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Too Bad to Benefit? Effect Heterogeneity of Public Training Programs*

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Abstract

This study analyzes the treatment effects of public training programs for the unemployed in Germany. Based on propensity score matching methods we extend the picture that has been sketched in previous studies by estimating treatment effects of medium-term programs for different sub-groups with respect to vocational education and age. Our results indicate that program participation has a positive impact on employment probabilities for all sub-groups. Participants also seem to find more often higher paid jobs than non-participants. However, we find only little evidence for the presence of heterogeneous treatment effects, and the magnitude of the differences is quite small. Our results are thus—at least in part—conflicting with the strategy to increasingly provide training to individuals with better employment prospects.

Keywords: Program Evaluation; Active Labor Market Policy; Effect Heterogeneity; Public Training Programs; Matching

JEL: J64, J68, H43

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1 Introduction

One central aim of active labor market policy (ALMP) is to increase the employment prospects of unemployed individuals. For this purpose, the Federal Employment Agency in Germany (FEA) spends a substantial amount of money on measures such as job creation schemes, public training programs, or employment subsidies. For instance, about 20.5 billion Euros were spent on ALMP measures in 2002 (Eichhorst and Zimmermann, 2007). The most important part of ALMP in Germany are public training programs. With almost 7 billion Euros, these programs account for more than 32 percent of the expenditures. However, the number of participants decreased over the last years (see Figure 1). While more than 500,000 unemployed individuals entered a training program in 2000, this number approached only around 130,000 individuals in 2005. In 2006, it increased again to nearly 250,000 persons entering such programs.

[Figure 1 about here]

There already exists a number of studies evaluating the effectiveness of public training programs in Germany. For a recent review of the results see, e.g., Caliendo and Steiner (2005).[1] The results are quite heterogeneous—depending on the method, the investigation period and the underlying data set. Earlier studies often find insignificant or even negative effects, see for example Lechner (1999, 2000) and Hujer and Wellner (2000). Recent studies are usually based on rich administrative data sets and most of them find at least for some sub-groups positive treatment effects, see, e.g., Lechner *et al.* (2005a, 2005b), Fitzenberger *et al.* (2006), and Schneider and Uhlendorff (2006). An example for a recent study finding negative effects is Hujer *et al.* (2006). However, the latter authors concentrate on the duration of the initial unemployment spell, and the negative impact of program participation probably reflects the lock-in effect of training programs. The major lesson of these mixed results seems to be that positive effects mainly occur—if at all—in the longer run, and that studies which find positive medium- or long-term effects are also reporting negative short-term effects.

[1] The international literature on the evaluation of ALMP is summarized by Grubb and Martin (2001) and Kluve (2006), among others.

The above mentioned studies focus on average effects of public training programs, partly differentiated by gender, program type and region. The contribution of this paper is to extend the picture sketched so far by answering the question whether the effects of public training programs in Germany are heterogenous with respect to the level of vocational education and age.[2] We examine the effects of three types of programs: (a) programs with a focus on class-room training, (b) programs with a focus on practical experience, and (c) training within practice firms, i.e., with a focus on simulating a real working environment. These three types are—in comparison to other ALMP measures in Germany—rather shorter programs with a median duration between 6 and 8 months.

There does not exist a clear hypothesis for the direction of potential effect heterogeneity. For example, one could think of at least two opposing effects that may affect individuals with and without a vocational degree in a different way. On the one hand, public training programs may involve diminishing marginal returns, i.e., the more human capital the given individual has already accumulated, the less the training program enhances his or her human capital. On the other hand, the effect of medium-term training programs—the focus of our study—may be positively related to the human capital that has already been accumulated by the individual. In contrast to long-term programs, which are in general aiming to provide a vocational degree, and hence supposedly are human capital enhancing by themselves, shorter programs can—at least according to this line of argumentation—only activate already accumulated human capital. In other words, people without a vocational degree would benefit to a smaller extent from participation since skills are provided which are primarily complementary to a vocational degree. In summary, the direction and the extent of potential effect heterogeneity is an empirical question and its estimation is the aim of this paper.

Two recent contributions point into a similar direction as our paper. Lechner and Wunsch (2007) analyze the effectiveness of several West German training and employment programs in 2000–2002 and investigate treatment effects at a fairly disaggregated level, using a—compared to our study—relatively small inflow sample

[2]Caliendo *et al.* (2006) investigate a similar question for job creation schemes in Germany and present evidence for the presence of effect heterogeneity. Although previous results of negative average effects are confirmed in their study, some strata of the population benefit from participation in job creation schemes.

into unemployment. They find evidence for effect heterogeneity and show that job seekers with relatively good *a priori* employment prospects are worse off because of large lock-in effects from which they recover only very slowly, while job seekers with disadvantageous *a priori* employment prospects show below average lock-in effects and positive employment effects for some of the shorter training programs—including job related training. Biewen *et al.* (2007) use similar data and analyze effect heterogeneity by regressing outcome variables after matching on different socio-economic covariates. They find little heterogeneity along observed characteristics, although in some cases older and less educated participants seem to benefit less or not at all from program participation.

In comparison to Lechner and Wunsch (2007) and Biewen *et al.* (2007) we have access to a much larger sample of participants in training programs. This allows us to apply matching methods within several sub-groups—e.g., within the sample of women without any vocational degree—and to investigate the effect heterogeneity in greater detail. Moreover, we analyze the effects on monthly earnings by comparing the shares of individuals with and without training in different quartiles of the earnings distribution. This approach provides insights into the effect of program participation on the probability to find higher and lower paid jobs, respectively. Our analysis is based on an inflow sample into training programs for the year 2002. We ensure that the control group consists of individuals who are as long unemployed as the participants by matching exactly on the previous unemployment duration. Furthermore, a propensity score matching aims to balance differences in a wide range of observable characteristics—including detailed information on previous employment history and regional indicators.

Our results indicate that program participation has a positive impact on employment probabilities for all sub-groups. Moreover, participants seem to find more often higher paid jobs than non-participants. We present only little evidence for the presence of heterogeneous treatment effects and the magnitude of the differences is quite small. If we compare the treatment effects for the most important program type on the employment probability two years after program entry, we find no significant differences with respect to age and vocational education within the same gender. Only if we compare men and women with each other, we find that for this program type young men have a significantly higher treatment effect than older women. Moreover, in case of this program type, the lock-in effect is remarkably shorter for male participants without a vocational degree. Similar results are found for the remaining two program types. The overall picture therefore suggests quite homogenous effects of program participation across sub-groups. Our results are thus—at least in part—conflicting with the strategy to increasingly provide training to individuals with better employment prospects. This strategy has been implemented in Germany as a part of the reform of active labor market policy in 2003. After the reform the caseworkers are asked to evaluate the employment prospects of the unemployed in advance and to provide training only to individuals with a relatively high probability of entering employment after training participation. However, this does not take into account the relative gain compared to the situation without training.

The remainder of this paper is structured as follows: Section 2 provides information on our data and briefly describes the program types being analyzed. Section 3 presents the econometric methods, and Section 4 discusses the results. Finally, Section 5 concludes.

2 Data

We use a sample of a particularly rich administrative data set, the Integrated Employment Biographies (IEB) of the FEA.[3] It contains detailed daily information on employment subject to social security contribution including occupational and sectoral information, receipt of transfer payments during periods of unemployment, job search, and participation in different programs of ALMP. Furthermore, the IEB comprises a large variety of covariates—e.g., age, marital status, number of dependent children, disability, nationality and education.

[3] The IEB is in general not publicly available. Only a 2.2 percent random sample (the Integrated Employment Biographies Sample, IEBS) can be obtained for research purposes. See, e.g., Hummel *et al.* (2005) for details on the IEBS. The IEB consists of four different administrative data sources: the employees' history (BeH), the benefit recipients' history (LeH), the job seekers' data base (ASU/BewA), and the program participants' master data set (MTH). For a detailed description see, e.g., Schneider *et al.* (2007).

Since the public training programs currently in place in Germany are quite heterogenous, we concentrate on and differentiate between three particular types: (a) type 1: occupation-related or general training, (b) type 2: practice training in key qualifications, and (c) type 3: practice firms. Participants in type 1 learn specific skills required for a certain vocation (e.g., computer-aided design for a technician/tracer) or receive qualifications that are of general vocational use (e.g., MS Office, computer skills). Type 2 is a predominantly practically oriented program with only few theoretical parts. It follows the principle 'learning by doing'. Often the measure is combined with internships. Within type 3 the simulation of real operations is conducted, and most of the times technical training is provided. For example, participants are endowed with practical skills of wood working and processing at work benches and machines under the supervision of instructors.

Figure 2 shows that type 1 is by far the most important program type. In the pre-reform period, about 60 percent of all participants in public training programs were assigned to this particular type. It became even more important after the reform in 2003 as this share increased to more than 70 percent. Moreover, the three types together account for roughly 85 percent of all participants in public training programs over the period 2000–2004.

[Figure 2 about here]

Our sample of participants consists of roughly 64,000 unemployed persons entering the three program types in 2002. More precisely, we observe 25,959 participants in type 1, 15,902 participants in type 2, and 22,081 participants in type 3. This sample allows us to draw conclusions on the average participant starting a given program in 2002.[4]

As Figure 3 indicates, the three program types are—in comparison to other ALMP measures in Germany—rather shorter measures. After one year, more than 90 percent of the participants have left each type. The median program duration is about 8 months for type 1 and roughly 6 months for types 2 and 3. While a comparatively large fraction of participants finishes type 1 exactly after 12 months,

[4]The number of participants entering a program differs between the analyzed quarters. We take this into account by applying corresponding weights for the calculation of the average treatment effects on the treated.

an even larger share finishes type 3 exactly after 6 months. For type 2 we observe a sizeable fraction who ends the measure exactly after 6 or 12 months, respectively.

[Figure 3 about here]

In order to apply the matching approach as described in Section 3, around 600,000 non-participants were drawn. Both participants and non-participants are aged between 17 and 65 years.[5]

As we focus on the effect heterogeneity of program participation with respect to vocational education and age, we divide our sample into sub-samples for each program type. With respect to vocational education, the four sub-samples per program type consist of male and female participants and non-participants with and without a vocational degree.[6] As Table 1 shows, the resulting sample sizes are reasonably large. Only for the sub-sample of female participants in type 1 without a vocational degree we end up with less than 2,000 observations.

[Table 1 about here]

With respect to age, we divide the sample into six sub-samples for each program type according to gender and three age groups. These age groups were constructed by choosing thresholds in order to end up with sub-samples of more or less the same size. The first age group includes individuals who are 33 years or younger at the (fictitious) program entry, the second group consists of persons aged between 34 and 42 years, and the third group comprises individuals who are at least 43 years old. Here, (fictitious) program entry refers to the point in time where a particular program starts for actual participants, while it is used as a reference point for non-participants.[7] The resulting sample sizes are depicted in Table 2. While the number of observations of participants is fairly equally distributed within the different sub-samples of program types 1 and 3, this does not entirely apply for type 2. In this

[5] One could argue for stricter age restrictions, for example because of early retirement regulations in Germany. However, if one is interested in the average effects of treatment on the treated and there are participants older than 55 or 60 years, there is no reason to exclude these individuals.

[6] We consider completed in-firm training and off-firm training as well as degrees from a vocational school, a technical school, a university, or a university of applied sciences as vocational degrees.

[7] The specific criteria a non-participant has to meet are further discussed in Section 3.

case, the groups of male and female participants between 34 and 42 years consist of less than 2,000 observations, respectively.

[Table 2 about here]

The success of program participation is evaluated by looking at the probability of being employed starting at the (fictitious) program entry over a period of 24 months. This period is based on the fact that we focus on program participation in the year 2002, and can observe reliable data for all employment states until December 31, 2004. Individuals are regarded as employed if they hold a job in the primary labor market. For instance, participation in job creation schemes is not included in this outcome measure. Moreover, the administrative data set only includes employment that is subject to social security contributions.[8] Self-employment can thus not be observed in our data. Additionally, we evaluate the effect of program participation on monthly earnings in the primary labor market. In other words, we apply the described definition of employment and consider remunerations associated with those spells in terms of monthly earnings.

3 Evaluation Approach

Ideally, one would like to compare the outcomes for the individuals participating in public training programs (Y^1) with the outcomes for the same individuals if they had not participated (Y^0). If D denotes participation in this context—where $D = 1$ if a person participates in the program and $D = 0$ otherwise—the actual outcome for individual i can be written as:

$$Y_i = Y_i^1 \cdot D_i + Y_i^0 \cdot (1 - D_i) \ . \tag{1}$$

The individual treatment effect would then be given by the difference $\Delta_i = Y_i^1 - Y_i^0$. However, it is impossible to calculate this difference because one of the outcomes is counterfactual. Instead, the evaluation literature concentrates on population average gains from treatment—usually on the average treatment effect on the treated (ATT

[8]This means that, e.g., we do not observe self-employment earnings, and remunerations are only reported up to the social security contribution ceiling.

or Δ_{ATT}) which is formally given by:

$$\Delta_{ATT} = E(\Delta|D=1) = E(Y^1|D=1) - E(Y^0|D=1) \ . \tag{2}$$

It is the principle task of any evaluation study to find a credible estimate for the second term on the right hand side of equation (2), which is unobservable.

One possible solution could be to simply compare the mean outcomes of participants and non-participants. However, if $E(Y^0|D=1) \neq E(Y^0|D=0)$, estimating the ATT by the difference between the sub-population means of these two groups will yield a selection bias. On the other hand, if treatment assignment is *strongly ignorable*, i.e., if selection is on observable characteristics X (unconfoundedness or conditional independence assumption), and if observable characteristics of participants and non-participants overlap (common support), the matching estimator is an appealing choice to estimate the desired counterfactual (Rosenbaum and Rubin, 1983). Under these conditions, the distribution of the counterfactual outcome Y^0 for the participants is the same as the observed distribution of Y^0 for the comparison group *conditional on the vector of covariates* X. Formally,

$$E(Y^0|X, D=1) = E(Y^0|X, D=0) \ . \tag{3}$$

Entering this relation into (2) allows estimating the ATT by comparing mean outcomes of matched participants and non-participants. Rosenbaum and Rubin (1983) show that if treatment assignment is strongly ignorable *given* X, it is also strongly ignorable *given any balancing score* that is a function of X.[9] One possible balancing score is the propensity score $P(X)$, i.e., the probability of participating in a given program. Mueser *et al.* (2007) present evidence that if administrative data is used to measure the performance of training programs, propensity score matching is generally most effective.

