}	0.021	0.021	0.016	0.026	0.021
(Specialized) upper secondary school	0.033	0.033	0.035	0.044	0.037	0.048
Technical college or university degree	012	021	025	017	019	023
Health restriction or disability	026	017	018	020	018	021
Searching for full-time employment	0.017	0.019	0.019	0.027^{*}	0.017	0.026
Partner is full-time employed	009	008	007	007	006	005
Short-term labour market history						
Last daily income		00007	00003	0.00006	00006	0.00008
Last job was full-time employment		0.015	0.015	0.01	0.015	0.01
Months employed in last 6 months		006	006	004	007	004
Months employed in last 2 years		0.004**	0.004**	0.003^*	0.004**	0.003^{*}
No. of employers in last 2 years		013*	012*	013*	013*	012*
No. of unemployment spells in last 2 years		0.019^*	0.019^*	0.02^{*}	0.019^*	0.02^{*}
No. of programs in last 2 years		0.043^{***}	0.043^{***}	0.04^{***}	0.043^{***}	0.039^{***}
Long-term labour market history						
Months employed in last 10 years		0005	0005	0004	0004	0004
No. of employers in last 10 years		0.002	0.002	0.002	0.002	0.002
No. of unemployment spells in last 10 years		011***	012***	008*	012***	009*
No. of programs in last 10 years		001	001	005	001	006
Obs.	4463	4463	4463	4463	4463	4463
log-Likelihood	-1876.79	-1830.22	-1822.63	-1724.23	-1827.95	-1714.90
P-value joint significance personality traits			0.006			0.004
P-value joint significance search variables				0		0
P-value joint significance additional variables					0.416	0.767
P-value joint significance personality and search variables						1.50e-38
P-value joint significance personality and additional variables						0.038
P-value joint significance all unobservables						2.00e-36
Mean Value	0.156	0.156	0.156	0.156	0.156	0.156

Notes: Depicted are average marginal effects for selected control variables. In all estimations we control for additional information on sociodemographics, short- and long-term labour market history, the regional unemployment rate, the month of entry into unemployment and the time between the entry into unemployment and the interview. Full estimation results can be found in the appendix. ***/**/* indicate statistically significance at the 1%/5%/10%-level.

Table 9: Logit estimates - Participation in wage subsidies

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Personality traits			0.633			-
Openness (standardized)			0.009			0.008
Conscientiousness (standardized)			0.006			0.004
Extraversion (standardized)			004			006
Neuroticism (standardized)			008			008
Locus of control (standardized)			003			001
Job search and employment outlook variables				000*		000*
Ln(Reservation wage)				028*		029*
Number of own applications (mean)				0.0004***		0.0004**
Search channel(s) (Number of)				0.01***		0.009***
Subjective (overall) probability of treatment						
middle				0.001		0.000
high				0.021		0.022
low				014		013
Expected probability to find a job in the next 6 months						
probable				0.000		0.000
very probable				0.009		0.009
improbable				048***		053***
Additional characteristics					0.001	0.0000
Number of good friends outside the family					0.001	0.0009
Problems with child care					003	003
Father: A-level qualifications (1=yes)					019	020
Life satisfaction						
middle					000**	000*
high					020**	020*
low					0.002	0.007
Socio-demographic characteristics	0.005	000	000	004	0000	0.0000
Female	0.005	003	002	004	0009	0.0002
Age 45-55 years	0.094***	0.099***	0.095***	0.109***	0.097***	0.103***
Married (or cohabiting)	012	015	013	015	014	013
Migration background (1=yes)	0.014	0.019	0.021	0.022	0.019	0.025
Two (or more) children	0.027	0.024	0.023	0.025	0.032	0.033
(Specialized) upper secondary school	071***	056*	059**	055*	048	050
Technical college or university degree	0.002	0.005	0.005	0.005	0.009	0.01
Health restriction or disability	055***	050***	051***	051***	051***	052***
Searching full-time employment	0.027*	0.03*	0.03*	0.029*	0.03*	0.028*
Partner is full-time employed	0.012	0.016	0.015	0.013	0.018	0.015
Short-term labour market history Last daily income		0006***	0006***	0005***	0006***	0006***
· ·						
Last job was full-time employment Months employed in last 6 months		002 008*	0005	0.003 009*	001 008*	0.004 009**
* *			008*			
Months employed in last 2 years No. of employers in last 2 years		0.002 019***	0.002 019***	0.002 020***	0.002 020***	0.002 021***
No. of unemployment spells in last 2 years		0.008	0.008	0.009	0.009	0.01
No. of programs in last 2 years		0.026***	0.005	0.009	0.009	0.01
Long-term labour market history		0.020	0.025	0.024	0.020	0.024
Months employed in last 10 years		0.0007	0.0007	0.0007	0.0008	0.0008
No. of employers in last 10 years		0.0007	0.0007	0.0007	0.0008	0.0008
No. of unemployment spells in last 10 years		010**	010**	010**	010**	011**
No. of programs in last 10 years		0.009	0.009	0.009	0.008	0.009
Obs.	4270	4270	4270	4270	4270	4270
log-Likelihood	-1487.20	-1429.19	-1425.98	-1405.32	-1425.17	-1399.56
=	-1407.20	-1429.19		-1405.52	-1425.17	
P-value joint significance personality traits			0.285	2.06. 00		0.421
P-value joint significance search variables				2.06e-09	0.11	1.20e-08
P-value joint significance additional variables					0.11	0.162
P-value joint significance personality and search variables						1.39e-07
P-value joint significance personality and additional variables						0.29
P-value joint significance all unobservables	0.117	0.117	0.117	0.117	0.117	8.76e-08
Mean Value Hitrate	$0.117 \\ 0.611$	$0.117 \\ 0.644$	$0.117 \\ 0.648$	$0.117 \\ 0.651$	$0.117 \\ 0.649$	$0.117 \\ 0.658$
11101.000	0.011	0.044	0.040	0.091	0.049	0.000

Notes: Depicted are average marginal effects for selected control variables. In all estimations we control for additional information on sociodemographics, short- and long-term labour market history, the regional unemployment rate, the month of entry into unemployment and the time between the entry into unemployment and the interview. Full estimation results can be found in the appendix. ***/**/* indicate statistically significance at the 1%/5%/10%-level.

Table 10: Consequences for estimation quality: Goodness of fit

Specification	(1)	(2)	(3)	(4)	(5)	(6)
		Any	ALMP	participa	ation	
McFadden's R ²	0.012	0.031	0.033	0.053	0.033	0.056
$\%$ of full model R^2	22.2	55.3	58.3	95.3	58.3	100
Difference in %-points	22.2	33.1	3.00	36.9	-37.0	41.7
McKelvey and Zavoina's R ²	0.021	0.054	0.057	0.092	0.057	0.097
$\%$ of full model \mathbb{R}^2	21.8	55.6	58.5	95.2	58.6	100
Difference in %-points	21.8	33.8	2.93	36.7	-36.6	41.4
Effron's R ²	0.017	0.042	0.044	0.071	0.044	0.074
$\%$ of full model R^2	22.9	56.1	59.1	95.6	59.0	100
Difference in %-points	22.9	33.2	2.98	36.5	-36.6	41.0
_			hort-teri	n trainir	ig	
McFadden's R ²	0.021	0.042	0.044	0.062	0.044	0.065
$\%$ of full model R^2	32.9	64.7	67.8	95.7	67.4	100
Difference in %-points	32.9	31.8	3.12	27.9	-28.3	32.6
McKelvey and Zavoina's R ²	0.041	0.078	0.081	0.11	0.081	0.12
$\%$ of full model R^2	33.8	64.7	67.5	95.4	67.7	100
Difference in %-points	33.8	30.9	2.82	27.9	-27.7	32.3
Effron's R ²	0.025	0.050	0.052	0.073	0.052	0.076
$\%$ of full model R^2	33.2	65.8	68.7	95.6	68.5	100
Difference in %-points	33.2	32.6	2.93	26.9	-27.0	31.5
			Long-terr		_	
McFadden's R ²	0.027	0.051	0.055	0.11	0.052	0.11
% of full model R ²	24.2	46.0	49.6	95.6	47.1	100
Difference in %-points	24.2	21.8	3.55	46.0	-48.5	52.9
McKelvey and Zavoina's R ²	0.056	0.099	0.11	0.19	0.10	0.20
% of full model R ²	27.7	48.8	52.7	95.6	50.0	100
Difference in %-points	27.7	21.1	3.90	42.8	-45.5	50.0
Effron's R ²	0.025	0.049	0.052	0.11	0.050	0.11
% of full model R ²	23.0	44.0	46.7	96.0	45.1	100
Difference in %-points	23.0	21.0	2.70	49.3	-50.8	54.9
				ubsidies		
McFadden's R ²	0.037	0.074	0.076	0.090	0.077	0.093
% of full model R ²	39.3	79.5	81.7	96.0	82.3	100
Difference in %-points	39.3	40.2	2.22	14.3	-13.8	17.7
McKelvey and Zavoina's R ²	0.074	0.15	0.15	0.18	0.15	0.19
% of full model R ²	39.6	80.0	82.1	95.6	83.1	100
Difference in %-points	39.6	40.4	2.15	13.5	-12.6	16.9
Effron's R ²	0.027	0.062	0.063	0.076	0.065	0.080
% of full model R ²	33.6	77.6	79.5	95.2	81.5	100
Difference in %-points	33.6	44.0	1.88	15.7	-13.7	18.5

Table 11: Consequences for propensity scores and ranks: Correlation coefficients

		Base 1 vs. Full	Non-		Base 2 vs. Full	Non-
	Full sample	Participants	participants	Full sample	Participants	participant
Propensity score correlation			$Any \ ALMP$	participation		
Pearson's r	0.48	0.45	0.48	0.75	0.73	0.74
1 earson s i	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Rank correlation	(0.00)	{0.00}	(0.00)	(0.00)	(0.00)	{0.00}
Spearman's rho	0.46	0.44	0.46	0.72	0.71	0.71
Spearman's Tho	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Concordance	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Kendall's tau	0.32	0.30	0.32	0.53	0.51	0.52
rendan 5 tau	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Distribution comparison	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Paired t-test	0.00	031	0.026	0.00	018	0.015
Taired t-test	{1.00}	{0.00}	{0.00}	{1.00}	{0.00}	{0.00}
Wilcoxon signed-ranks test	0.44	-14.47	13.71	0.19	-11.16	10.34
Wilcoxoli signed-ranks test	{0.66}	{0.00}	{0.00}	{0.85}	{0.00}	{0.00}
Rank distribution comparison	10.003	10.003	10.003	10.00}	10.003	ξυ.υυγ
Friedman test	0.54	136.64	134.13	0.042	99.26	76.51
riiedinan test		{0.00}	{0.00}			
	{0.46}	{0.00}	()	{0.84}	{0.00}	{0.00}
D :			Snort-terr	n training		
Propensity score correlation	0.55	0.50	0.50	0.01	0.70	0.00
Pearson's r	0.57	0.50	0.58	0.81	0.79	0.80
D 1 1 1	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Rank correlation						
Spearman's rho	0.57	0.49	0.58	0.80	0.77	0.78
	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Concordance						
Kendall's tau	0.40	0.34	0.41	0.60	0.58	0.59
	$\{0.00\}$	{0.00}	$\{0.00\}$	$\{0.00\}$	{0.00}	$\{0.00\}$
Distribution comparison	,	,	,	,	,	,
Paired t-test	0.00	036	0.015	0.00	019	0.008
	{1.00}	{0.00}	{0.00}	{1.00}	{0.00}	{0.00}
Wilcoxon signed-ranks test	3.29	-11.79	12.12	1.06	-9.38	7.80
Wilcoxon signed-ranks test	{0.00}		{0.00}		{0.00}	{0.00}
Rank distribution comparison	{0.00}	$\{0.00\}$	{0.00}	$\{0.29\}$	{0.00}	{0.00}
-	22.00	90.90	171.04	10.19	E7 19	75.04
Friedman test	33.00	80.20	171.94	10.12	57.13	75.94
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
			Long-term	n training		
Propensity score correlation						
Pearson's r	0.47	0.47	0.44	0.66	0.68	0.63
	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Rank correlation						
Spearman's rho	0.50	0.49	0.47	0.68	0.68	0.66
	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Concordance						
Kendall's tau	0.34	0.34	0.33	0.49	0.49	0.47
	{0.00}	{0.00}	$\{0.00\}$	{0.00}	{0.00}	{0.00}
Distribution comparison	()	()	(* **)	()	()	()
Paired t-test	0.00	070	0.013	0.00	050	0.009
	{1.00}	{0.00}	{0.00}	{1.00}	{0.00}	{0.00}
Wilcoxon signed-ranks test	7.50	-11.61	14.35	6.41	-10.46	12.59
neonon signou-tailes test	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Rank distribution comparison	լս.սս}	լս.սս}	ξυ.υυ}	10.00}	10.00}	10.00}
Friedman test	181.90	47 79	311.19	160.75	E4 99	207 52
Friedman test		47.73			54.23	287.52
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
D			$Wage\ s$	ubsidies		
Propensity score correlation		,				
Pearson's r	0.60	0.64	0.58	0.88	0.90	0.87
	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Rank correlation						
Spearman's rho	0.60	0.67	0.58	0.88	0.89	0.87
	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$
Concordance	-		•			
Kendall's tau	0.43	0.48	0.41	0.70	0.72	0.69
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Distribution comparison	(/)	()	()	(v)	()	(- ~~)
Paired t-test	0.00	045	0.006	0.00	015	0.002
1 31104 0 0050	{1.00}	{0.00}	{0.00}	{1.00}	{0.00}	{0.002
Wilcomon simual accelerate	$\{1.00\}$ 7.26		,		,	
Wilcoxon signed-ranks test		-8.68	11.41	3.08	-6.09	5.88
D 1 11 (27)	$\{0.00\}$	$\{0.00\}$	$\{0.00\}$	$\{0.29\}$	$\{0.00\}$	$\{0.00\}$
Rank distribution comparison				22.2		
Friedman test	128.24	29.22	196.69	20.52	30.20	46.58
I I I Callifori						

Note: Base 0 - Baseline specification including only socio-demographics, Base 1 - Baseline specification including socio-demographics and labor market history, Full - Full specification including socio-demographics, labor market history and all usually unobserved variables. Depicted is the standardized mean bias separated for each group of control variables and overall. P-values are shown in braces.

Table 12: Consequences for the matching quality: MSB

	Raw	Base 1	Base 2	Full
	An	y ALMP	participat	\overline{ion}
Socio-demographics	3.74	1.73	1.84	2.15
Labor market history	7.03	4.55	1.11	2.25
Personality traits	5.39	3.42	4.22	1.70
Job search and employment outlook	16.0	13.3	13.8	2.47
Additional characteristics	5.33	2.58	3.00	1.26
Overall	5.90	3.65	2.78	2.13
			n $training$	
Socio-demographics	4.55	2.10	2.56	2.00
Labor market history	6.77	5.50	1.99	1.51
Personality traits	6.00	4.68	5.72	3.25
Job search and employment outlook	16.5	14.6	13.8	1.86
Additional characteristics	5.70	2.20	4.16	1.75
Overall	6.33	4.27	3.57	1.90
		Long-tern	n training	
Socio-demographics	4.44	2.91	2.83	3.29
Labor market history	9.06	7.38	2.96	2.02
Personality traits	6.48	5.90	9.54	1.70
Job search and employment outlook	24.3	23.6	24.6	5.16
Additional characteristics	3.92	2.27	6.47	3.73
Overall	7.51	6.05	5.21	3.00
		Wage s	ubsidies	
Socio-demographics	6.60	3.43	3.89	3.74
Labor market history	14.1	9.22	2.58	2.73
Personality traits	5.15	4.32	4.22	6.20
Job search and employment outlook	15.0	14.2	15.5	5.09
Additional characteristics	7.69	4.95	6.52	4.58
Overall	9.49	6.17	4.60	3.74

Note: Base 0 - Baseline specification including only socio-demographics, Base 1 - Baseline specification including socio-demographics and labor market history, Full - Full specification including socio-demographics, labor market history and all usually unobserved variables. Depicted is the mean standardized bias separated for each group of control variables and overall.