There are several propensity score matching methods suggested in the literature, see, e.g., Caliendo and Kopeinig (2008) for an overview. Based on the characteristics of our data, we opt to apply nearest-neighbor matching without replace-

[9]When there are many covariates, it is impractical to match directly on covariates because of the curse of dimensionality. See, e.g., Zhao (2007) for some comments on this problem.

ment. This matching method has the advantage of being the most straightforward matching estimator: a given participant is matched with a non-participant who is closest in terms of the estimated propensity score. We avoid an increased variance of the estimator as we match without replacement (Smith and Todd, 2005), which is justified since the ratio between participants and non-participants—i.e., potential matching partners—is comparatively high in our data. Hence, the constructed counterfactual outcome is based only on distinct non-participants. To check the sensitivity of our results with respect to the matching algorithm, we additionally applied other methods to our data and find evidence for robust estimates (see Section 4.4 for details).

For the variance of the estimated treatment effects, we base our inference on the assumption that the estimators are asymptotically normally distributed. This distribution is derived from the difference of two weighted means of two independent observations. Lechner (2002) employs a similar approach. We checked the accuracy of this approximation by also calculating the variance of the estimated treatment effects based on bootstrapping procedures. Although nearest neighbor matching does not satisfy the basic conditions for the bootstrap and the bootstrap variance diverges from the actual variance (Abadie and Imbens, 2006), this alternative method implies very similar variances of the estimated treatment effects and does not change the implications presented below.

The focus of the subsequent analysis lies on the differences in treatment effects between separated sub-groups. To assess whether these differences are significantly different from zero, we assume that the treatment effects follow a normal distribution and that they are independent from each other.[10]

The probability of participation in the three program types under consideration is estimated conditional on a number of observable characteristics using binary probit models with participation as the dependent variable. These characteristics include socio-demographic-characteristics (e.g., age, nationality, marital status), regional information (regional type, unemployment rate), educational and vocational attainment, the (un-)employment history (four years prior to program entry), and

[10] If we drop the assumption of independence, i.e., if we allow for non-zero correlation between treatment effects, implications only marginally change.

information on the last employment spell (duration, income, business sector).[11] We run these regressions separately for the different sub-samples of participants and non-participants according to program type, gender, and level of vocational education or age, respectively.

The distribution of the estimated propensity score is depicted in Figures 4 and 5. A visual analysis already suggests that the overlap between the group of participants and non-participants in general is sufficient within all sub-samples. Nonetheless, in some cases there are parts of the distribution where participants seem to lack comparable non-participants. However, by using the usual 'Minmax' criterion, where treated individuals are excluded from the sample whose propensity score lies above the highest propensity score in the comparison group, only 4 (24) individuals are dropped in the sub-samples previously stratified with respect to the level of vocational eduction (with respect to age).

[Figures 4 and 5 about here]

After estimating the propensity score we match each participant with a distinct non-participant within the different sub-samples by exact covariate matching plus propensity score matching.[12] Non-participants are required to not having participated in the *respective* type of public training program before and in the quarter of the participant's program entry. The variables used for exact matching are previous duration of unemployment (in months) and quarter of (fictitious) program entry. Therefore, we stratify the sub-samples by these variables first, and then implement propensity score matching for each cell without replacing the matched non-participant.

This procedure ensures that matched participants and non-participants (a) are previously unemployed for the same duration at the (fictitious) program entry, and (b) are (fictitiously) entering the program in the same quarter. While the latter condition makes sure that seasonal influences are held constant and that the observation period is the same for matched pairs, the former condition builds on similar arguments as, e.g., Sianesi (2004) put forward. She argues that participation de-

[11] The exact specifications are not reported here, but are available from the authors upon request.

[12] The matching algorithm is implemented using the `PSMATCH2` Stata ado-package by Leuven and Sianesi (2003).

cisions in ALMP are to be viewed subsequently over time in unemployment, since choices faced by unemployed individuals are not whether to participate or not to participate at all, but rather whether to join a program now or not to participate for now. According to this line of argumentation, it is fundamental to ensure the same elapsed duration in unemployment for matched treated and controls.

However, we use program entry as our point of reference rather than following entrants into unemployment over time (inflow sample into unemployment). The estimates we present below can thus be viewed as the outcome of the joining-waiting decision after the same elapsed duration of unemployment for given individuals. Our approach allows us to estimate the ATT for average participants in given program types in 2002—as opposed to the ATT for participants in given program types of a specific entry cohort in unemployment. Importantly, exact matching on the previous unemployment duration only considers the past up to the (fictitious) entry into the given program. Future outcomes are not considered in this context. In particular, non-participants can potentially participate in the given program type *after* the (fictitious) program entry. Sianesi (2004) employs a similar definition of non-participation. She argues—for the case of Sweden—that in principle any unemployed individual will join a program at some time, provided he remains unemployed long enough. We think that Sweden is similar to Germany in this respect. Hence, a restriction on future outcomes—i.e., to require non-participation in the follow-up period after the (fictitious) program entry—is supposed to affect estimated treatment effects negatively, since a substantial fraction of the 'never treated'-individuals would *de facto* be observed to leave the unemployment register.[13]

After forming the matched pairs, a suitable way to assess the matching quality is comparison of the standardized bias before matching, SB^b, to the standardized bias after matching, SB^a. The standardized biases are defined as

$$SB^b = \frac{(\overline{X}_1 - \overline{X}_0)}{\sqrt{0.5 \cdot (V_1(X) + V_0(X))}} \quad ; \quad SB^a = \frac{(\overline{X}_{1M} - \overline{X}_{0M})}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{0M}(X))}} \ , \qquad (4)$$

[13]For instance, Lechner and Wunsch (2007) require non-participation in the follow-up period after the (fictitious) program entry for comparison individuals. Applying the same definition of non-participation to our data lowers the estimated treatment effects (see Section 4.4 for details). Although we opted for the above stated definition of non-participation and do not exclude future participants, the alternative approach clearly has the advantage of employing a very straightforward definition of non-participation.

where X_1 (V_1) is the mean (variance) in the treated group before matching and X_0 (V_0) the analogue for the comparison group. X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values after matching (Rosenbaum and Rubin, 1985). Following the example of Sianesi (2004) we also re-estimate the propensity score on the matched sample to compute the pseudo-R^2 before and after matching.

Tables 3 and 4 suggest that the quality of our matching procedures is satisfactory: the percentage biases of a number of covariates are apparently reduced and any significant differences in these covariates disappear after matching. More specifically, the standardized bias for each covariate is below 6 percent after matching. Moreover, the mean standardized bias of the matched samples are noticeably smaller than that of the unmatched sample (between 0.8 and 1.9 percent in the different sub-samples). Likewise, the pseudo-R^2 after matching are fairly low and decrease substantially compared to before matching. Tables A3–A5 (see Appendix) include more details concerning the matching quality by program type, e.g., regarding the balancing of covariates.

[Tables 3 and 4 about here]

Training programs may have an influence on the employment probability as well as on the (potential) earnings of the participants. Evaluating the causal effect on the employment probability is straightforward and given by a simple comparison of treatment and control group. In contrast to that, a simple comparison of the realized wages does not give us a clear measure of the causal effect of program participation. Realized earnings are the product of the employment probability and the observed individual earnings, i.e., realized earnings are only a 'crude' measure of the effect on productivity (Lechner and Melly, 2007). Measuring the causal effect on the earnings would require taking into account the selection into the observed employment, e.g., by making use of an instrument which influences the employment probability but not the earnings.[14] In general, such an instrument is not available.

However, we argue that we can nonetheless gain interesting insights into the effects of participation on the (observed) monthly earnings by comparing the earnings

[14]Lechner and Melly (2007) propose to estimate bounds for the earnings effects as an alternative method. However, this approach goes beyond the scope of this paper.

distributions between treated and controls. From a policy point of view, it is interesting to know to which extent the share of individuals ending up in higher paid jobs is increased by participating in training programs. This effect is given by a comparison of the shares of individuals entering a job above certain thresholds or within a given strata. This is not the causal effect on the—only partially observed—earnings capacity, but the causal effect on the realized monthly earnings. And in contrast to a simple comparison of mean earnings, we can gather information on whether new jobs are mainly lower or higher paid jobs—given participation or non-participation. The mentioned thresholds (or strata) are in our case based on the overall distribution of monthly earnings two years after program entry. In other words, we calculate quartiles of the earnings distribution for participants and matched non-participants across program types—given positive monthly earnings are observed—and compare the fraction of treated and controls between these thresholds for the sub-groups under consideration.

4 Results

After applying the matching approach as described above, the ATT can be calculated as the difference in mean outcomes between the groups of matched participants and non-participants. Below, we present estimates of differences in employment probabilities and monthly earnings generated from employment in the primary labor market for a period of two years after the (fictitious) program entry.[15] While average treatment effects for the whole sample are discussed in Subsection 4.1, the effect heterogeneity of these effects with respect to vocational education is regarded in Subsection 4.2 and with respect to age in Subsection 4.3. Subsequently, we consider the sensitivity of our results in Subsection 4.4.

4.1 Average Treatment Effects

To obtain a general impression of the ATT on employment probabilities and monthly earnings, we aggregate the matched sub-groups for each program type and calculate

[15]We thus follow the prevailing approach in the recent evaluation literature. A different approach concentrates on treatment effects only after the end of the program. For advantages and disadvantages of both approaches see, e.g., Caliendo and Kopeinig (2008).

treatment effects as the difference in mean outcomes between participants and non-participants in the resulting samples. Although this procedure was implemented both for the matched sub-samples previously stratified according to the level of vocational education and with respect to age groups, the latter results are not reported in this section since they do not differ.[16]

The treatment effects display ATT on employment probabilities and monthly earnings effects, respectively, for a period of 24 months after the (fictitious) program entry. These effects, for one thing, consist of lock-in effects for the group of participants due to reduced search activities while participating in a program (van Ours, 2004), and for another (as an opposing effect), of an expected increase in employment probabilities through and after completing the program.

Employment Probabilities

For program type 1, we find that participation has a significantly positive impact on the probability of being employed starting about 13 months after program entry (see Figure 6). However, in previous months the impact of being locked-in in the program leads to significantly negative point estimates of the ATT. Two years after program entry we observe a point estimate of about 8.5 percentage points.

[Figure 6 about here]

Our findings on the general effectiveness of type 2 are also rather positive. Although the effect of being locked-in in the program is apparent, we find that participation (significantly) increases the probability of being employed already starting about 7 (8) months after program entry. Two years after program entry, the point estimate is slightly lower than for type 1, but still amounts to roughly 7.5 percentage points.

A positive impact of participation on employment probabilities is also found for program type 3. We compute a point estimate of about 6 percentage points two years after program entry. Here, the treatment effect becomes significantly positive about 10 months after entering the program.

[16] However, these results are available from the authors upon request.

Monthly Earnings Effects

For all program types and over the whole two-year-period after program entry, the ATT on monthly earnings (see Figure A1, Appendix) do not exhibit major differences compared to the ATT on employment probabilities described above and will thus not be further discussed in Sections 4.2 and 4.3.[17] However, to give an idea about the magnitude of the monthly earnings effects two years after entering the program, participants in type 1 (2 and 3) earn about 130 Euros (100 Euros) per month more than comparable non-participants.

[Figure 7 about here]

Figure 7 displays the monthly earnings distribution along with the employment effects two years after program entry. Again, the above described positive employment effects for each program type can be observed. Moreover, it is possible to assess to what type of jobs (in terms of monthly earnings) the positive employment effects lead. Therefore, individuals with earnings from unsubsidized employment in the primary labor market are divided into quartiles. The fourth quartile includes gross monthly earnings up to 1,050 Euros, the third quartile up to 1,439 Euros, the second up to 1,890 Euros and the first quartile includes monthly earnings above 1,890 Euros. The graphs show that participants of types 1 and 3 enter additional jobs in the top three quartiles of the earnings distribution (and in particular show a significant increase in the first quartile), while for participants of type 2 we observe significantly increased shares in both the middle quartiles. For all types, the fraction of participants in the bottom quartile is about the same as it were without participation.

4.2 Treatment Effects with regard to Vocational Education

The following section describes the effect heterogeneity of treatment effects with respect to the participants' level of vocational education. For this purpose, we distinguish between male and female participants with and without a vocational degree.

[17] Figures and Tables concerning these results can be found in the Appendix.

Employment Probabilities

For all three types, the resulting treatment effects across all sub-groups within each type are quite similar. Nonetheless, some differences appear among the three types (as already discussed in the previous section) and some small differences occur within each type.

For type 1, positive treatment effects can be observed starting about 13 months after program entry for individuals with a vocational degree (see Figure 8a). For individuals without a vocational degree, we find (significantly) positive treatment effects after 9 (10) for men, and (significantly) positive treatment effects after 13 (16) months for women. Also the point estimates of the ATT two years after entering the program show minor differences for the different sub-groups: for male (female) individuals with a vocational degree they amount to about 9 (8.5) percentage points, while for both sub-groups of individuals without a vocational degree they amount to roughly 8 percentage points (compare Table 5).

[Figure 8 and Table 5 about here]

For type 2, treatment effects become positive about 6–7 months after program entry for all sub-groups (see Figure 8b). However, the magnitude of the estimated treatment effects varies (compare Table 5): while the point estimate for female participants without a vocational degree amounts to almost 9 percentage points two years after entering the program, the ATT is estimated to be 5 percentage points for male participants without a vocational degree. With roughly 7.5 percentage points the estimated ATT for individuals with a vocational degree lie in between.

For type 3, we observe a similar pattern for women, irrespective of their level of vocational education (see Figure 8c). The estimated ATT become positive about 10 months after program entry and lie between 6.5 and 7 percentage points two years after program entry (compare Table 5). While it also takes about 10 months after program entry to observe positive treatment effects for male participants of this program type, the point estimates two years after program entry are lower than for female participants. For male participants with a vocational degree the point estimate of the ATT amounts to about 6 percentage points, while it only lies around 4.5 percentage points for men without a vocational degree.

In summary, it is important to note that we find—with respect to the ATT two years after program entry—only one significant difference between sub-groups. For program type 2, men without a degree gain significantly less by participating in training than women without a degree. No other significant differences are observed.

Monthly Earnings Effects

There are also only minor differences in monthly earnings effects across sub-groups within each program type, as is the case for the ATT on employment probabilities just discussed.