Table 13: Baseline results: Average treatment effects on treated

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
			Anu A	LMP Partic	ipation		
Employed after 12 months	139*** (0.012)	136*** (0.011)	131*** (0.011)	131*** (0.012)	129*** (0.012)	131*** (0.011)	129*** (0.012)
Employed after 30 months	041*** (0.012)	035*** (0.011)	035*** (0.011)	034*** (0.011)	037*** (0.012)	032*** (0.011)	036*** (0.012)
Months employed within 30 months	-3.000*** (0.244)	-2.839*** (0.217)	-2.623*** (0.217)	-2.627^{***} (0.221)	-2.627*** (0.223)	-2.587*** (0.217)	-2.613*** (0.226)
Cumulated earnings within 30 months	-5232*** (577)	-4132*** (478)	-3633*** (472)	-3602*** (478)	-3432*** (469)	-3552*** (471)	-3437*** (474)
Obs.	6861	6861	6861	6861	6861	6861	6861
				rt-term train			
Employed after 12 months	105*** (0.015)	101*** (0.014)	095*** (0.014)	095*** (0.014)	096*** (0.014)	094*** (0.014)	096*** (0.014)
Employed after 30 months	017 (0.015)	009 (0.016)	009 (0.017)	008 (0.017)	013 (0.017)	007 (0.017)	011 (0.017)
Months employed within 30 months	-2.060*** (0.304)	-1.853*** (0.287)	-1.651^{***} (0.283)	-1.648*** (0.28)	-1.747*** (0.276)	-1.608*** (0.288)	-1.708^{***} (0.279)
Cumulated earnings within 30 months	-4439*** (727)	-2724*** (585)	-2051*** (572)	-2010*** (572)	-2026*** (551)	-1964*** (579)	-1966*** (558)
Obs.	5376	5376	5376	5376	5376	5376	5376
			Lor	ng-term train	ning		
Employed after 12 months	193*** (0.02)	201*** (0.02)	210*** (0.02)	210*** (0.021)	208*** (0.022)	210*** (0.021)	210*** (0.022)
Employed after 30 months	022 (0.020)	032 (0.021)	043** (0.022)	041* (0.022)	043* (0.024)	041* (0.022)	040^* (0.024)
Months employed within 30 months	-3.580*** (0.427)	-3.726*** (0.378)	-3.948*** (0.386)	-3.942*** (0.389)	-3.745*** (0.433)	-3.918*** (0.393)	-3.757*** (0.441)
Cumulated earnings within 30 months	-5185*** (1058)	-5789*** (832)	-6227*** (823)	-6166*** (841)	-5883*** (955)	-6139*** (823)	-6053*** (989)
Obs.	4463	4463	4463	4463	4463	4463	4463
			V	Vage subsidi	es		
Employed after 12 months	142*** (0.024)	149*** (0.023)	157*** (0.024)	155*** (0.024)	169*** (0.024)	156*** (0.024)	167*** (0.025)
Employed after 30 months	$0.100^{***} (0.023)$	$0.093^{***} (0.023)$	$0.082^{***} $ (0.023)	$0.082^{***} $ (0.024)	$0.071^{***} (0.025)$	$0.084^{***} $ (0.024)	$0.07^{***} (0.025)$
Months employed within 30 months	-1.292*** (0.488)	-1.381*** (0.381)	-1.527*** (0.393)	-1.490*** (0.405)	-1.820*** (0.413)	-1.512*** (0.411)	-1.805*** (0.442)
Cumulated earnings within 30 months	3137** (1218)	3368*** (904)	3616*** (897)	3682*** (909)	3094*** (975)	3729*** (906)	3049*** (996)
Obs.	4270	4270	4270	4270	4270	4270	4270

Table 14: Consequences for estimated treatment effects

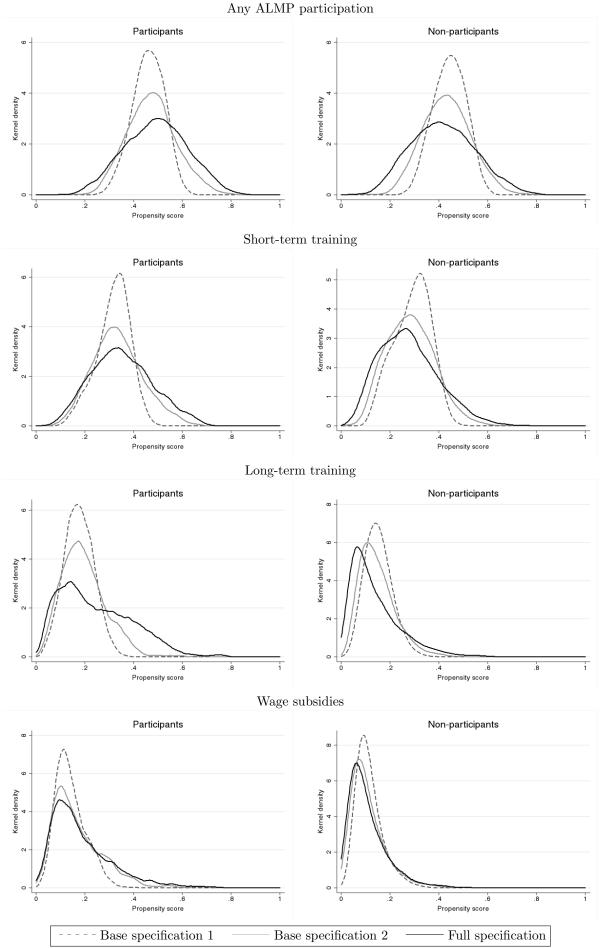
Specification	Base 0 v	s. Full	Base 1 v	s. Full
•	absolute	in $\%$	absolute	in $\%$
	Any	\overline{ALMP}	participatio	\overline{n}
Employed after 12 months	0.0069 (0.0058)	5.0	0.0020 (0.0041)	1.5
Employed after 30 months	-0.0011 (0.0048)	-3.1	-0.0015 (0.0037)	-12.5
Months employed within 30 months	0.23^* (0.12)	8.1	0.010 (0.087)	0.4
Cumulated earnings within 30 months	694** (291)	16.8	196 (205)	5.4
-	Si	hort-terr	n training	
Employed after 12 months	$0.0045 \\ (0.0056)$	4.5	-0.0013 (0.0046)	-1.4
Employed after 30 months	-0.0019 (0.0055)	-21.1	-0.0016 (0.0043)	-17.8
Months employed within 30 months	0.15 (0.13)	8.1	-0.056 (0.11)	-3.6
Cumulated earnings within 30 months	758*** (270)	27.8	85 (212)	4.1
-	L	ong-terr	n training	
Employed after 12 months	-0.0089 (0.012)	-4.4	0.00039 (0.0097)	1.9
Employed after 30 months	-0.0077 (0.012)	-24.1	$0.0032 \\ (0.011)$	7.4
Months employed within 30 months	-0.031 (0.27)	-0.8	0.19 (0.22)	4.7
Cumulated earnings within 30 months	-265 (630)	-4.6	$ \begin{array}{r} 173 \\ (561) \end{array} $	2.8
		Wage s	ubsidies	
Employed after 12 months	-0.018* (0.010)	-12.1	-0.011 (0.0088)	-7.0
Employed after 30 months	-0.023** (0.0091)	-24.7	-0.012 (0.0089)	-14.6
Months employed within 30 months	-0.42^{**} (0.21)	-30.7	-0.28 (0.20)	-18.2
Cumulated earnings within 30 months	-319 (538)	-9.5	-567 (462)	-15.7

Note: Depicted are the difference between base specification 0 (including only socio-demographics) and the full specification, as well as the difference between base specification 1 (including socio-demographics and the labor market history) and the full specification, for estimated average treatment effects on the treated as the difference in mean outcomes between participants and matched non-participants using epanechnikov kernel propensity score matching with bandwidth 0.06. Standard errors are in parentheses and based on bootstrapping with 100 replications. ***/**/* indicate statistically significance at the 1%/5%/10%-level.

Table 15: Sensitivity analysis - high-skilled workers: Average treatment effects on treated

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
			Anu A	LMP Partie	ripation		
Employed after 12 months	222*** (0.027)	209*** (0.028)	214*** (0.029)	212*** (0.03)	183*** (0.031)	212*** (0.029)	189*** (0.032)
Employed after 30 months	$071^{***} (0.027)$	073*** (0.028)	077** (0.03)	079** (0.031)	070** (0.032)	069** (0.031)	076** (0.033)
Months employed within 30 months	-4.853*** (0.564)	-4.541^{***} (0.576)	-4.570*** (0.587)	-4.590*** (0.622)	-3.963*** (0.665)	-4.489*** (0.617)	-4.165*** (0.676)
Cumulated earnings within 30 months	-11528*** (1840)	-11027*** (1815)	-9603*** (1884)	-9539*** (1972)	-7974*** (1990)	-9380*** (1884)	-8448*** (2025)
Obs.	1357	1357	1357	1357	1357	1357	1357
				ort-term trai			
Employed after 12 months	170*** (0.038)	161*** (0.04)	147*** (0.043)	154*** (0.043)	125** (0.049)	148*** (0.045)	113** (0.049)
Employed after 30 months	068^* (0.037)	067^* (0.038)	046 (0.043)	057 (0.044)	061 (0.048)	050 (0.045)	054 (0.053)
Months employed within 30 months	-4.437^{***} (0.799)	-4.177^{***} (0.787)	-3.625*** (0.831)	-3.885*** (0.855)	-3.417*** (0.995)	-3.786*** (0.887)	-3.167*** (1.057)
Cumulated earnings within 30 months	-11054*** (2664)	-11034*** (2491)	-7373*** (2409)	-7649*** (2586)	-6325** (2818)	-7281*** (2324)	-6257^{**} (2829)
Obs.	1039	1039	1039	1039	1039	1039	1039
				ng-term train	ning		
Employed after 12 months	222*** (0.043)	222*** (0.046)	212*** (0.053)	239*** (0.053)	223*** (0.059)	227^{***} (0.053)	191*** (0.067)
Employed after 30 months	053 (0.042)	061 (0.046)	062 (0.056)	092^* (0.054)	098* (0.058)	060 (0.057)	080 (0.068)
Months employed within 30 months	-4.367^{***} (0.899)	-4.342*** (0.913)	-4.137*** (1.013)	-4.737^{***} (1.057)	-4.732^{***} (1.192)	-4.284*** (1.111)	-4.085*** (1.424)
Cumulated earnings within 30 months	-9289*** (3054)	-10709*** (2966)	-8707*** (3204)	-9914*** (3329)	-12279*** (3737)	-10199*** (3264)	-8479* (4353)
Obs.	984	984	984	984	984	984	984
			V	Vage subsidi	es		
Employed after 12 months	239*** (0.055)	228*** (0.068)	202*** (0.076)	193** (0.08)	208** (0.086)	205** (0.084)	263*** (0.093)
Employed after 30 months	$0.032 \\ (0.053)$	0.014 (0.058)	$0.012 \\ (0.071)$	$0.041 \\ (0.071)$	009 (0.079)	$0.028 \\ (0.077)$	040 (0.085)
Months employed within 30 months	-2.835** (1.160)	-2.600** (1.155)	-2.544^* (1.479)	-1.978 (1.509)	-2.643* (1.606)	-2.404 (1.630)	-3.884** (1.802)
Cumulated earnings within 30 months	-593 (3997)	-1359 (3813)	404 (4616)	2416 (4898)	1422 (4548)	1391 (4925)	-78 (5552)
Obs.	916	916	916	916	916	916	916

Figure 1: Distribution of propensity scores by specification and treatment status

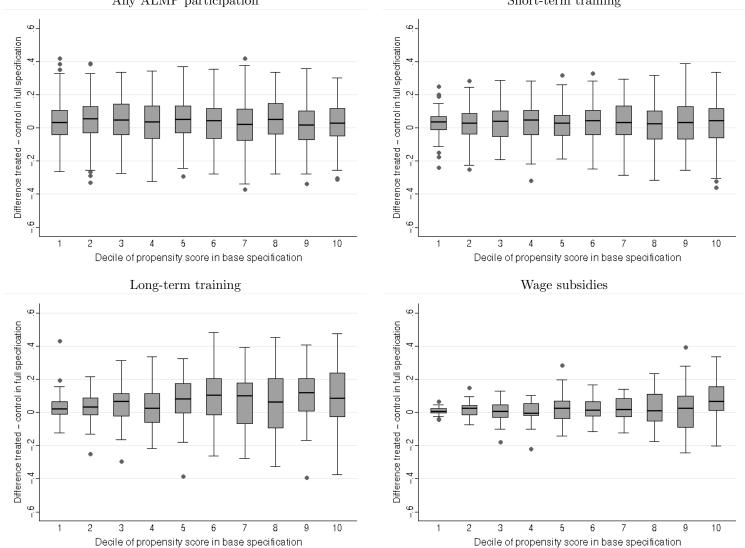


Note: Base 1 - Baseline specification including only socio-demographics, Base 2 - Baseline specification including socio-demographics and labour market history, Full - Full specification including socio-demographics, labour market history and all usually unobserved variables. 36

Figure 2: Distribution: Matched propensity score differences between treated and controls

Any ALMP participation

Short-term training



Note: Depicted is the distribution of the propensity score difference between participants and matched non-participants when including all usually unobserved variables using epanechnikov kernel propensity score matching with bandwidth 0.06 for each decile of the propensity score distribution in base specification 2 (socio-demographics and labour market history).

Any ALMP participation Short-term training Difference treated – control in full specification – 2 0 2 4 . 6 Difference treated – control in full specification φ. 2 3 5 6 10 2 3 5 6 8 9 10 Decile of propensity score in base specification Decile of propensity score in base specification Wage subsidies Long-term training Difference treated - control in full specification Difference treated – control in full specification $-\frac{1}{2}$ $\frac{2}{2}$ $\frac{2}{2}$ $\frac{4}{2}$ œ. 5 6 10 10 3 5 6 8 Decile of propensity score in base specification Decile of propensity score in base specification

Figure 3: Distribution high-skilled: Matched propensity score differences between treated and controls

Note: Depicted is the distribution of the propensity score difference between participants and matched non-participants when including all usually unobserved variables using epanechnikov kernel propensity score matching with bandwidth 0.06 for each decile of the propensity score distribution in base specification 2 (socio-demographics and labour market history).