For type 1, Figure 9a shows the monthly earnings distribution along with the employment effects two years after program entry. Across all sub-groups, an additional fraction of participants enters jobs in the top quartiles of the earnings distribution—especially in the first quartile, where this increase is significantly positive for all sub-groups. Furthermore, the share of participants in the bottom quartile of the earnings distribution is at most equal or even significantly lower (for male participants with a vocational degree) compared to matched non-participants.

[Figure 9 about here]

When looking at the monthly earnings distribution for type 2 in company with the employment effects two years after program entry (see Figure 9b), we can distinguish a slightly different impact of program participation for men and women: while we observe employment in additional jobs located in the second and third quartile of the earnings distribution for men (with a tendency towards the top quartile for those with a vocational degree), we find that additional jobs are mainly located in the second and third quartile with a tendency towards the bottom quartile for women—especially for those without a vocational degree.

For type 3, again, we find only minor differences across the sub-groups (see Figure 9c). Nevertheless, we can distinguish two clusters: for female participants with a vocational degree and male participants in general, additional jobs are generated in the top three quartiles of the monthly earnings distribution (with a tendency towards the first and second quartile for men with a degree, a slight tendency towards the top quartile for men without a degree, and a tendency towards the second and third quartile for women with a degree). Women without a vocational degree, however, find additional jobs in the three bottom quartiles, and especially in the fourth quartile. But this happens—and that is important—without a reduction of the share of individuals in the first quartile.

4.3 Treatment Effects with regard to Age

For the analysis of the employment effects of training programs with respect to age, we distinguish three roughly equally sized age groups: individuals below 34 years, between 34 and 42 years, and above 42 years. Again, we first show effects on employment probabilities, and subsequently assess the impact of training programs on the monthly earnings distribution two years after program entry.

Employment Probabilities

The general impression also carries over as far as the analysis of treatment effects with respect to age is concerned: the extent to which the ATT on employment probabilities vary between the sub-groups under consideration is quite small, and these differences are in almost all cases not significant.

[Figure 10 and Table 6 about here]

More specifically, for type 1 the estimated treatment effects are very similar across the age groups under consideration (see Figure 10a and Table 6). Nonetheless, we calculate lower estimates for women in general, and especially for women who are at least 43 years old. For this sub-group, two years after program entry the point estimates are between 1.6 and 3.3 percentage points lower than the estimates for the other sub-groups. However, the ATT two years after program entry are in general not significantly different across sub-groups—and in particular not within the same gender. Only if we compare the point estimates for the youngest group of male and for the oldest group of female participants, we find a significant difference.

The treatment effects for type 2, likewise, exhibit in general no significant differences across sub-groups two years after program entry (see Figure 10b and Table 6). An exception applies for male participants, where we find a significantly lower point estimate for participants below 34 years if compared to those above 42 years. Moreover, while the overall picture suggests higher ATT for men than for women, an exception is the age group below 34 years. The ATT two years after program entry for men in this age group is particularly low (3.7 percentage points). But also if female participants in this age group are considered, treatment effects are relatively low.

For type 3, we estimate relatively low—but still significantly positive—treatment effects for women above 42 years two years after program entry (see Figure 10c and Table 6). The estimated effects for male participants in the same age-group are also lower than in the other sub-groups, for which the ATT lie between 5.8 and 8.1 percentage points. The lock-in effects of program participation seem to be less persistent for men, as across all age groups the ATT become positive after around 9 months for men compared to 10–13 months for women. However, two years after program entry we calculate significantly different treatment effects compared to other sub-groups only for female participants above 42 years. The point estimate for this sub-group is significantly lower compared to men below 34 years and women between 34 and 42 years.

Monthly Earnings Effects

The impact of participation in public training programs on the monthly earnings distribution two years after program entry is depicted in Figure 11. The overall picture suggests that the share of participants in the upper quartiles of the earnings distribution is generally higher than the share of matched non-participants, while this is for most sub-groups—and in particular as far as male individuals are considered—not the case in the bottom quartile.

[Figure 11 about here]

For type 1, the share of participants which is located in the top quartile of the monthly earnings distribution two years after program entry is across all sub-groups significantly higher than the respective share of comparison individuals (see Figure 11a). On the other hand, the differences between the shares in the bottom quartile of the earnings distribution are not significant. The shares of participants in the second and third quartile of the earnings distribution are across all sub-groups higher for participants than for matched non-participants.

For types 2 and 3, the overall picture is less consistent than for type 1. Although the share of participants in the top quartile of the monthly earnings distribution is generally higher than the share of non-participants, we find significantly increased fractions only for male participants between 34 and 42 years as well as above 42 years (for both types). On the other hand, the share of male participants in type 2 between 34 and 42 years is significantly lower in the bottom quartile than the corresponding share of controls. Two other sub-groups exhibit a significantly higher share of treated individuals in the bottom quartile: female participants in type 2 above 42 years and male participants in type 3 between 34 and 42 years.

4.4 Sensitivity Analysis

To assess the sensitivity of our results with respect to the matching method, we additionally employ some alternative algorithms. Besides nearest neighbor matching without replacement, on which the above described results are based on, we calculate treatment effects based on (a) nearest neighbor matching with replacement, (b) caliper matching without replacement (with a maximum tolerance level of 0.001), and (c) radius matching (with a maximum tolerance level of 0.001). The results based on these three procedures reflect those presented above very closely. This is in line with Mueser *et al.* (2007) who also report quite similar results across a variety of matching methods if these methods are based on the same set of control variables.

As mentioned earlier, one could in principle choose a stricter definition of non-participation. Lechner and Wunsch (2007), for instance, distinguish participants from persons of the control group by conditioning on future non-participation. In their study, the impact of participation on employment probabilities two years after program entry is negative for most analyzed types. If we use a similar definition of non-participation, we find that this has an impact on the results presented here: depending on the respective sub-group, two years after program entry employment effects are 1.3–5.5 (mean: 3.8) percentage points lower for type 1, 0.1–4.6 (2.2) for type 2, and 0.0–6.0 (2.5) for type 3.

5 Conclusion

This paper studies the effects of participation in public training programs for the unemployed in Germany. We apply propensity score matching methods and estimate the treatment effects for participants in the year 2002 using a rich administrative data set. We focus, next to average treatment effects on the treated, on treatment effects for different sub-groups of participants with respect to vocational education and age.

Considering three medium-term program types—with a median duration between 6 and 8 months and together accounting for roughly 85 percent of all participants in public training programs—our results indicate that program participation has a positive impact on employment probabilities for all sub-groups and program types. Moreover, participants seem to find more often higher paid jobs than non-participants. We present only little evidence for the presence of heterogeneous treatment effects, and the magnitude of these difference is quite small.

As far as the most important program type is concerned, we do not identify significant differences in treatment effects two years after entering the program across sub-groups of the same gender with respect to vocational eduction and age. Only if we compare sub-groups of male and female participants with each other, we find a significantly different ATT between the sub-groups of young men and old women. Also in case of this program type, the lock-in effect is remarkably shorter for male participants without a vocational degree. Similar results are found for the remaining two program types. Therefore, the overall picture suggests quite homogenous effects of program participation across sub-groups.

Our results are thus—at least in part—conflicting with the strategy to increasingly provide training to individuals with better employment prospects. This strategy has been implemented in Germany as a part of the reform of ALMP in 2003. After the reform, the caseworkers are asked to evaluate the employment prospects of the unemployed in advance and provide training only to individuals with a relatively high probability of entering employment after training participation. This does not take into account the relative gain compared to the situation without training. Although we find some evidence for a complementary relationship between advantageous employment prospects and the effectiveness of training in specific cases, our finding of positive treatment effects for all sub-groups raises the question whether the exclusion of 'bad' risks from training programs is a good strategy to reduce unemployment.

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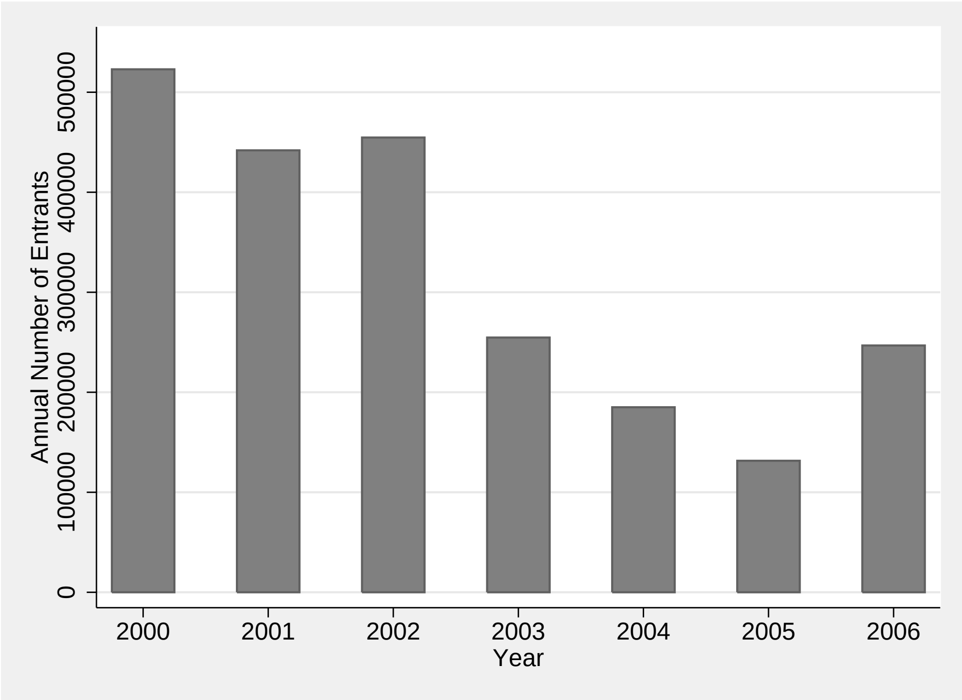
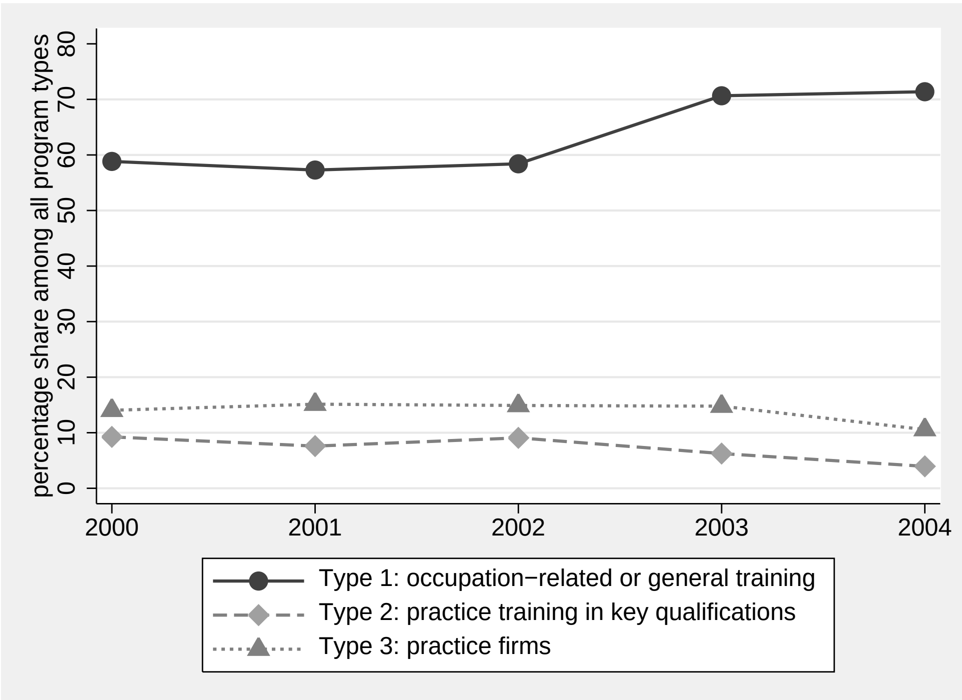
Figure 1: Entrants in Public Training Programs (2000–2006).



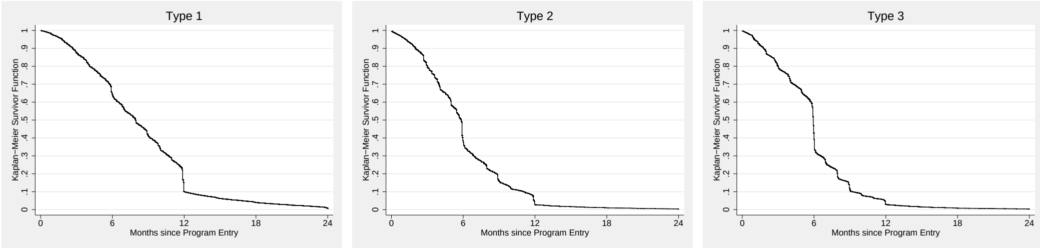
Source: Federal Employment Agency (FEA).

Figure 2: Entrants in Public Training Programs by Program Type (2000–2004).



Source: Federal Employment Agency (FEA).

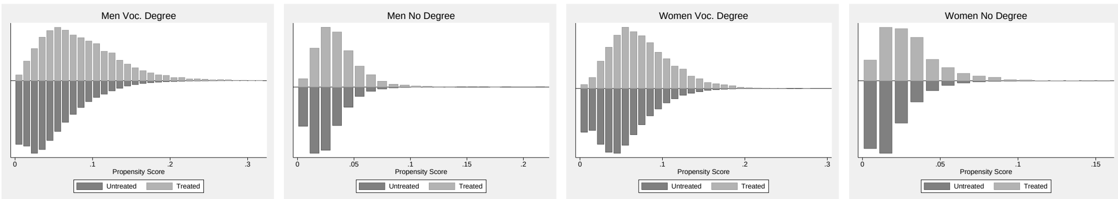
Figure 3: Actual Program Durations (Participants 2002).



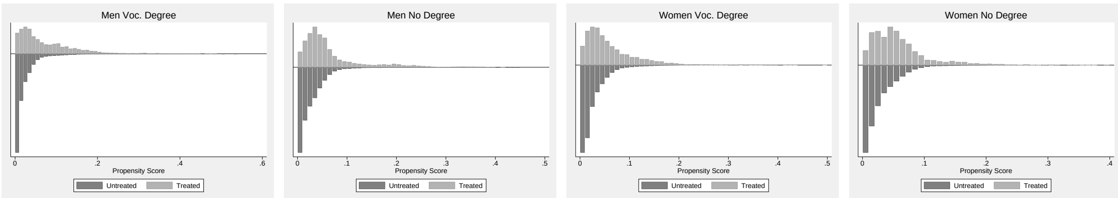
Source: IEB, own calculations.