A Supplementary Appendix

Table A.1: Baseline results: Average treatment effects on treated of any ALMP

Employed after 12 months IPW13 (0.0 Kernel 1 (bw=0.02) Kernel 2 (bw=0.06)	9*** 912)	(1)136*** (0.011)136***	(2)129*** (0.011)	(3) 130***	(4)	(5)	(6)
IPW13 (0.0 Kernel 1 (bw=0.02) Kernel 2 (bw=0.06)		(0.011)		130***	100***		
IPW13 (0.0 Kernel 1 (bw=0.02) Kernel 2 (bw=0.06)		(0.011)		130***	100***		
Kernel 2 (bw=0.06)		136***	(0.011)	(0.012)	129*** (0.012)	129*** (0.011)	130*** (0.012)
,		(0.011)	129*** (0.012)	130*** (0.012)	129*** (0.012)	130*** (0.011)	129*** (0.012)
		136*** (0.011)	131*** (0.011)	131*** (0.012)	129*** (0.012)	131*** (0.011)	129*** (0.012)
Kernel 3 (bw=0.2)		136*** (0.011)	139*** (0.011)	139*** (0.011)	133*** (0.011)	138*** (0.011)	133*** (0.011)
Employed after 24 months							
IPW0	22* 012)	015 (0.011)	011 (0.011)	011 (0.012)	016 (0.012)	010 (0.012)	016 (0.012)
Kernel 1 (bw= 0.02)		015 (0.011)	011 (0.012)	011 (0.012)	019 (0.012)	012 (0.012)	017 (0.012)
Kernel 2 (bw= 0.06)		015 (0.011)	012 (0.011)	013 (0.011)	018 (0.012)	011 (0.012)	017 (0.012)
Kernel 3 (bw= 0.2)		017 (0.012)	020* (0.011)	020* (0.011)	021* (0.012)	018 (0.011)	020* (0.012)
Employed after 30 months							
iPW04	1*** 012)	035*** (0.011)	033*** (0.011)	033*** (0.011)	036*** (0.012)	031*** (0.011)	035*** (0.012)
Kernel 1 (bw= 0.02)		035*** (0.011)	033*** (0.012)	034*** (0.012)	038*** (0.012)	032*** (0.011)	036*** (0.012)
Kernel 2 (bw= 0.06)		035*** (0.011)	035*** (0.011)	034*** (0.011)	037*** (0.012)	032*** (0.011)	036*** (0.012)
Kernel 3 (bw= 0.2)		037*** (0.011)	039*** (0.011)	039*** (0.011)	039*** (0.011)	037*** (0.011)	038*** (0.011)
Months employed within 30 months							
IPW -3.00	00*** 244)	-2.823*** (0.215)	-2.569*** (0.219)	-2.569*** (0.222)	-2.586*** (0.224)	-2.537^{***} (0.221)	-2.594*** (0.227)
Kernel 1 (bw= 0.02)		-2.825*** (0.217)	-2.567^{***} (0.223)	-2.582^{***} (0.225)	-2.634^{***} (0.227)	-2.557^{***} (0.219)	-2.617*** (0.23)
Kernel 2 (bw= 0.06)		-2.839*** (0.217)	-2.623*** (0.217)	-2.627^{***} (0.221)	-2.627^{***} (0.223)	-2.587*** (0.217)	-2.613*** (0.226)
Kernel 3 (bw= 0.2)		-2.904*** (0.223)	-2.898*** (0.218)	-2.890*** (0.22)	-2.782*** (0.22)	-2.849*** (0.217)	-2.767*** (0.222)
Cumulated earnings within 30 months							
IPW -523	32*** 77)	-4140*** (484)	-3511*** (473)	-3466*** (476)	-3438*** (477)	-3444*** (474)	-3446*** (479)
Kernel 1 (bw= 0.02)		-4146*** (483)	-3515*** (482)	-3464*** (483)	-3449*** (472)	-3456*** (465)	-3420*** (483)
Kernel 2 (bw= 0.06)		-4132*** (478)	-3633*** (472)	-3602*** (478)	-3432*** (469)	-3552*** (471)	-3437*** (474)
Kernel 3 (bw= 0.2)		-4596*** (491)	-4443*** (469)	-4405*** (474)	-3875*** (469)	-4335*** (467)	-3860*** (472)
Obs. 68	861	6861	6861	6861	6861	6861	6861

Table A.2: Baseline results: Average treatment effects on treated of short-term training

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months IPW	105*** (0.015)	102*** (0.014)	093*** (0.014)	093*** (0.014)	096*** (0.014)	092*** (0.014)	097*** (0.014)
Kernel 1 (bw= 0.02)	(0.020)	102*** (0.015)	093*** (0.015)	096*** (0.015)	095*** (0.014)	093*** (0.015)	094*** (0.015)
Kernel 2 (bw=0.06)		101*** (0.014)	095*** (0.014)	095*** (0.014)	096*** (0.014)	094*** (0.014)	096*** (0.014)
Kernel 3 (bw= 0.2)		100*** (0.015)	102*** (0.014)	102*** (0.014)	099*** (0.014)	101*** (0.014)	099*** (0.014)
Employed after 24 months IPW	0.005 (0.015)	0.013 (0.014)	0.018 (0.015)	0.018 (0.015)	0.01 (0.015)	0.02 (0.015)	0.01 (0.015)
Kernel 1 (bw=0.02)		0.012 (0.015)	$0.018 \\ (0.015)$	$0.016 \\ (0.015)$	$0.006 \\ (0.015)$	$0.016 \\ (0.015)$	0.012 (0.015)
Kernel 2 (bw=0.06)		$0.015 \\ (0.014)$	$0.016 \\ (0.015)$	$0.016 \\ (0.015)$	$0.008 \\ (0.015)$	$0.017 \\ (0.015)$	$0.01 \\ (0.015)$
Kernel 3 (bw=0.2)		0.014 (0.015)	$0.01 \\ (0.014)$	$0.01 \\ (0.014)$	$0.008 \\ (0.014)$	$0.011 \\ (0.014)$	$0.009 \\ (0.014)$
Employed after 30 months IPW	017 (0.015)	009 (0.016)	007 (0.017)	006 (0.017)	012 (0.017)	005 (0.017)	011 (0.017)
Kernel 1 (bw=0.02)		011 (0.016)	009 (0.017)	009 (0.017)	015 (0.017)	006 (0.017)	007 (0.017)
Kernel 2 (bw=0.06)		009 (0.016)	009 (0.017)	008 (0.017)	013 (0.017)	007 (0.017)	011 (0.017)
Kernel 3 (bw=0.2)		011 (0.016)	014 (0.016)	013 (0.016)	016 (0.016)	012 (0.016)	015 (0.016)
Months employed within 30 months							
IPW	-2.060*** (0.304)	-1.889*** (0.288)	-1.580*** (0.282)	-1.571*** (0.281)	$-1.705^{***} (0.278)$	-1.541*** (0.284)	-1.692*** (0.279)
Kernel 1 (bw= 0.02)		-1.892*** (0.293)	-1.594*** (0.291)	-1.638*** (0.291)	-1.750^{***} (0.283)	-1.590*** (0.298)	-1.633*** (0.287)
Kernel 2 (bw=0.06)		-1.853*** (0.287)	-1.651*** (0.283)	-1.648*** (0.28)	$-1.747^{***} (0.276)$	-1.608*** (0.288)	-1.708*** (0.279)
Kernel 3 (bw=0.2)		-1.897*** (0.285)	$-1.907^{***} (0.274)$	-1.896*** (0.273)	-1.865*** (0.268)	-1.864*** (0.275)	-1.848*** (0.268)
Cumulated earnings within 30 months IPW	-4439*** (727)	-2793*** (586)	-1966*** (574)	-1902*** (572)	-2015*** (563)	-1889*** (575)	-1981*** (567)
Kernel 1 (bw= 0.02)	. ,	-2778*** (595)	-1890*** (582)	-1931*** (592)	-1987*** (559)	-1863*** (587)	-1825*** (576)
Kernel 2 (bw=0.06)		-2724*** (585)	-2051*** (572)	-2010*** (572)	-2026*** (551)	-1964*** (579)	-1966*** (558)
Kernel 3 (bw=0.2)		-3250*** (594)	-2999*** (562)	-2945*** (560)	-2660*** (535)	-2907*** (561)	-2627*** (537)
Obs.	5376	5376	5376	5376	5376	5376	5376

Table A.3: Baseline results: Average treatment effects on treated of long-term training

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months							
IPW	193*** (0.02)	204^{***} (0.02)	211*** (0.02)	212^{***} (0.021)	209*** (0.021)	211*** (0.021)	210*** (0.022)
Kernel 1 (bw=0.02)		202*** (0.02)	207*** (0.021)	207*** (0.021)	202*** (0.023)	210*** (0.021)	204*** (0.023)
Kernel 2 (bw=0.06)		201*** (0.02)	210*** (0.02)	210*** (0.021)	208*** (0.022)	210*** (0.021)	210*** (0.022)
Kernel 3 (bw=0.2)		196*** (0.02)	202*** (0.02)	203*** (0.02)	203*** (0.02)	202*** (0.02)	204*** (0.021)
Employed after 24 months		, ,	, ,	, ,	, ,	, ,	, ,
IPW	$0.002 \\ (0.021)$	004 (0.021)	012 (0.022)	013 (0.022)	014 (0.023)	011 (0.022)	017 (0.023)
Kernel 1 (bw=0.02)		$0.0009 \\ (0.022)$	008 (0.023)	009 (0.022)	014 (0.025)	009 (0.023)	010 (0.025)
Kernel 2 (bw=0.06)		003 (0.021)	012 (0.022)	010 (0.022)	009 (0.024)	011 (0.023)	009 (0.025)
Kernel 3 (bw= 0.2)		001 (0.021)	005 (0.021)	006 (0.021)	009 (0.022)	005 (0.021)	009 (0.023)
Employed after 30 months							
IPW	022 (0.020)	035^* (0.021)	042** (0.021)	042** (0.021)	044^* (0.023)	041* (0.021)	045^* (0.023)
Kernel 1 (bw=0.02)		030 (0.021)	043^* (0.022)	039^* (0.022)	048** (0.024)	044** (0.023)	043^* (0.024)
Kernel 2 (bw=0.06)		032 (0.021)	043** (0.022)	041^* (0.022)	043^* (0.024)	041* (0.022)	040^* (0.024)
Kernel 3 (bw= 0.2)		025 (0.021)	032 (0.021)	033 (0.021)	037^* (0.022)	031 (0.021)	036 (0.022)
Months employed within 30 months							
IPW	-3.580*** (0.427)	-3.787*** (0.38)	-3.942*** (0.382)	-3.972*** (0.382)	-3.809*** (0.42)	-3.926*** (0.386)	-3.869*** (0.423)
Kernel 1 (bw= 0.02)		-3.687*** (0.382)	-3.863*** (0.4)	-3.877*** (0.396)	-3.751*** (0.446)	-3.912*** (0.414)	-3.772*** (0.447)
Kernel 2 (bw=0.06)		-3.726*** (0.378)	-3.948*** (0.386)	-3.942*** (0.389)	-3.745*** (0.433)	-3.918*** (0.393)	-3.757*** (0.441)
Kernel 3 (bw= 0.2)		-3.647*** (0.362)	-3.772*** (0.363)	-3.801*** (0.363)	-3.729*** (0.393)	-3.750*** (0.364)	-3.746*** (0.398)
Cumulated earnings within 30 months		,	,	, ,	, ,	,	,
IPW	-5185*** (1058)	-5965*** (833)	-6269*** (796)	-6254*** (806)	-5934*** (920)	-6214*** (793)	-6035*** (940)
Kernel 1 (bw=0.02)		-5810*** (846)	-6143*** (879)	-6100*** (871)	-5750*** (992)	-6202*** (875)	-5928*** (1019)
Kernel 2 (bw=0.06)		-5789*** (832)	-6227*** (823)	-6166*** (841)	-5883*** (955)	-6139*** (823)	-6053*** (989)
Kernel 3 (bw= 0.2)		-5379*** (832)	-5727*** (794)	-5765*** (796)	-5693*** (835)	-5696*** (795)	-5742*** (859)
Obs.	4463	4463	4463	4463	4463	4463	4463

Table A.4: Baseline results: Average treatment effects on treated of wage subsidies

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months IPW	142*** (0.024)	150*** (0.023)	159*** (0.024)	159*** (0.024)	171*** (0.024)	158*** (0.024)	169*** (0.024)
Kernel 1 (bw=0.02)		150*** (0.023)	159*** (0.024)	157^{***} (0.024)	165*** (0.025)	160*** (0.025)	163*** (0.025)
Kernel 2 (bw=0.06)		149*** (0.023)	$157^{***} (0.024)$	$155^{***} (0.024)$	169*** (0.024)	156*** (0.024)	$167^{***} (0.025)$
Kernel 3 (bw= 0.2)		144*** (0.023)	148*** (0.023)	148*** (0.023)	157*** (0.023)	149*** (0.023)	155*** (0.023)
Employed after 24 months IPW	0.139*** (0.024)	0.138*** (0.025)	0.127*** (0.026)	0.13*** (0.026)	0.118*** (0.026)	0.129*** (0.026)	0.121*** (0.027)
Kernel 1 (bw=0.02)		$0.138^{***} $ (0.025)	$0.128^{***} $ (0.026)	$0.13^{***} (0.026)$	$0.121^{***} (0.028)$	$0.127^{***} (0.027)$	$0.127^{***} (0.028)$
Kernel 2 (bw=0.06)		$0.137^{***} (0.025)$	$0.128^{***} (0.026)$	$0.131^{***} (0.026)$	$0.12^{***} (0.027)$	$0.126^{***} (0.026)$	$0.123^{***} (0.028)$
Kernel 3 (bw= 0.2)		0.139*** (0.024)	$0.134^{***} (0.025)$	$0.135^{***} (0.025)$	$0.129^{***} (0.025)$	$0.135^{***} (0.025)$	$0.132^{***} (0.026)$
Employed after 30 months IPW	0.100*** (0.023)	0.095*** (0.023)	0.081*** (0.024)	0.081*** (0.024)	0.067*** (0.024)	0.082*** (0.024)	0.069*** (0.024)
Kernel 1 (bw= 0.02)	,	0.094*** (0.023)	0.081*** (0.025)	0.078*** (0.025)	0.069*** (0.025)	0.08*** (0.025)	0.071*** (0.025)
Kernel 2 (bw=0.06)		0.093*** (0.023)	$0.082^{***} $ (0.023)	$0.082^{***} (0.024)$	$0.071^{***} (0.025)$	0.084*** (0.024)	$0.07^{***} (0.025)$
Kernel 3 (bw= 0.2)		0.098*** (0.022)	$0.094^{***} $ (0.023)	0.093*** (0.023)	0.083*** (0.023)	0.093*** (0.023)	$0.084^{***} $ (0.023)
Months employed within 30 months $$\operatorname{IPW}$$	-1.292*** (0.488)	-1.374*** (0.389)	-1.553*** (0.4)	-1.520*** (0.402)	-1.891*** (0.413)	-1.519*** (0.397)	-1.817*** (0.414)
Kernel 1 (bw= 0.02)	(01-00)	-1.370*** (0.392)	-1.554*** (0.408)	-1.527*** (0.419)	-1.770*** (0.443)	-1.527*** (0.421)	-1.710*** (0.44)
Kernel 2 (bw=0.06)		-1.381*** (0.381)	-1.527*** (0.393)	-1.490*** (0.405)	-1.820*** (0.413)	-1.512*** (0.411)	-1.805*** (0.442)
Kernel 3 (bw= 0.2)		-1.316*** (0.36)	-1.387*** (0.365)	-1.378*** (0.37)	-1.595*** (0.376)	-1.387*** (0.367)	-1.546*** (0.38)
Cumulated earnings within 30 months $\ensuremath{\mathrm{IPW}}$	3137** (1218)	3485*** (910)	3674*** (877)	3702*** (882)	3031*** (913)	3729*** (868)	3131*** (911)
Kernel 1 (bw= 0.02)	, ,	3475*** (929)	3687*** (916)	3805*** (955)	3371*** (1050)	3712*** (927)	3293*** (1004)
Kernel 2 (bw=0.06)		3368*** (904)	3616*** (897)	3682*** (909)	3094*** (975)	3729*** (906)	3049*** (996)
Kernel 3 (bw=0.2)		3178*** (934)	3399*** (878)	3403*** (882)	3053*** (896)	3420*** (883)	3166*** (908)
Obs.	4270	4270	4270	4270	4270	4270	4270