Figure 4: Common Support Differentiated by Vocational Education.

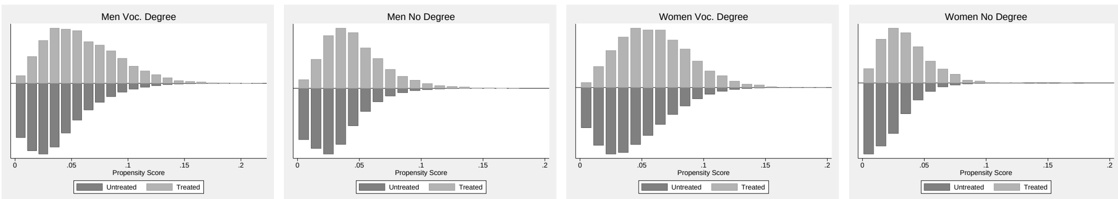
(a) Type 1



(b) Type 2



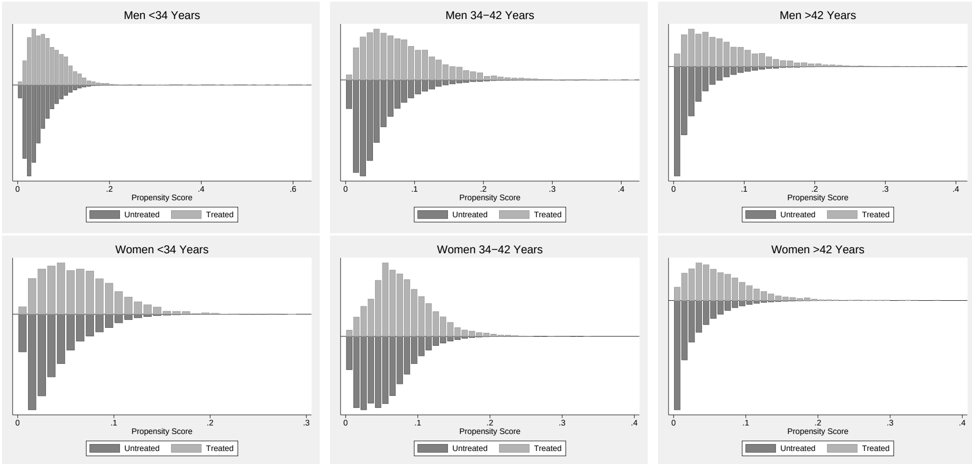
(c) Type 3



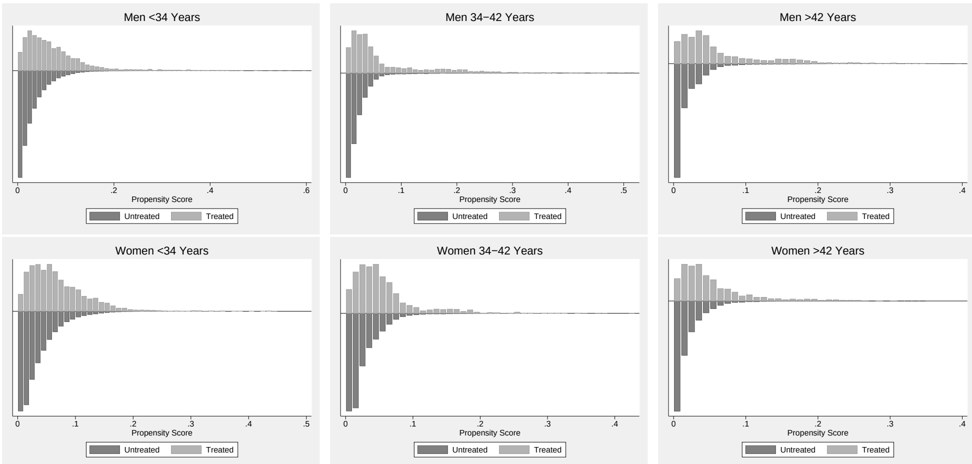
Note: Distribution of the estimated propensity scores before matching. Participants are depicted in the upper half, non-participants in the lower half of each figure.

Figure 5: Common Support Differentiated by Age Groups.

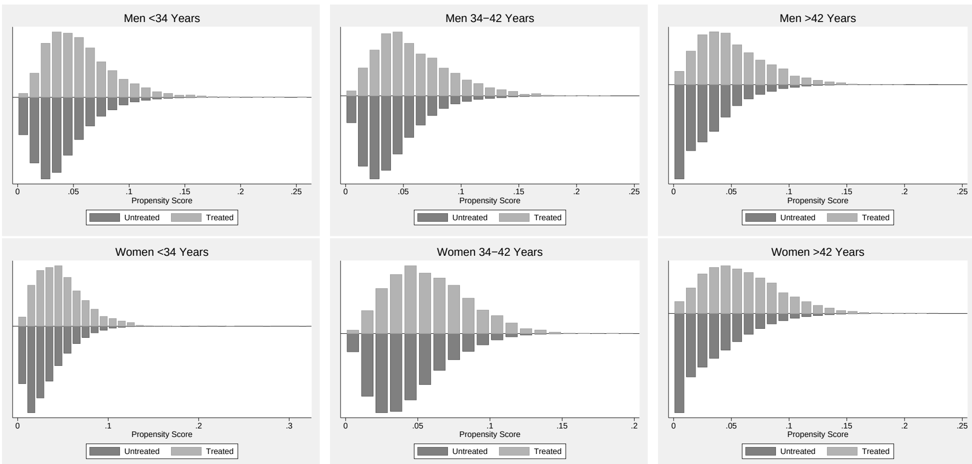
(a) Type 1



(b) Type 2

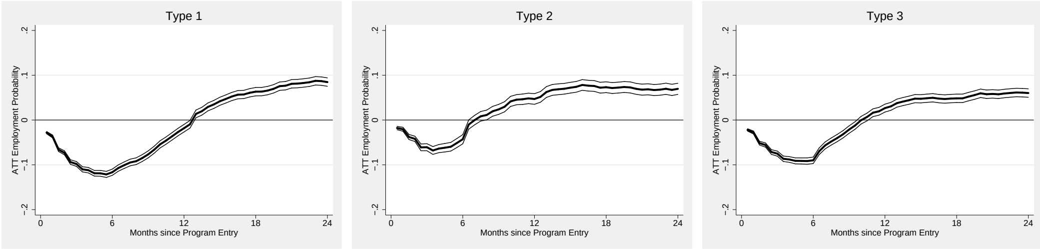


(c) Type 3



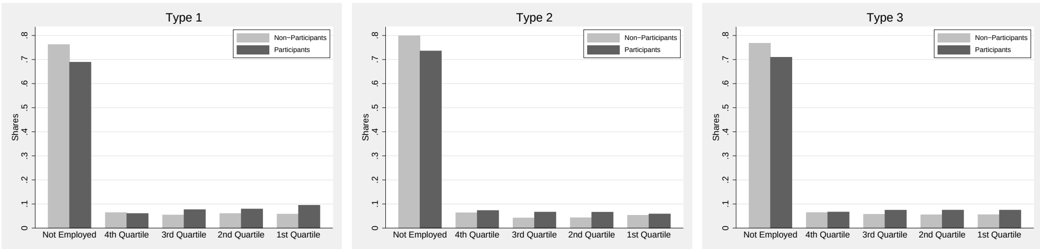
Note: Distribution of the estimated propensity scores before matching. Participants are depicted in the upper half, non-participants in the lower half of each figure.

Figure 6: ATT Employment Probabilities.



Note: Thick lines are point estimates of the ATT based on aggregated matched sub-samples with respect to vocational education, while thin lines represent 95 percent confidence intervals. The ATT for for the aggregated matched sub-samples with respect to age look very similar and are thus not displayed.

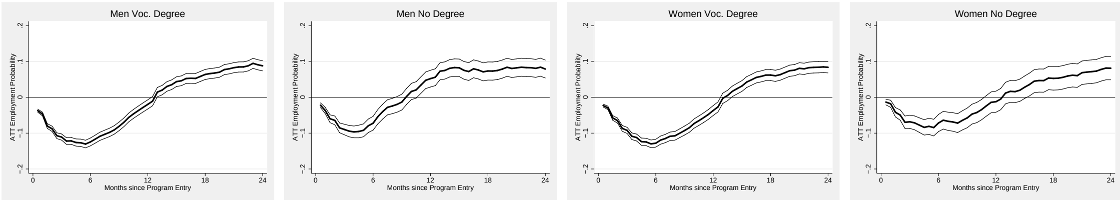
Figure 7: Monthly Earnings Distribution and Employment Effects 24 Months after Program Entry.



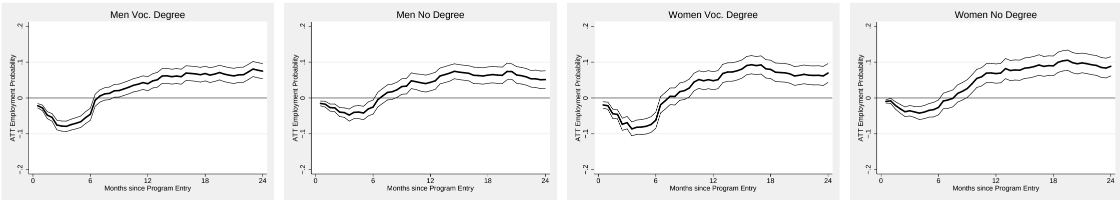
Note: Quartiles are based on the distribution of monthly earnings in the matched samples, aggregated across program types. 4th quartile: gross monthly earnings <1,050 Euros; 3rd quartile: gross monthly earnings 1,050–1,439 Euros; 2nd quartile: gross monthly earnings 1,440–1,890 Euros; 1st quartile: gross monthly earnings >1,890 Euros.

Figure 8: ATT Employment Probabilities Differentiated by Vocational Education.

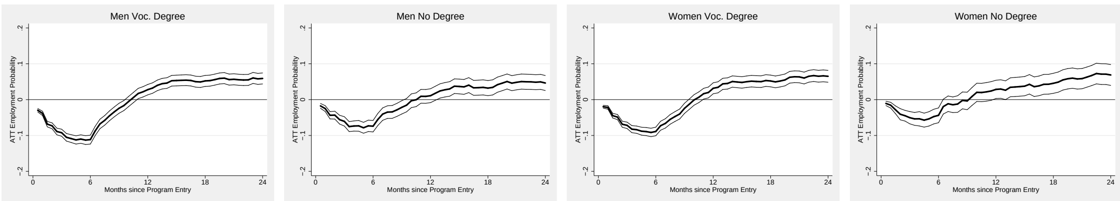
(a) Type 1



(b) Type 2



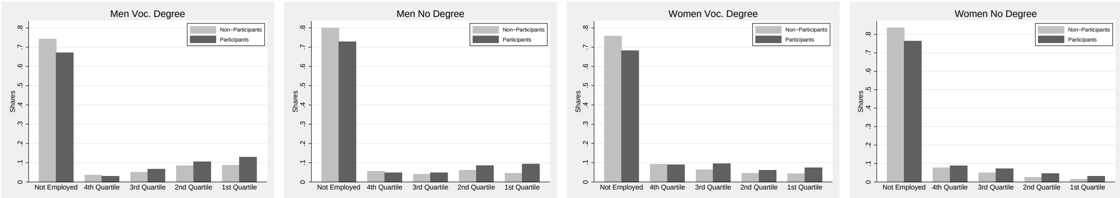
(c) Type 3



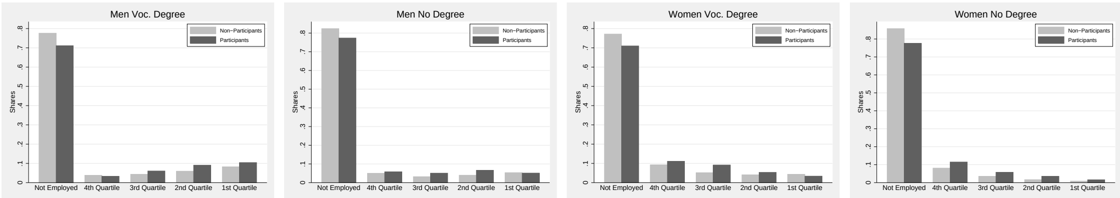
Note: Thick lines are point estimates of the ATT for the respective sub-group, while thin lines represent 95 percent confidence intervals.

Figure 9: Monthly Earnings Distribution and Employment Effects 24 Months after Program Entry, Differentiated by Vocational Education.

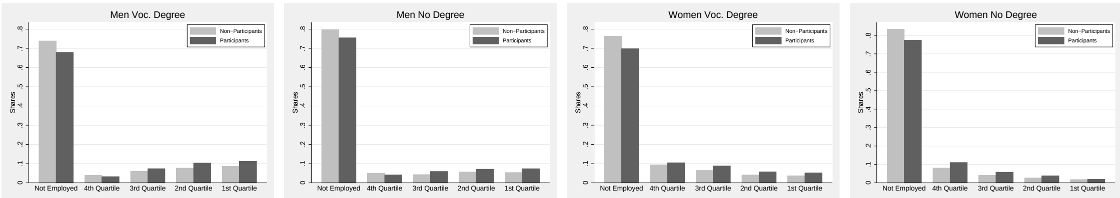
(a) Type 1



(b) Type 2



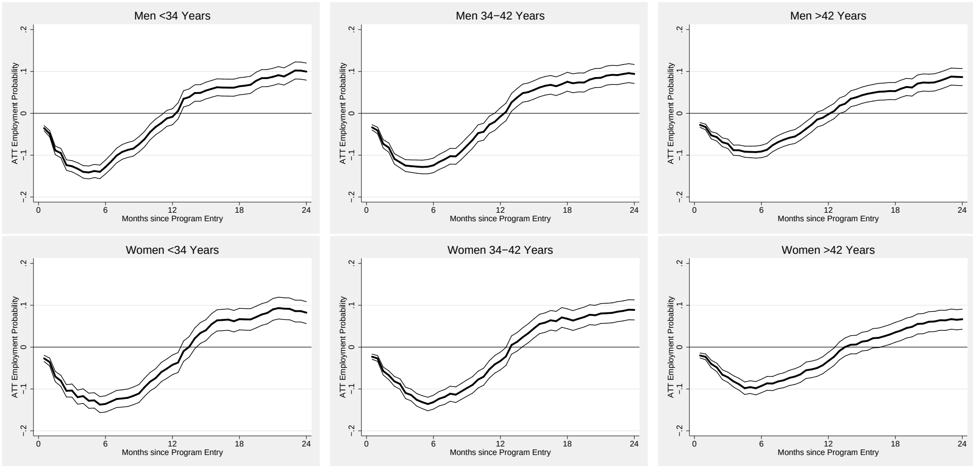
(c) Type 3



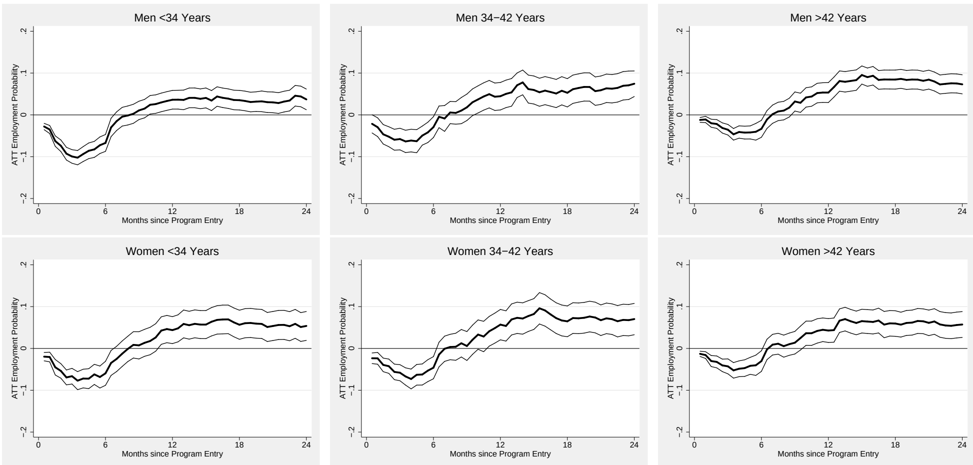
Note: Quartiles are based on the distribution of monthly earnings in the matched samples, aggregated across program types. 4th quartile: gross monthly earnings <1,050 Euros; 3rd quartile: gross monthly earnings 1,050–1,439 Euros; 2nd quartile: gross monthly earnings 1,440–1,890 Euros; 1st quartile: gross monthly earnings >1,890 Euros.

Figure 10: ATT Employment Probabilities Differentiated by Age Groups.

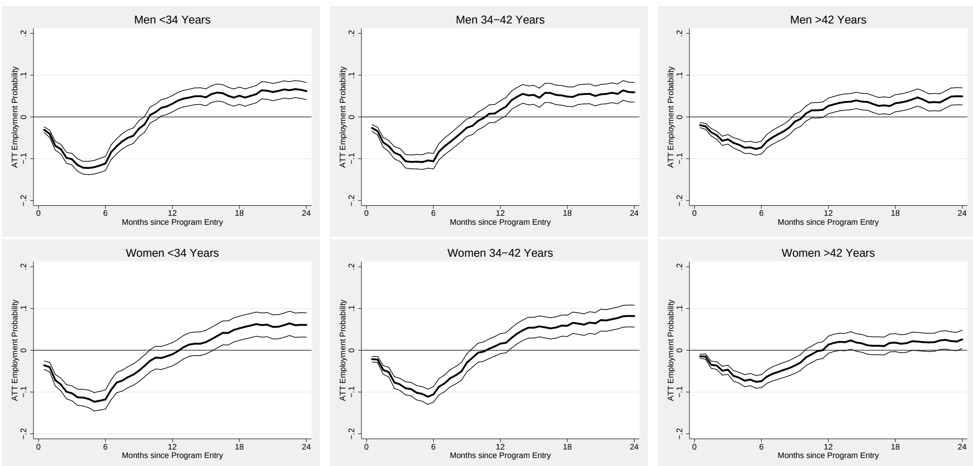
(a) Type 1



(b) Type 2



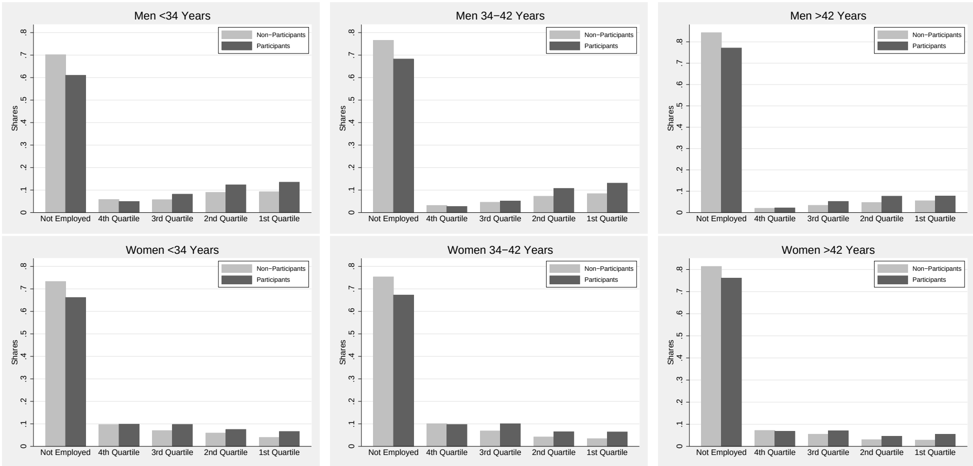
(c) Type 3



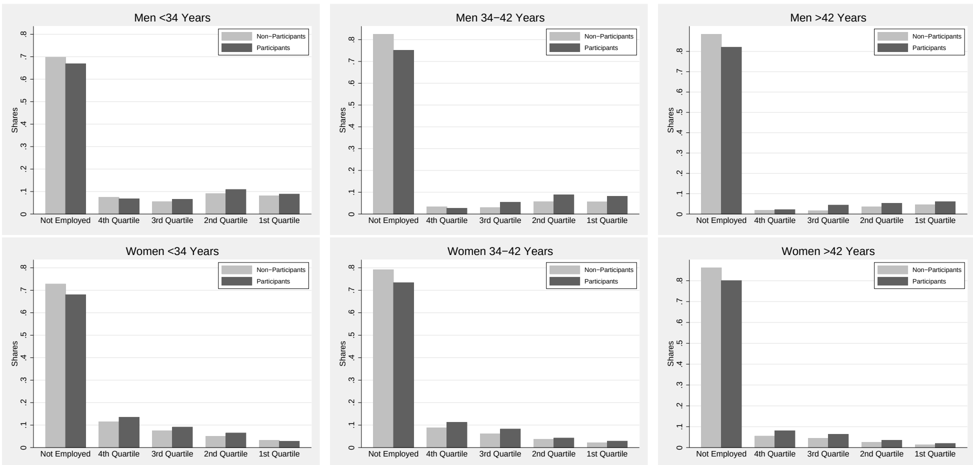
Note: Thick lines are point estimates of the ATT for the respective sub-group, while thin lines represent 95 percent confidence intervals.

Figure 11: Monthly Earnings Distribution and Employment Effects 24 Months after Program Entry, Differentiated by Age Groups.

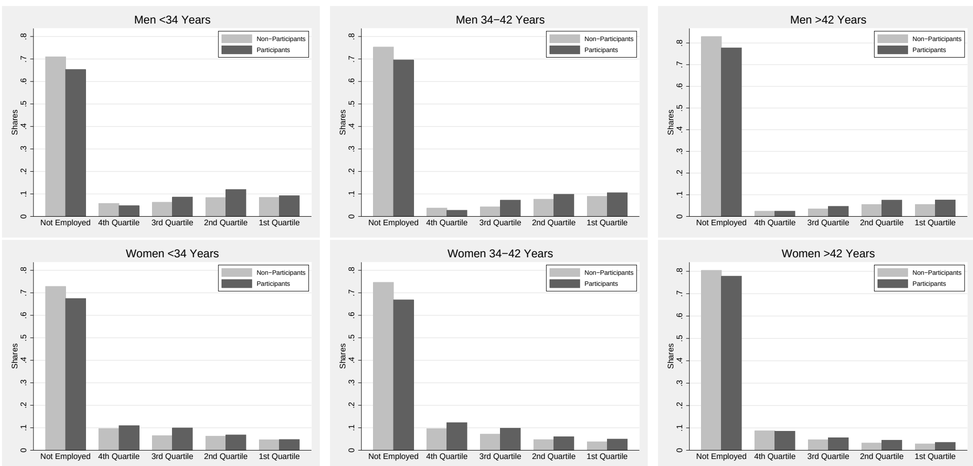
(a) Type 1



(b) Type 2



(c) Type 3



Note: Quartiles are based on the distribution of monthly earnings in the matched samples, aggregated across program types. 4th quartile: gross monthly earnings <1,050 Euros; 3rd quartile: gross monthly earnings 1,050–1,439 Euros; 2nd quartile: gross monthly earnings 1,440–1,920 Euros; 1st quartile: gross monthly earnings >1,920 Euros.

Table 1: Sub-Sample Sizes Differentiated by Vocational Education.

		Male		Female	
		Participants	Non-Participants	Participants	Non-Participants
Type 1	No Degree	3,206	126,383	1,756	94,621
	Voc. Degree	11,463	208,997	9,441	173,464
Type 2	No Degree	3,510	126,383	2,602	94,621
	Voc. Degree	5,110	208,997	4,605	173,464
Type 3	No Degree	3,932	126,383	2,061	94,621
	Voc. Degree	8,382	208,997	7,645	173,464

Note: Completed in-firm training and off-firm training as well as degrees from a vocational school, a technical school, a university, or a university of applied sciences are considered as vocational degrees.

Table 2: Sub-Sample Sizes Differentiated by Age Groups.

		Male		Female	
		Participants	Non-Participants	Participants	Non-Participants
Type 1	$<$34 years	5,759	119,615	3,582	83,993
	34–42 years	4,423	82,550	4,141	72,831
	$>$42 years	4,536	135,350	3,509	112,446
Type 2	$<$34 years	3,961	119,615	3,039	83,993
	34–42 years	1,905	82,550	1,954	72,831
	$>$42 years	2,801	135,350	2,242	112,446
Type 3	$<$34 years	4,885	119,615	2,686	83,993
	34–42 years	3,483	82,550	3,231	72,831
	$>$42 years	3,982	135,350	3,814	112,446

Table 3: Matching Quality within Sub-Samples, Differentiated by Vocational Education.

Type	Sex	Vocational Education		Mean %-Bias	Max. %-Bias	Pseudo-R^2
1	Female	Voc. Degree	Before Matching	8.905	31.803	0.041
			After Matching	0.972	2.611	0.001
1	Male	Voc. Degree	Before Matching	12.398	40.073	0.063
			After Matching	0.983	2.837	0.001
1	Female	No Degree	Before Matching	10.465	26.845	0.036
			After Matching	1.330	3.597	0.002
1	Male	No Degree	Before Matching	9.541	22.733	0.030
			After Matching	1.289	2.971	0.002
2	Female	Voc. Degree	Before Matching	10.900	46.361	0.069
			After Matching	1.157	3.355	0.002
2	Male	Voc. Degree	Before Matching	11.909	47.814	0.101
			After Matching	1.153	3.442	0.002
2	Female	No Degree	Before Matching	9.682	40.362	0.058
			After Matching	1.534	3.408	0.003
2	Male	No Degree	Before Matching	9.868	43.488	0.075
			After Matching	1.098	3.578	0.001
3	Female	Voc. Degree	Before Matching	8.401	26.462	0.026
			After Matching	0.988	3.403	0.001
3	Male	Voc. Degree	Before Matching	9.833	39.831	0.044
			After Matching	1.030	2.998	0.001
3	Female	No Degree	Before Matching	7.849	21.602	0.023
			After Matching	1.465	4.192	0.003
3	Male	No Degree	Before Matching	10.084	24.600	0.033
			After Matching	1.202	3.847	0.002

Note: Reported indicators refer to 75 variables that are at least included in the specification.

Table 4: Matching Quality within Sub-Samples, Differentiated by Age Groups.

Type	Sex	Age		Mean %-Bias	Max. %-Bias	Pseudo-R^2
1	Female	<34 years	Before Matching	12.391	48.062	0.055
			After Matching	0.949	3.672	0.002
1	Male	<34 years	Before Matching	11.567	40.533	0.047
			After Matching	0.746	2.222	0.001
1	Female	34–42 years	Before Matching	10.233	41.393	0.049
			After Matching	1.141	3.452	0.001
1	Male	34–42 years	Before Matching	14.809	35.076	0.067
			After Matching	1.161	3.511	0.002
1	Female	>42 years	Before Matching	16.253	65.459	0.097
			After Matching	1.288	3.836	0.002
1	Male	>42 years	Before Matching	17.296	60.275	0.104
			After Matching	0.881	2.700	0.001
2	Female	<34 years	Before Matching	11.615	51.886	0.070
			After Matching	1.539	4.256	0.003
2	Male	<34 years	Before Matching	12.085	48.487	0.092
			After Matching	1.529	4.635	0.003
2	Female	34–42 years	Before Matching	9.746	42.853	0.052
			After Matching	1.736	5.497	0.005
2	Male	34–42 years	Before Matching	12.672	58.718	0.094
			After Matching	1.641	4.787	0.004
2	Female	>42 years	Before Matching	10.395	53.757	0.077
			After Matching	1.280	4.519	0.003
2	Male	>42 years	Before Matching	12.402	58.541	0.102
			After Matching	1.887	5.680	0.003
3	Female	<34 years	Before Matching	11.860	36.372	0.042
			After Matching	1.491	5.067	0.003
3	Male	<34 years	Before Matching	9.743	30.744	0.039
			After Matching	0.998	3.283	0.001
3	Female	34–42 years	Before Matching	8.642	30.207	0.025
			After Matching	0.842	2.871	0.001
3	Male	34–42 years	Before Matching	9.124	29.356	0.036
			After Matching	1.323	3.596	0.002
3	Female	>42 years	Before Matching	12.351	56.536	0.062
			After Matching	1.414	3.375	0.002
3	Male	>42 years	Before Matching	12.472	58.976	0.064
			After Matching	0.991	3.276	0.002

Note: Reported indicators refer to 75 variables that are at least included in the specification.