Table A.5: Sensitivity analysis: Average treatment effects on treated of any ALMP for high-skilled

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months							
IPW	222*** (0.027)	214*** (0.027)	213*** (0.028)	214*** (0.028)	193*** (0.03)	212*** (0.028)	194*** (0.03)
Kernel 1 (bw=0.02)		210*** (0.029)	211*** (0.03)	211*** (0.031)	187*** (0.031)	224*** (0.03)	177*** (0.035)
Kernel 2 (bw=0.06)		209*** (0.028)	214*** (0.029)	212*** (0.03)	183*** (0.031)	212*** (0.029)	189*** (0.032)
Kernel 3 (bw= 0.2)		212*** (0.026)	213*** (0.027)	212*** (0.027)	199*** (0.029)	211*** (0.027)	198*** (0.03)
Employed after 24 months							
IPW	085*** (0.027)	078^{***} (0.029)	092*** (0.03)	095*** (0.03)	089*** (0.032)	089*** (0.03)	094*** (0.033)
Kernel 1 (bw= 0.02)		073** (0.03)	087*** (0.032)	094*** (0.033)	079** (0.035)	095*** (0.034)	073** (0.036)
Kernel 2 (bw=0.06)		071** (0.029)	088*** (0.03)	091*** (0.031)	072** (0.033)	084*** (0.031)	080** (0.034)
Kernel 3 (bw= 0.2)		077^{***} (0.028)	084*** (0.028)	085*** (0.029)	086*** (0.03)	$079^{***} (0.029)$	087*** (0.031)
Employed after 30 months							
IPW	071*** (0.027)	076*** (0.028)	078*** (0.029)	082*** (0.029)	087*** (0.031)	071** (0.029)	087*** (0.031)
Kernel 1 (bw=0.02)		073** (0.029)	076** (0.031)	082** (0.033)	072** (0.033)	072** (0.033)	069** (0.034)
Kernel 2 (bw=0.06)		073*** (0.028)	077** (0.03)	079** (0.031)	070** (0.032)	069** (0.031)	076** (0.033)
Kernel 3 (bw= 0.2)		069*** (0.026)	075*** (0.028)	$077^{***} $ (0.028)	084*** (0.03)	067** (0.029)	084*** (0.031)
Months employed within 30 months							
IPW	-4.853*** (0.564)	-4.659^{***} (0.576)	-4.629*** (0.578)	-4.675*** (0.579)	-4.325*** (0.627)	-4.553*** (0.587)	-4.380*** (0.641)
Kernel 1 (bw= 0.02)		-4.584*** (0.601)	-4.482*** (0.608)	-4.644*** (0.659)	-4.108*** (0.693)	-4.662*** (0.674)	-3.920*** (0.74)
Kernel 2 (bw=0.06)		-4.541*** (0.576)	-4.570^{***} (0.587)	-4.590*** (0.622)	-3.963*** (0.665)	-4.489*** (0.617)	$-4.165^{***} (0.676)$
Kernel 3 (bw= 0.2)		-4.632*** (0.546)	$-4.617^{***} $ (0.554)	-4.616^{***} (0.572)	-4.379*** (0.614)	$-4.517^{***} (0.568)$	-4.371^{***} (0.626)
Cumulated earnings within 30 months							
IPW	-11528*** (1840)	-11302*** (1836)	-9937*** (1813)	-9989*** (1828)	-8771*** (1860)	-9718*** (1807)	-8924*** (1908)
Kernel 1 (bw= 0.02)		-11075*** (1914)	-9659*** (1960)	-9384*** (2025)	-8007*** (2070)	-9601*** (2082)	-8211*** (2326)
Kernel 2 (bw=0.06)		-11027*** (1815)	-9603*** (1884)	-9539*** (1972)	-7974*** (1990)	-9380*** (1884)	-8448*** (2025)
Kernel 3 (bw= 0.2)		-11291*** (1803)	-10044*** (1754)	-9894*** (1816)	-9162*** (1813)	-9741*** (1753)	-9143*** (1843)
Obs.	1357	1357	1357	1357	1357	1357	1357

Table A.6: Sensitivity analysis: Average treatment effects on treated of short-term training for high-skilled

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months IPW	170*** (0.038)	166*** (0.04)	145*** (0.04)	142*** (0.04)	122*** (0.042)	133*** (0.04)	112*** (0.043)
Kernel 1 (bw=0.02)		162*** (0.041)	155*** (0.047)	155*** (0.048)	142^{***} (0.052)	167*** (0.048)	131** (0.055)
Kernel 2 (bw=0.06)		161*** (0.04)	$147^{***} (0.043)$	154^{***} (0.043)	125** (0.049)	148*** (0.045)	113** (0.049)
Kernel 3 (bw= 0.2)		168*** (0.037)	155*** (0.04)	152*** (0.04)	132*** (0.044)	146*** (0.04)	129*** (0.044)
Employed after 24 months IPW	080** (0.038)	077** (0.039)	070* (0.041)	070* (0.041)	068 (0.043)	060 (0.041)	066 (0.044)
Kernel 1 (bw=0.02)		067 (0.042)	069 (0.048)	079* (0.046)	082 (0.053)	085* (0.047)	079 (0.054)
Kernel 2 (bw=0.06)		072^* (0.041)	058 (0.044)	071 (0.044)	063 (0.049)	076^* (0.045)	053 (0.052)
Kernel 3 (bw= 0.2)		075** (0.037)	070^* (0.04)	069* (0.04)	063 (0.044)	064 (0.04)	066 (0.045)
Employed after 30 months IPW	068* (0.037)	071** (0.036)	057 (0.04)	057 (0.04)	064 (0.044)	044 (0.041)	057 (0.044)
Kernel 1 (bw= 0.02)		058 (0.04)	057 (0.046)	064 (0.047)	071 (0.051)	046 (0.047)	073 (0.056)
Kernel 2 (bw=0.06)		067^* (0.038)	046 (0.043)	057 (0.044)	061 (0.048)	050 (0.045)	054 (0.053)
Kernel 3 (bw= 0.2)		066* (0.035)	058 (0.04)	058 (0.04)	060 (0.044)	049 (0.041)	058 (0.046)
Months employed within 30 months							
IPW	-4.437^{***} (0.799)	-4.305^{***} (0.763)	-3.743*** (0.784)	-3.674*** (0.801)	-3.416*** (0.862)	-3.425*** (0.802)	-3.188*** (0.896)
Kernel 1 (bw= 0.02)		-4.119*** (0.825)	-3.921*** (0.939)	-3.956*** (0.933)	-3.932*** (1.070)	-4.021*** (0.958)	-3.683*** (1.159)
Kernel 2 (bw=0.06)		-4.177^{***} (0.787)	-3.625*** (0.831)	-3.885*** (0.855)	-3.417*** (0.995)	-3.786*** (0.887)	-3.167*** (1.057)
Kernel 3 (bw= 0.2)		-4.315*** (0.719)	-3.944*** (0.769)	-3.904*** (0.78)	-3.598*** (0.877)	-3.751*** (0.785)	-3.548*** (0.902)
Cumulated earnings within 30 months $\ensuremath{\mathrm{IPW}}$	-11054*** (2664)	-11394*** (2406)	-7848*** (2304)	-7745*** (2367)	-6209** (2431)	-6928*** (2250)	-5853** (2463)
Kernel 1 (bw= 0.02)	, ,	-11072*** (2705)	-7907*** (2704)	-8216*** (2893)	-6292** (3077)	-7705*** (2528)	-7128** (3154)
Kernel 2 (bw=0.06)		-11034*** (2491)	-7373*** (2409)	-7649*** (2586)	-6325** (2818)	-7281*** (2324)	-6257** (2829)
Kernel 3 (bw= 0.2)		-11123*** (2235)	-8540*** (2213)	-8331*** (2294)	-7107*** (2463)	-8064*** (2173)	-7062*** (2486)
Obs.	1039	1039	1039	1039	1039	1039	1039