Table 5: ATT Employment Probabilities Differentiated by Vocational Education.

Type	Sex	Vocational Education	Month After Program Entry	Emp. Prob. NP	Emp. Prob. P	Δ_{ATT}	Lower Bound 95% CI	Upper Bound 95% CI
1	Female	Voc. Degree	6	0.1905	0.0625	-0.1280	-0.1390	-0.1171
			12	0.2370	0.2001	-0.0368	-0.0507	-0.0230
			18	0.2709	0.3330	0.0621	0.0466	0.0776
			24	0.2812	0.3650	0.0838	0.0681	0.0996
1	Male	Voc. Degree	6	0.2304	0.1058	-0.1246	-0.1354	-0.1137
			12	0.2677	0.2479	-0.0198	-0.0325	-0.0070
			18	0.3143	0.3781	0.0638	0.0498	0.0778
			24	0.3144	0.4022	0.0878	0.0738	0.1019
1	Female	No Degree	6	0.1392	0.0675	-0.0717	-0.0956	-0.0478
			12	0.1758	0.1635	-0.0123	-0.0417	0.0171
			18	0.1954	0.2482	0.0527	0.0201	0.0853
			24	0.1805	0.2618	0.0812	0.0488	0.1136
1	Male	No Degree	6	0.1648	0.0925	-0.0724	-0.0916	-0.0532
			12	0.1958	0.2479	0.0521	0.0287	0.0755
			18	0.2373	0.3107	0.0734	0.0481	0.0987
			24	0.2286	0.3075	0.0788	0.0539	0.1038
2	Female	Voc. Degree	6	0.1928	0.1307	-0.0621	-0.0848	-0.0395
			12	0.2226	0.2706	0.0481	0.0229	0.0733
			18	0.2402	0.3199	0.0797	0.0541	0.1054
			24	0.2530	0.3227	0.0696	0.0433	0.0960
2	Male	Voc. Degree	6	0.1944	0.1489	-0.0455	-0.0624	-0.0286
			12	0.2415	0.2813	0.0398	0.0201	0.0595
			18	0.2634	0.3316	0.0682	0.0476	0.0887
			24	0.2603	0.3352	0.0749	0.0539	0.0960
2	Female	No Degree	6	0.1224	0.0961	-0.0263	-0.0471	-0.0055
			12	0.1494	0.2174	0.0680	0.0412	0.0949
			18	0.1606	0.2502	0.0896	0.0621	0.1171
			24	0.1614	0.2497	0.0883	0.0616	0.1150
2	Male	No Degree	6	0.1458	0.1205	-0.0253	-0.0450	-0.0056
			12	0.1743	0.2180	0.0436	0.0200	0.0673
			18	0.1867	0.2505	0.0637	0.0409	0.0865
			24	0.2038	0.2552	0.0514	0.0269	0.0758
3	Female	Voc. Degree	6	0.1767	0.0879	-0.0888	-0.1007	-0.0768
			12	0.2222	0.2540	0.0317	0.0164	0.0470
			18	0.2637	0.3158	0.0521	0.0357	0.0685
			24	0.2724	0.3376	0.0652	0.0486	0.0817
3	Male	Voc. Degree	6	0.2352	0.1237	-0.1115	-0.1239	-0.0991
			12	0.2644	0.2923	0.0279	0.0134	0.0424
			18	0.3106	0.3628	0.0523	0.0369	0.0676
			24	0.3093	0.3684	0.0591	0.0438	0.0745
3	Female	No Degree	6	0.1113	0.0675	-0.0437	-0.0644	-0.0231
			12	0.1528	0.1814	0.0286	0.0031	0.0541
			18	0.1826	0.2282	0.0456	0.0176	0.0735
			24	0.1844	0.2533	0.0688	0.0398	0.0979
3	Male	No Degree	6	0.1637	0.0896	-0.0740	-0.0900	-0.0580
			12	0.1991	0.2101	0.0110	-0.0084	0.0304
			18	0.2344	0.2666	0.0322	0.0111	0.0533
			24	0.2302	0.2765	0.0464	0.0255	0.0673

Note: NP: Non-Participants; P: Participants; CI: confidence interval.

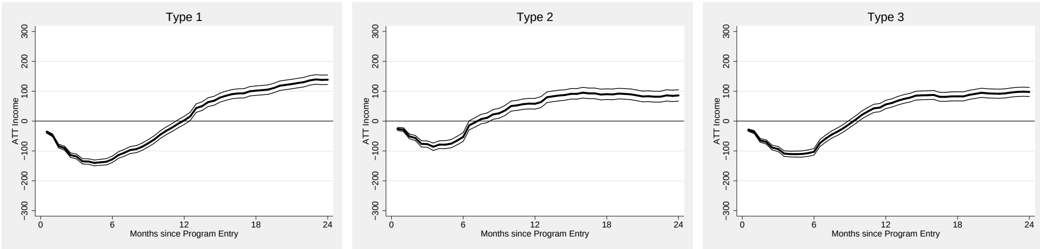
Table 6: ATT Employment Probabilities Differentiated by Age Groups.

Type	Sex	Age Group	Month After Program Entry	Emp. Prob. NP	Emp. Prob. P	Δ_{ATT}	Lower Bound 95% CI	Upper Bound 95% CI
1	Female	<34 years	6	0.2207	0.0850	-0.1357	-0.1551	-0.1163
			12	0.2683	0.2260	-0.0423	-0.0658	-0.0188
			18	0.2883	0.3551	0.0668	0.0411	0.0925
			24	0.3047	0.3871	0.0823	0.0562	0.1085
1	Male	<34 years	6	0.2605	0.1323	-0.1283	-0.1448	-0.1117
			12	0.3033	0.2951	-0.0082	-0.0274	0.0109
			18	0.3524	0.4170	0.0646	0.0441	0.0850
			24	0.3394	0.4390	0.0997	0.0793	0.1200
1	Female	34–42 years	6	0.1886	0.0571	-0.1315	-0.1480	-0.1149
			12	0.2362	0.2031	-0.0331	-0.0543	-0.0119
			18	0.2733	0.3410	0.0677	0.0441	0.0914
			24	0.2808	0.3697	0.0889	0.0650	0.1128
1	Male	34–42 years	6	0.2243	0.0999	-0.1244	-0.1418	-0.1069
			12	0.2607	0.2532	-0.0075	-0.0283	0.0133
			18	0.2985	0.3739	0.0754	0.0529	0.0979
			24	0.2966	0.3906	0.0940	0.0714	0.1167
1	Female	>42 years	6	0.1417	0.0490	-0.0928	-0.1089	-0.0767
			12	0.1873	0.1543	-0.0330	-0.0536	-0.0125
			18	0.2268	0.2621	0.0353	0.0116	0.0591
			24	0.2224	0.2890	0.0666	0.0426	0.0906
1	Male	>42 years	6	0.1624	0.0712	-0.0912	-0.1060	-0.0763
			12	0.1892	0.1870	-0.0022	-0.0202	0.0158
			18	0.2364	0.2894	0.0530	0.0324	0.0736
			24	0.2184	0.3050	0.0866	0.0662	0.1070
2	Female	<34 years	6	0.2168	0.1573	-0.0595	-0.0882	-0.0308
			12	0.2511	0.2949	0.0438	0.0116	0.0760
			18	0.2965	0.3532	0.0566	0.0219	0.0914
			24	0.2963	0.3501	0.0538	0.0192	0.0883
2	Male	<34 years	6	0.2505	0.1834	-0.0671	-0.0872	-0.0469
			12	0.2791	0.3153	0.0362	0.0139	0.0585
			18	0.3238	0.3590	0.0352	0.0118	0.0586
			24	0.3313	0.3683	0.0370	0.0123	0.0617
2	Female	34–42 years	6	0.1472	0.1012	-0.0461	-0.0725	-0.0196
			12	0.2059	0.2628	0.0569	0.0206	0.0932
			18	0.2304	0.2953	0.0648	0.0280	0.1017
			24	0.2274	0.2976	0.0702	0.0328	0.1077
2	Male	34–42 years	6	0.1541	0.1248	-0.0293	-0.0542	-0.0044
			12	0.1905	0.2352	0.0446	0.0118	0.0775
			18	0.2186	0.2714	0.0528	0.0190	0.0866
			24	0.2109	0.2854	0.0745	0.0439	0.1051
2	Female	>42 years	6	0.1147	0.0845	-0.0303	-0.0549	-0.0056
			12	0.1449	0.1878	0.0428	0.0143	0.0713
			18	0.1624	0.2219	0.0595	0.0290	0.0901
			24	0.1717	0.2289	0.0572	0.0263	0.0881
2	Male	>42 years	6	0.1161	0.0828	-0.0333	-0.0536	-0.0130
			12	0.1342	0.1876	0.0534	0.0295	0.0772
			18	0.1498	0.2343	0.0845	0.0617	0.1072
			24	0.1516	0.2247	0.0731	0.0503	0.0959
3	Female	<34 years	6	0.2296	0.1119	-0.1177	-0.1405	-0.0948
			12	0.2851	0.2756	-0.0095	-0.0372	0.0183
			18	0.2992	0.3518	0.0526	0.0237	0.0816
			24	0.3047	0.3654	0.0606	0.0315	0.0897
3	Male	<34 years	6	0.2475	0.1362	-0.1114	-0.1283	-0.0944
			12	0.2830	0.3147	0.0318	0.0122	0.0513
			18	0.3303	0.3812	0.0509	0.0303	0.0715
			24	0.3246	0.3864	0.0618	0.0412	0.0823
3	Female	34–42 years	6	0.1894	0.0838	-0.1056	-0.1242	-0.0870
			12	0.2450	0.2609	0.0159	-0.0080	0.0399
			18	0.2720	0.3306	0.0586	0.0331	0.0842
			24	0.2796	0.3614	0.0818	0.0557	0.1080
3	Male	34–42 years	6	0.2150	0.1091	-0.1059	-0.1245	-0.0874
			12	0.2387	0.2560	0.0173	-0.0044	0.0389
			18	0.2902	0.3389	0.0487	0.0252	0.0722
			24	0.2865	0.3454	0.0589	0.0354	0.0824
3	Female	>42 years	6	0.1390	0.0650	-0.0740	-0.0894	-0.0586
			12	0.1841	0.1975	0.0134	-0.0071	0.0339
			18	0.2175	0.2358	0.0182	-0.0032	0.0397
			24	0.2312	0.2574	0.0262	0.0042	0.0482
3	Male	>42 years	6	0.1595	0.0863	-0.0733	-0.0887	-0.0578
			12	0.1860	0.2124	0.0264	0.0077	0.0452
			18	0.2295	0.2622	0.0328	0.0123	0.0533
			24	0.2227	0.2720	0.0494	0.0289	0.0698

Note: NP: Non-Participants; P: Participants; CI: confidence interval.

Appendix

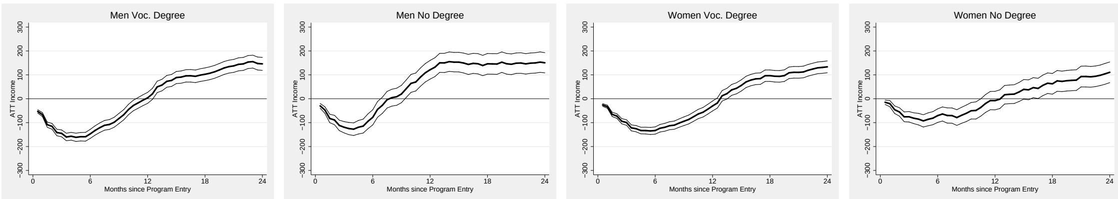
Figure A1: ATT Monthly Earnings.



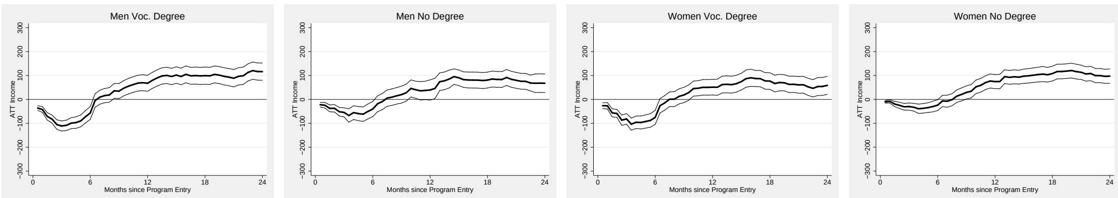
Note: Gross monthly earnings from employment (in Euros). Thick lines are point estimates of the ATT based on aggregated matched sub-samples with respect to vocational education, while thin lines represent 95 percent confidence intervals. The ATT for for the aggregated matched sub-samples with respect to age look very similar and are thus not displayed.

Figure A2: ATT Monthly Earnings Differentiated by Vocational Education.