Table A.7: Sensitivity analysis: Average treatment effects on treated of long-term training for high-skilled

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months IPW	222*** (0.043)	230*** (0.045)	217*** (0.045)	227*** (0.045)	199*** (0.049)	222*** (0.045)	205*** (0.051)
Kernel 1 (bw=0.02)		221*** (0.049)	198*** (0.055)	250*** (0.059)	225*** (0.065)	262*** (0.057)	201*** (0.068)
Kernel 2 (bw=0.06)		222*** (0.046)	212*** (0.053)	239*** (0.053)	223*** (0.059)	227*** (0.053)	191*** (0.067)
Kernel 3 (bw= 0.2)		220*** (0.043)	217*** (0.046)	230*** (0.047)	203*** (0.055)	222*** (0.047)	197*** (0.06)
Employed after 24 months IPW	030 (0.042)	030 (0.05)	041 (0.05)	052 (0.051)	052 (0.052)	042 (0.052)	056 (0.055)
Kernel 1 (bw=0.02)	(0.042)	023 (0.054)	056 (0.061)	067 (0.062)	080 (0.065)	068 (0.063)	055 (0.072)
Kernel 2 (bw=0.06)		020 (0.051)	035 (0.054)	058 (0.055)	066 (0.065)	031 (0.06)	040 (0.074)
Kernel 3 (bw= 0.2)		027 (0.048)	035 (0.049)	048 (0.051)	043 (0.06)	031 (0.053)	045 (0.067)
Employed after 30 months IPW	053 (0.042)	065 (0.045)	063 (0.047)	077 (0.047)	089* (0.046)	060 (0.049)	087* (0.05)
Kernel 1 (bw=0.02)		056 (0.047)	069 (0.06)	104* (0.056)	115* (0.061)	085 (0.061)	086 (0.068)
Kernel 2 (bw=0.06)		061 (0.046)	062 (0.056)	092^* (0.054)	098^* (0.058)	060 (0.057)	080 (0.068)
Kernel 3 (bw= 0.2)		056 (0.044)	063 (0.048)	077^* (0.047)	081 (0.053)	054 (0.051)	075 (0.059)
Months employed within 30 months IPW	-4.367*** (0.899)	-4.444*** (0.884)	-4.338*** (0.875)	-4.567*** (0.892)	-4.195*** (0.925)	-4.369*** (0.884)	-4.241*** (0.995)
Kernel 1 (bw=0.02)		-4.292*** (0.96)	-4.111*** (1.127)	-4.860*** (1.194)	-4.796*** (1.226)	-5.276*** (1.138)	-4.323*** (1.394)
Kernel 2 (bw=0.06)		-4.342*** (0.913)	-4.137*** (1.013)	-4.737^{***} (1.057)	-4.732*** (1.192)	-4.284*** (1.111)	-4.085*** (1.424)
Kernel 3 (bw= 0.2)		-4.295*** (0.858)	-4.253*** (0.892)	-4.580*** (0.907)	-4.268*** (1.100)	-4.215*** (0.951)	-4.107^{***} (1.253)
Cumulated earnings within 30 months IPW	-9289*** (3054)	-11130*** (2882)	-9549*** (2750)	-10106*** (2871)	-9833*** (2851)	-9537*** (2688)	-9821*** (2908)
Kernel 1 (bw= 0.02)	, ,	-10147*** (3162)	-8325** (3603)	-9507** (3752)	-11786*** (3987)	-12738*** (3568)	-8735** (4109)
Kernel 2 (bw=0.06)		-10709*** (2966)	-8707*** (3204)	-9914*** (3329)	-12279*** (3737)	-10199*** (3264)	-8479* (4353)
Kernel 3 (bw= 0.2)		-10072*** (2725)	-9147*** (2790)	-9838*** (2901)	-10133*** (3368)	-9244*** (2782)	-9563** (3738)
Obs.	984	984	984	984	984	984	984

Table A.8: Sensitivity analysis: Average treatment effects on treated of wage subsidies for high-skilled

	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)
Employed after 12 months IPW	239*** (0.055)	214*** (0.062)	220*** (0.065)	225*** (0.066)	212*** (0.066)	212*** (0.067)	220*** (0.07)
Kernel 1 (bw=0.02)		222*** (0.067)	217*** (0.082)	200** (0.09)	179* (0.091)	173* (0.091)	241** (0.101)
Kernel 2 (bw=0.06)		228*** (0.068)	202*** (0.076)	193** (0.08)	208** (0.086)	205** (0.084)	263*** (0.093)
Kernel 3 (bw= 0.2)		231*** (0.059)	224*** (0.069)	219*** (0.072)	228*** (0.075)	245*** (0.08)	264*** (0.085)
Employed after 24 months IPW	$0.068 \\ (0.055)$	0.087 (0.057)	0.045 (0.06)	0.045 (0.061)	0.047 (0.057)	0.037 (0.062)	0.023 (0.061)
Kernel 1 (bw=0.02)		$0.096 \\ (0.068)$	$0.018 \ (0.077)$	$0.064 \\ (0.077)$	$0.065 \\ (0.077)$	$0.105 \\ (0.083)$	025 (0.091)
Kernel 2 (bw=0.06)		0.084 (0.061)	$0.058 \\ (0.072)$	$0.085 \\ (0.074)$	$0.07 \\ (0.076)$	$0.058 \\ (0.079)$	008 (0.083)
Kernel 3 (bw= 0.2)		$0.074 \\ (0.054)$	$0.057 \\ (0.063)$	$0.061 \\ (0.067)$	$0.056 \\ (0.064)$	0.034 (0.072)	$0.009 \\ (0.08)$
Employed after 30 months IPW	0.032 (0.053)	0.022 (0.055)	007 (0.058)	007 (0.059)	012 (0.058)	005 (0.063)	021 (0.063)
Kernel 1 (bw=0.02)		$0.015 \\ (0.063)$	025 (0.078)	0.029 (0.077)	014 (0.082)	0.07 (0.085)	044 (0.092)
Kernel 2 (bw= 0.06)		0.014 (0.058)	$0.012 \\ (0.071)$	$0.041 \\ (0.071)$	009 (0.079)	$0.028 \ (0.077)$	040 (0.085)
Kernel 3 (bw= 0.2)		$0.025 \\ (0.052)$	0.017 (0.059)	0.02 (0.063)	$0.006 \\ (0.066)$	$0.007 \\ (0.071)$	024 (0.077)
Months employed within 30 months IPW	-2.835** (1.160)	-2.331** (1.062)	-2.713** (1.147)	-2.704** (1.136)	-2.728** (1.121)	-2.783** (1.252)	-3.037** (1.234)
Kernel 1 (bw=0.02)		-2.502** (1.237)	-3.180** (1.570)	-2.167 (1.613)	-2.432 (1.659)	-1.592 (1.709)	-4.058** (1.889)
Kernel 2 (bw= 0.06)		-2.600** (1.155)	-2.544^* (1.479)	-1.978 (1.509)	-2.643* (1.606)	-2.404 (1.630)	-3.884** (1.802)
Kernel 3 (bw= 0.2)		-2.709*** (0.96)	-2.692** (1.237)	-2.568^* (1.320)	-2.869** (1.352)	-3.138** (1.485)	-3.736** (1.701)
Cumulated earnings within 30 months $\ensuremath{\mathrm{IPW}}$	-593 (3997)	-946 (3441)	167 (3536)	437 (3546)	898 (3562)	292 (3813)	427 (3955)
Kernel 1 (bw= 0.02)		-1439 (4110)	-1379 (5115)	2732 (5239)	976 (4963)	3552 (5370)	-682 (5806)
Kernel 2 (bw=0.06)		-1359 (3813)	404 (4616)	2416 (4898)	1422 (4548)	1391 (4925)	-78 (5552)
Kernel 3 (bw= 0.2)		-807 (3129)	461 (4123)	1331 (4117)	978 (3928)	57 (4563)	-292 (5168)
Obs.	916	916	916	916	916	916	916