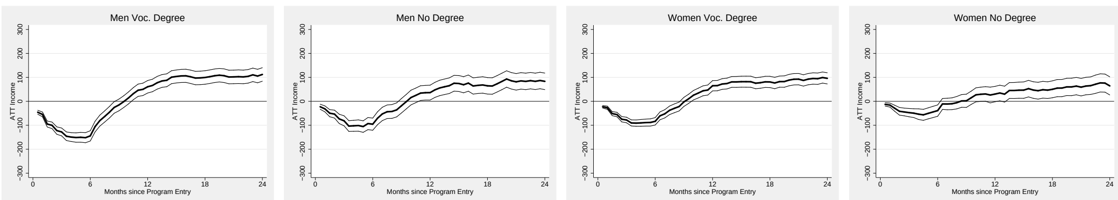
(a) Type 1



(b) Type 2



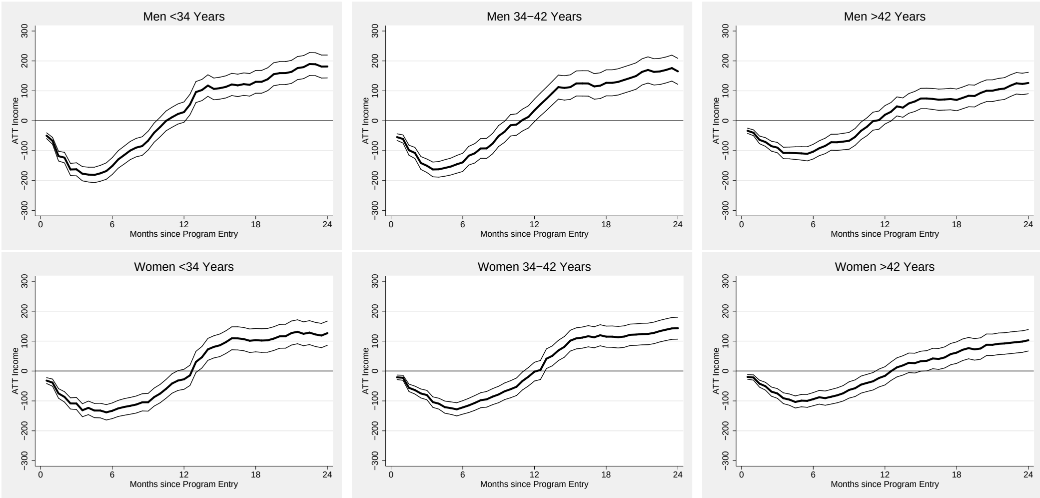
(c) Type 3



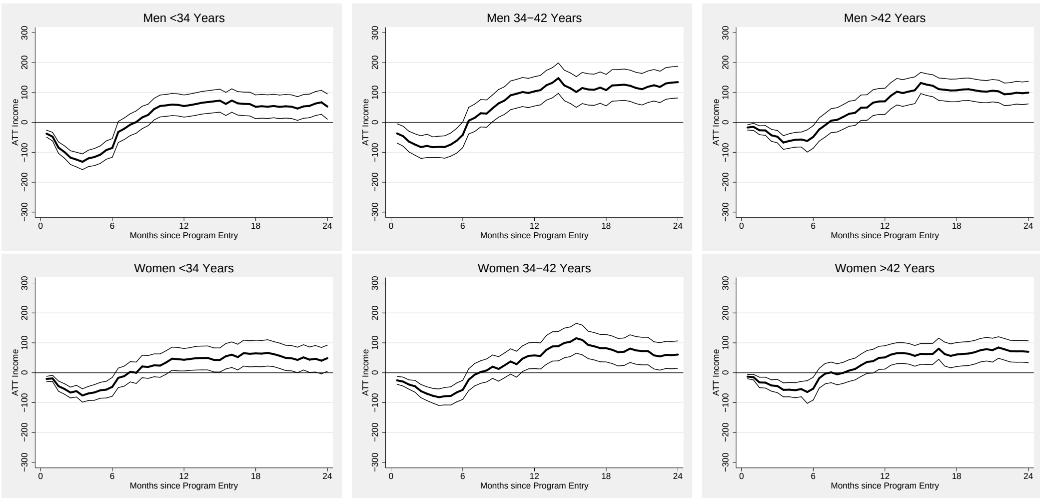
Note: Gross monthly earnings from employment (in Euros). Thick lines are point estimates of the ATT for the respective sub-group, while thin lines represent 95 percent confidence intervals.

Figure A3: ATT Monthly Earnings Differentiated by Age Groups.

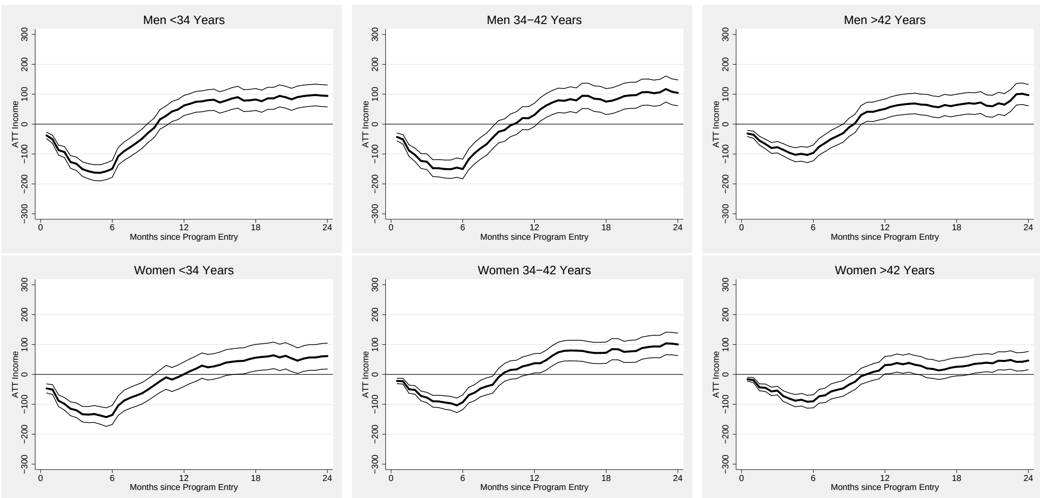
(a) Type 1



(b) Type 2



(c) Type 3



Note: Gross monthly earnings from employment (in Euros). Thick lines are point estimates of the ATT for the respective sub-group, while thin lines represent 95 percent confidence intervals.

Table A1: ATT Monthly Earnings Differentiated by Vocational Education.

Type	Sex	Vocational Education	Month After Program Entry	Av. Earnings NP	Av. Earnings P	Δ_{ATT}	Lower Bound 95% CI	Upper Bound 95% CI
1	Female	Voc. Degree	6	206.62	73.63	-132.98	-148.14	-117.82
			12	271.15	240.99	- 30.16	- 50.94	- 9.39
			18	307.64	404.26	96.62	72.70	120.54
			24	314.27	447.83	133.55	108.82	158.29
1	Male	Voc. Degree	6	301.29	154.32	-146.97	-165.89	-128.06
			12	348.20	351.97	3.77	- 19.18	26.73
			18	430.06	532.47	102.42	75.73	129.10
			24	428.86	574.88	146.01	118.88	173.14
1	Female	No Degree	6	140.04	69.45	- 70.59	- 98.94	- 42.25
			12	184.26	176.59	- 7.67	- 46.36	31.03
			18	209.20	271.65	62.45	19.13	105.77
			24	182.62	293.35	110.73	67.56	153.90
1	Male	No Degree	6	220.74	142.92	- 77.82	-109.48	- 46.15
			12	250.81	372.23	121.42	82.30	160.53
			18	309.02	455.23	146.21	103.00	189.42
			24	285.27	435.84	150.56	108.34	192.79
2	Female	Voc. Degree	6	217.05	141.94	- 75.11	-104.64	- 45.59
			12	244.40	295.64	51.24	18.55	83.93
			18	274.34	351.05	76.72	42.00	111.43
			24	291.46	350.17	58.71	21.22	96.19
2	Male	Voc. Degree	6	265.78	208.89	- 56.89	- 83.52	- 30.27
			12	343.30	410.83	67.53	34.05	101.01
			18	379.53	478.85	99.33	63.44	135.22
			24	368.83	485.06	116.23	80.14	152.33
2	Female	No Degree	6	113.04	89.00	- 24.04	- 46.70	- 1.39
			12	138.12	212.54	74.42	44.93	103.92
			18	145.24	253.26	108.02	77.11	138.92
			24	143.60	240.91	97.31	67.16	127.46
2	Male	No Degree	6	186.05	145.52	- 40.53	- 72.28	- 8.79
			12	236.68	276.13	39.45	- 2.94	81.85
			18	239.31	320.16	80.85	47.64	114.07
			24	254.06	321.61	67.55	28.61	106.50
3	Female	Voc. Degree	6	186.90	103.45	- 83.45	- 98.86	- 68.04
			12	235.43	300.43	65.00	43.54	86.46
			18	287.65	368.59	80.94	57.41	104.47
			24	295.52	391.46	95.94	72.63	119.24
3	Male	Voc. Degree	6	323.77	179.46	-144.31	-165.72	-122.89
			12	364.77	425.51	60.74	34.67	86.81
			18	432.25	531.76	99.50	71.32	127.69
			24	426.26	538.42	112.16	83.98	140.34
3	Female	No Degree	6	107.69	68.91	- 38.78	- 62.45	- 15.11
			12	158.26	188.52	30.27	- 1.81	62.35
			18	180.54	230.66	50.12	14.85	85.38
			24	187.09	251.54	64.44	26.67	102.22
3	Male	No Degree	6	217.35	121.92	- 95.43	-120.73	- 70.12
			12	259.94	296.25	36.31	5.26	67.36
			18	308.17	372.86	64.68	30.34	99.03
			24	295.70	379.05	83.35	48.86	117.84

Note: NP: Non-Participants; P: Participants; CI: confidence interval.

Table A2: ATT Monthly Earnings Differentiated by Age Groups.

Type	Sex	Age Group	Month After Program Entry	Av. Earnings NP	Av. Earnings P	Δ_{ATT}	Lower Bound 95% CI	Upper Bound 95% CI
1	Female	<34 years	6	230.11	97.21	-132.90	-159.09	-106.70
			12	290.27	262.67	- 27.60	- 61.13	5.93
			18	327.22	430.52	103.30	64.15	142.44
			24	341.62	468.31	126.68	86.22	167.14
1	Male	<34 years	6	348.33	196.91	-151.42	-179.65	-123.20
			12	407.36	436.26	28.91	- 5.18	62.99
			18	482.51	612.57	130.06	91.97	168.16
			24	469.87	651.28	181.41	143.15	219.67
1	Female	34–42 years	6	192.55	70.86	-121.68	-144.20	- 99.16
			12	250.53	248.48	- 2.05	- 33.48	29.38
			18	289.86	404.89	115.03	79.76	150.30
			24	305.28	448.63	143.36	106.68	180.03
1	Male	34–42 years	6	286.37	147.17	-139.19	-169.65	-108.73
			12	339.88	374.60	34.71	- 3.04	72.47
			18	419.05	545.77	126.73	83.20	170.25
			24	398.83	563.95	165.12	121.73	208.52
1	Female	>42 years	6	148.89	54.85	- 94.04	-115.99	- 72.09
			12	202.40	186.26	- 16.14	- 46.64	14.36
			18	248.02	309.62	61.60	25.66	97.54
			24	233.22	336.15	102.92	67.04	138.80
1	Male	>42 years	6	198.81	95.48	-103.33	-127.85	- 78.82
			12	227.02	246.83	19.81	- 10.98	50.60
			18	291.35	360.97	69.62	33.21	106.03
			24	261.82	387.98	126.16	90.33	161.98
2	Female	<34 years	6	214.08	166.92	- 47.16	- 78.61	- 15.71
			12	263.81	307.16	43.35	5.80	80.91
			18	314.20	378.84	64.64	20.59	108.69
			24	322.87	371.54	48.66	4.96	92.36
2	Male	<34 years	6	323.49	238.24	- 85.25	-116.47	- 54.04
			12	381.42	436.24	54.82	17.81	91.84
			18	451.24	503.54	52.30	12.58	92.02
			24	453.50	506.60	53.10	10.89	95.32
2	Female	34–42 years	6	163.17	105.94	- 57.23	- 89.17	- 25.29
			12	224.67	282.50	57.83	13.98	101.68
			18	249.86	331.91	82.05	36.04	128.06
			24	248.05	308.75	60.70	15.07	106.32
2	Male	34–42 years	6	218.57	177.07	- 41.51	- 84.30	1.29
			12	246.42	350.36	103.95	54.98	152.92
			18	292.89	401.05	108.16	55.57	160.76
			24	279.34	414.18	134.84	81.67	188.01
2	Female	>42 years	6	133.32	80.11	- 53.21	- 91.31	- 15.12
			12	154.05	205.20	51.15	12.15	90.15
			18	171.54	232.48	60.94	20.81	101.08
			24	165.93	235.94	70.01	33.32	106.70
2	Male	>42 years	6	133.32	80.11	- 53.21	- 91.31	- 15.12
			12	154.05	205.20	51.15	12.15	90.15
			18	171.54	232.48	60.94	20.81	101.08
			24	165.93	235.94	70.01	33.32	106.70
3	Female	<34 years	6	260.80	125.36	-135.43	-167.16	-103.71
			12	322.88	323.65	0.77	- 40.28	41.82
			18	359.07	415.25	56.18	11.88	100.47
			24	354.53	415.92	61.40	18.05	104.74
3	Male	<34 years	6	339.97	190.56	-149.41	-177.57	-121.24
			12	387.92	450.29	62.37	28.58	96.17
			18	459.78	542.12	82.34	45.65	119.03
			24	452.25	546.53	94.28	57.50	131.06
3	Female	34–42 years	6	199.68	106.70	- 92.98	-117.77	- 68.19
			12	264.48	301.88	37.40	4.98	69.81
			18	303.22	375.79	72.57	36.93	108.21
			24	318.04	418.51	100.48	62.84	138.11
3	Male	34–42 years	6	311.08	161.07	-150.01	-182.99	-117.03
			12	348.39	379.27	30.88	- 8.15	69.91
			18	435.88	511.31	75.43	32.06	118.81
			24	411.26	515.90	104.64	61.44	147.84
3	Female	>42 years	6	158.93	69.03	- 89.90	-111.77	- 68.03
			12	196.95	228.15	31.21	1.99	60.41
			18	235.84	261.54	25.70	- 4.75	56.14
			24	235.96	282.39	46.43	15.89	76.97
3	Male	>42 years	6	213.54	117.16	- 96.38	-122.77	- 69.99
			12	246.03	296.89	50.86	17.97	83.75
			18	301.82	366.04	64.23	28.21	100.24
			24	278.16	375.06	96.90	61.09	132.70

Note: NP: Non-Participants; P: Participants; CI: confidence interval.

Table A3: Overall Matching Quality, Type 1.

		Vocational Education			*Age*		
		Participants	Non-Participants	%-Bias	Participants	Non-Participants	%-Bias
Socio-demographic characteristics							
Age	Before Matching	37.142	39.389	-21.0	37.142	39.389	-21.0
	After Matching	37.151	37.051	0.9	37.158	37.138	0.2
German	Before Matching	0.0141	0.0254	- 8.1	0.0141	0.0254	- 8.1
	After Matching	0.0141	0.0146	- 0.3	0.0141	0.0142	- 0.1
Married	Before Matching	0.4780	0.4867	- 1.7	0.4780	0.4867	- 1.7
	After Matching	0.4783	0.4744	0.8	0.4785	0.4758	0.5
Dependent children: youngest kid 0–3 years old	Before Matching	0.0655	0.0496	6.8	0.0655	0.0496	6.8
	After Matching	0.0655	0.0650	0.2	0.0650	0.0653	- 0.2
Dependent children: youngest kid 4–14 years old	Before Matching	0.2407	0.1915	12.0	0.2407	0.1915	12.0
	After Matching	0.2411	0.2436	- 0.6	0.2411	0.2436	- 0.6
Educational Attainment							
No graduation	Before Matching	0.0569	0.1234	-23.4	0.0569	0.1234	-23.4
	After Matching	0.0568	0.0571	- 0.1	0.0568	0.0579	- 0.4
First stage of secondary level	Before Matching	0.3190	0.4747	-32.2	0.3190	0.4747	-32.2
	After Matching	0.3189	0.3175	0.3	0.3190	0.3137	1.1
Second stage of secondary level	Before Matching	0.4096	0.2833	26.8	0.4096	0.2833	26.8
	After Matching	0.4098	0.4075	0.5	0.4096	0.4105	- 0.2
Advanced technical college entrance qualification	Before Matching	0.0682	0.0384	13.3	0.0682	0.0384	13.3
	After Matching	0.0681	0.0688	- 0.3	0.0682	0.0700	- 0.8
General qualification for university entrance	Before Matching	0.1463	0.0802	21.0	0.1463	0.0802	21.0
	After Matching	0.1464	0.1491	- 0.8	0.1465	0.1479	- 0.5
Vocational Attainment							
No vocational degree	Before Matching	0.1918	0.3651	-39.4	0.1918	0.3651	-39.4
	After Matching	0.1913	0.1913	0.0	0.1913	0.1924	- 0.2
In-plant training	Before Matching	0.5946	0.5145	16.2	0.5946	0.5145	16.2
	After Matching	0.5953	0.5931	0.4	0.5954	0.5910	0.9
Off-the-job training, vocational school, technical school	Before Matching	0.1007	0.0693	11.3	0.1007	0.0693	11.3
	After Matching	0.1005	0.1010	- 0.2	0.1006	0.1021	- 0.6
University, advanced technical college	Before Matching	0.1129	0.0511	22.7	0.1129	0.0511	22.7
	After Matching	0.1129	0.1146	- 0.7	0.1127	0.1145	- 0.7
(Un–)Employment History							
Share of unemployment in 1st year before program entry	Before Matching	0.5840	0.5989	- 4.7	0.5840	0.5989	- 4.7
	After Matching	0.5842	0.5738	3.3	0.5841	0.5757	2.6
Share of unemployment in 2nd year before program entry	Before Matching	0.2408	0.3252	-24.2	0.2408	0.3252	-24.2
	After Matching	0.2409	0.2386	0.7	0.2408	0.2399	0.3
Share of unemployment in 3rd year before program entry	Before Matching	0.1981	0.2875	-25.9	0.1981	0.2875	-25.9
	After Matching	0.1978	0.1968	0.3	0.1979	0.1992	- 0.4
Share of unemployment in 4th year before program entry	Before Matching	0.1765	0.2575	-24.3	0.1765	0.2575	-24.3
	After Matching	0.1758	0.1760	- 0.0	0.1758	0.1785	- 0.8
Share of employment in 1st year before program entry	Before Matching	0.2425	0.2027	13.4	0.2425	0.2027	13.4
	After Matching	0.2426	0.2448	- 0.7	0.2426	0.2440	- 0.5
Share of employment in 2nd year before program entry	Before Matching	0.4681	0.3667	23.9	0.4681	0.3667	23.9
	After Matching	0.4687	0.4617	1.6	0.4685	0.4636	1.2
Share of employment in 3rd year before program entry	Before Matching	0.4781	0.3882	20.5	0.4781	0.3882	20.5
	After Matching	0.4791	0.4686	2.4	0.4791	0.4741	1.1
Share of employment in 4th year before program entry	Before Matching	0.4759	0.3994	17.4	0.4759	0.3994	17.4
	After Matching	0.4774	0.4709	1.5	0.4775	0.4733	0.9
Pseudo-R^2	Before Matching		0.058			0.058	
	After Matching		0.001			0.000	
Mean standardized bias	Before Matching		13.367			13.367	
	After Matching		0.687			0.493	

Note: Statistics are based on aggregated sub-samples before and after matching (previously stratified with respect to vocational education and age). Only selected variables are reported, while the specifications include more variables. However, mean standardized bias and pseudo-R^2 refer to 75 variables at least included in the different specifications.

Table A4: Overall Matching Quality, Type 2.

		Vocational Education			*Age*		
		Participants	Non-Participants	%-Bias	Participants	Non-Participants	%-Bias
Socio-demographic characteristics							
Age	Before Matching	35.698	39.389	-32.3	35.698	39.389	-32.3
	After Matching	35.673	35.822	- 1.3	35.671	35.591	0.7
German	Before Matching	0.0164	0.0254	- 6.3	0.0164	0.0254	- 6.3
	After Matching	0.0165	0.0174	- 0.6	0.0165	0.0169	- 0.3
Married	Before Matching	0.4112	0.4867	-15.2	0.4112	0.4867	-15.2
	After Matching	0.4113	0.4137	- 0.5	0.4112	0.4118	- 0.1
Dependent children: youngest kid 0–3 years old	Before Matching	0.0486	0.0496	- 0.5	0.0486	0.0496	- 0.5
	After Matching	0.0485	0.0490	- 0.2	0.0485	0.0450	1.6
Dependent children: youngest kid 4–14 years old	Before Matching	0.2082	0.1915	4.2	0.2082	0.1915	4.2
	After Matching	0.2087	0.2063	0.6	0.2087	0.2082	0.1
Educational Attainment							
No graduation	Before Matching	0.1241	0.1234	0.2	0.1241	0.1235	0.2
	After Matching	0.1242	0.1255	- 0.4	0.1243	0.1267	- 0.7
First stage of secondary level	Before Matching	0.5325	0.4747	11.6	0.5325	0.4747	11.6
	After Matching	0.5324	0.5327	- 0.1	0.5324	0.5298	0.5
Second stage of secondary level	Before Matching	0.2576	0.2833	- 5.8	0.2576	0.2833	- 5.8
	After Matching	0.2575	0.2534	0.9	0.2575	0.2558	0.4
Advanced technical college entrance qualification	Before Matching	0.0337	0.0384	- 2.5	0.0337	0.0384	- 2.5
	After Matching	0.0338	0.0360	- 1.2	0.0338	0.0352	- 0.7
General qualification for university entrance	Before Matching	0.0520	0.0801	-11.3	0.0520	0.0801	-11.3
	After Matching	0.0521	0.0524	- 0.1	0.0521	0.0526	- 0.2
Vocational Attainment							
No vocational degree	Before Matching	0.3862	0.3652	4.3	0.3862	0.3652	4.3
	After Matching	0.3856	0.3856	0.0	0.3855	0.3895	- 0.8
In-plant training	Before Matching	0.5069	0.5145	- 1.5	0.5069	0.5145	- 1.5
	After Matching	0.5075	0.5074	0.0	0.5076	0.5024	1.0
Off-the-job training, vocational school, technical school	Before Matching	0.0766	0.0693	2.8	0.0766	0.0693	2.8
	After Matching	0.0766	0.0767	- 0.0	0.0766	0.0767	- 0.0
University, advanced technical college	Before Matching	0.0303	0.0511	-10.6	0.0303	0.0511	-10.6
	After Matching	0.0303	0.0303	0.0	0.0303	0.0315	- 0.6
(Un–)Employment History							
Share of unemployment in 1st year before program entry	Before Matching	0.6352	0.5989	11.4	0.6352	0.5989	11.4
	After Matching	0.6344	0.6285	1.9	0.6344	0.6274	2.2
Share of unemployment in 2nd year before program entry	Before Matching	0.3267	0.3252	0.4	0.3267	0.3252	0.4
	After Matching	0.3249	0.3259	- 0.3	0.3249	0.3243	0.2
Share of unemployment in 3rd year before program entry	Before Matching	0.2688	0.2875	- 5.0	0.2688	0.2875	- 5.0
	After Matching	0.2666	0.2684	- 0.5	0.2666	0.2682	- 0.4
Share of unemployment in 4th year before program entry	Before Matching	0.2373	0.2575	- 5.6	0.2373	0.2575	- 5.6
	After Matching	0.2350	0.2347	0.1	0.2349	0.2368	- 0.5
Share of employment in 1st year before program entry	Before Matching	0.1842	0.2027	- 6.5	0.1842	0.2027	- 6.5
	After Matching	0.1847	0.1833	0.5	0.1847	0.1845	0.1
Share of employment in 2nd year before program entry	Before Matching	0.3799	0.3666	3.2	0.3799	0.3666	3.2
	After Matching	0.3811	0.3745	1.6	0.3811	0.3771	1.0
Share of employment in 3rd year before program entry	Before Matching	0.3958	0.3882	1.8	0.3958	0.3881	1.8
	After Matching	0.3975	0.3935	0.9	0.3974	0.3940	0.8
Share of employment in 4th year before program entry	Before Matching	0.3818	0.3994	- 4.1	0.3818	0.3994	- 4.1
	After Matching	0.3834	0.3843	- 0.2	0.3833	0.3814	0.5
Pseudo-R^2	Before Matching		0.076			0.076	
	After Matching		0.001			0.001	
Mean standardized bias	Before Matching		9.432			9.432	
	After Matching		0.638			0.856	

Note: Statistics are based on aggregated sub-samples before and after matching (previously stratified with respect to vocational education and age). Only selected variables are reported, while the specifications include more variables. However, mean standardized bias and pseudo-R^2 refer to 75 variables at least included in the different specifications.

Table A5: Overall Matching Quality, Type 3.

		Vocational Education			*Age*		
		Participants	Non-Participants	%-Bias	Participants	Non-Participants	%-Bias
Socio-demographic characteristics							
Age	Before Matching	37.782	39.389	-14.8	37.782	39.389	-14.8
	After Matching	37.786	37.802	- 0.1	37.787	37.783	0.0
German	Before Matching	0.0149	0.0254	- 7.5	0.0149	0.0254	- 7.5
	After Matching	0.0149	0.0155	- 0.4	0.0149	0.0163	- 1.0
Married	Before Matching	0.4971	0.4867	2.1	0.4971	0.4867	2.1
	After Matching	0.4977	0.4942	0.7	0.4976	0.4967	0.2
Dependent children: youngest kid 0–3 years old	Before Matching	0.0601	0.0496	4.6	0.0601	0.0496	4.6
	After Matching	0.0601	0.0562	1.7	0.0601	0.0588	0.6
Dependent children: youngest kid 4–14 years old	Before Matching	0.2308	0.1915	9.7	0.2308	0.1915	9.7
	After Matching	0.2310	0.2298	0.3	0.2310	0.2329	- 0.5
Educational Attainment							
No graduation	Before Matching	0.0967	0.1234	- 8.6	0.0967	0.1234	- 8.6
	After Matching	0.0967	0.0933	1.1	0.0967	0.0949	0.6
First stage of secondary level	Before Matching	0.4290	0.4747	- 9.2	0.4290	0.4747	- 9.2
	After Matching	0.4288	0.4335	- 0.9	0.4288	0.4326	- 0.8
Second stage of secondary level	Before Matching	0.3890	0.2833	22.5	0.3890	0.2833	22.5
	After Matching	0.3892	0.3880	0.2	0.3892	0.3883	0.2
Advanced technical college entrance qualification	Before Matching	0.0322	0.0384	- 3.4	0.0322	0.0384	- 3.4
	After Matching	0.0323	0.0302	1.2	0.0323	0.0315	0.4
General qualification for university entrance	Before Matching	0.0531	0.0801	-10.9	0.0531	0.0801	-10.9
	After Matching	0.0531	0.0551	- 0.8	0.0531	0.0528	0.1
Vocational Attainment							
No vocational degree	Before Matching	0.2722	0.3652	-20.1	0.2722	0.3652	-20.1
	After Matching	0.2715	0.2715	- 0.0	0.2714	0.2720	- 0.1
In-plant training	Before Matching	0.6170	0.5145	20.8	0.6170	0.5145	20.8
	After Matching	0.6177	0.6167	0.2	0.6177	0.6182	- 0.1
Off-the-job training, vocational school, technical school	Before Matching	0.0792	0.0693	3.8	0.0792	0.0693	3.8
	After Matching	0.0793	0.0809	- 0.6	0.0793	0.0792	0.1
University, advanced technical college	Before Matching	0.0316	0.0511	- 9.8	0.0316	0.0511	- 9.8
	After Matching	0.0316	0.0309	0.4	0.0316	0.0307	0.5
(Un–)Employment History							
Share of unemployment in 1st year before program entry	Before Matching	0.5917	0.5989	- 2.3	0.5917	0.5989	- 2.3
	After Matching	0.5913	0.5858	1.7	0.5913	0.5835	2.5
Share of unemployment in 2nd year before program entry	Before Matching	0.2782	0.3252	-13.0	0.2782	0.3252	-13.0
	After Matching	0.2775	0.2771	0.1	0.2776	0.2764	0.3
Share of unemployment in 3rd year before program entry	Before Matching	0.2353	0.2875	-14.6	0.2353	0.2875	-14.6
	After Matching	0.2345	0.2354	- 0.2	0.2345	0.2381	- 1.0
Share of unemployment in 4th year before program entry	Before Matching	0.2128	0.2575	-13.0	0.2128	0.2575	-13.0
	After Matching	0.2118	0.2147	- 0.8	0.2118	0.2159	- 1.2
Share of employment in 1st year before program entry	Before Matching	0.2399	0.2027	12.6	0.2399	0.2027	12.6
	After Matching	0.2401	0.2434	- 1.1	0.2400	0.2424	- 0.8
Share of employment in 2nd year before program entry	Before Matching	0.4560	0.3667	21.0	0.4560	0.3666	21.0
	After Matching	0.4565	0.4559	0.1	0.4565	0.4531	0.8
Share of employment in 3rd year before program entry	Before Matching	0.4655	0.3882	17.7	0.4655	0.3881	17.7
	After Matching	0.4662	0.4632	0.7	0.4662	0.4605	1.3
Share of employment in 4th year before program entry	Before Matching	0.4630	0.3994	14.5	0.4630	0.3994	14.5
	After Matching	0.4640	0.4621	0.4	0.4641	0.4590	1.2
Pseudo-R^2	Before Matching		0.029			0.029	
	After Matching		0.000			0.001	
Mean standardized bias	Before Matching		9.904			9.905	
	After Matching		0.582			0.615	

Note: Statistics are based on aggregated sub-samples before and after matching (previously stratified with respect to vocational education and age). Only selected variables are reported, while the specifications include more variables. However, mean standardized bias and pseudo-R^2 refer to 75 variables at least included in the different specifications.