Too Bad to Benefit? Effect Heterogeneity of Publicly Financed Training in Germany*

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Abstract

This study analyzes the treatment effects of publicly financed training programs for the unemployed in Germany. Based on conditional propensity score matching methods we extend the picture that has been sketched in previous studies. Besides estimating average treatment effects on the treated, we explicitly concentrate on treatment effects for different sub-groups of participants with respect to vocational education. Our results indicate that the effects of participation on employment, unemployment, and support probabilities involve effect heterogeneity. In particular, low-skilled individuals notably benefit from participation in the most important program type (occupation-related or general training). In context of the recent reform, we thus draw the conclusion that increasingly selecting the fittest unemployed into this program type is a questionable approach.

Keywords: Program Evaluation; Active Labor Market Policy; Effect Heterogeneity; Publicly Financed Training

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 substantial amounts of money on measures such as public employment services, training programs, or employment subsidies. For instance, about 13.8 billion Euros were spent on ALMP measures in 2003. The most important part of ALMP in Germany are publicly financed training programs, accounting for more than 36% of this amount. However, the number of participants in these programs decreased over the last years (see Figure 1). While 522,939 unemployed individuals entered a training program in 2000, this number approaches only 131,521 individuals in 2005.

A number of studies already evaluates the general effectiveness of publicly financed training programs in Germany.[1] So far, the results are quite heterogeneous—depending on the method, the investigation period and the underlying data set.[2] Examples for insignificant or even negative effects are Lechner (1999, 2000), Hujer and Wellner (2000), and Hujer *et al.* (2006). Papers that find inconclusive results are Hübler (1997) or Kraus *et al.* (1999), and papers with positive findings are Fitzenberger and Prey (2000), Fitzenberger *et al.* (2006), and Lechner *et al.* (2005a, 2005b). The major lesson of these mixed results seems to be that positive effects mainly occur—if at all—in the long run, and that studies which find positive long-term effects are also reporting negative short-term effects.

However, the focus of these studies lies on average effects of publicly financed training programs in Germany. The contribution of this paper is to extend the picture sketched so far. We answer a related, but somehow advanced question: are

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

[2] For a recent review of the results see e.g. Caliendo and Steiner (2005).

the effects of publicly financed training programs in Germany heterogenous with respect to gender and vocational education? 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, some strata of the population benefit from participation in job creation schemes. Since an adequate targeting of ALMP measures requires knowledge about the specific effectiveness, analog insights are desirable with respect to publicly financed training programs.

In addition, the target group of publicly financed training programs in Germany has recently shifted. Individuals with comparatively good employment prospects have been increasingly considered as participants since persons entering these programs are supposed to meet the criterion of a reasonable individual-specific integration forecast (subjectively assessed by the caseworker) after the reform in 2003. While this procedure intends to improve effectiveness, it is not clear whether this actually happens. Moreover, individuals with comparatively bad employment prospects are systematically excluded from participation. Besides equity considerations, one could argue that these individuals should represent the particular target group as they exhibit the largest potential to increase their employment prospects. By analyzing the effect heterogeneity of publicly financed training programs, we thus address an issue that is also important and relevant from a political perspective. If, for example, publicly financed training turns out to be particularly effective for individuals without a vocational degree, the strategic shift in the target group will not be supported.

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

In this paper, 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 like age, marital status, number of dependent children, disability, nationality and education.

The IEB contains information from 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). The BeH comprises remuneration notifications of employers about employment subject to social security contributions. This information is included in the IEB from 1990 onwards. The LeH contains information about phases of benefit receipt starting in 1990. The LeH benefits mainly include unemployment benefits and unemployment assistance. The ASU/BewA contains data on individuals searching for a job. For 1997 and subsequent years, additional information about the labor market status of a given individual is provided by this administrative data source. The MTH contains basic information about participation in active labor market programs—including publicly financed training programs—as well as about individual characteristics. Entries into programs of ALMP are identified from January 2000 onwards.

[3]The IEB is in general not publicly available. Only a 2.2% 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.

Since publicly financed training programs currently in place in Germany are quite heterogenous (especially with respect to content and duration), we concentrate on two particular types in what follows:

- Type 1: occupation-related or general training, and
- Type 2: group training with occupation-related certificate.

With respect to the number of participants, the the former type represents the most important short-term and the latter the most important long-term program.

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). Numerically, this type constitutes the most important type among all publicly financed training programs. In 2002, roughly 60% of all participants in training programs were assigned to this type. Figure 2 shows that this measure is short-term oriented with a median duration of about 8 months for participants entering in 2000 and 2001. About 20% of those participants finished the scheme at exactly 12 months, while only about 8% leave the program later in time.

Type 2 is a group training measure aiming to provide an occupation-related certificate. More specifically, a group of participants attends the same retraining measure at an educational institution. The measure also includes periods of practical training in certified companies/organizations. The aim is to provide participants a vocational degree by passing an examination at the respective chamber. The median duration of this type is almost 24 months (see Figure 2). A comparatively large number of participants finishes the measure exactly at 24 or 36 months, respectively.

Our sample of participants in these two program types consists of about 280 unemployed persons per quarter entering the respective type, i.e., we observe more than 2.200 participants per program type for the years 2000 and 2001. This sample allows us to draw conclusions on the average participant starting a program in this period of time.[4]

In order to apply the matching approach as described in section 3, 80 non-participants were drawn per participant. Those individuals had to be in the same labor market status as the corresponding participant prior to program entry, i.e., they had to be unemployed for the same duration. In this context, unemployment is defined as being not regularly employed. Non-participants are in addition required to not having participated in the respective type of publicly financed training program before and in the quarter of the participant's program entry. Moreover, the non-participants are required to live in the same regional type and to have the same gender as the participant. Finally, 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 gender and vocational education, we divide our sample into four sub-samples per program type, consisting of male and female participants and non-participants with and without a vocational degree, respectively. About 43% of the participants in program type 2 have no vocational degree, while this share with roughly 22% is much lower among participants in program type 1 (see Table 1). This difference can be explained by the fact that program type 2 leads to a vocational degree—it should thus be relatively more attractive for low-qualified individuals.

The success of program participation is evaluated by taking three different outcome measures into account: (i) unemployment, (ii) employment, and (iii) support. Individuals are regarded as unemployed if they are officially registered as

[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.

[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 the treatment on the treated and there are participants older than 55 or 60 years, there is no reason to exclude these individuals.

unemployed and—simultaneously—seeking for a job. On the other hand, employment only refers to jobs in the primary labor market. For instance, participation in job creation schemes and short-time employment (alone) are not included in this outcome measure. Since our definition of unemployment is a rather narrow one, we additionally look at the receipt of any kind of support as a third outcome measure to complement our analysis. These outcomes are measured starting at the (fictitious) program entry over a maximum period of 48 months.

3 Evaluation Approach

Ideally, one would like to compare the outcomes for the individuals participating in publicly financed 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 unobservable. Instead, the evaluation literature concentrates on population average gains from treatment—usually on the average treatment effect on the treated (ATT 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 subpopulation 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, CIA), 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) moreover 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.[6] One possible balancing score is the propensity score $P(X)$, i.e. the probability of participating in a given program.

There are several propensity score matching methods suggested in the literature.[7] Based on the characteristics of our data, we opt to apply nearest-neighbor (NN) matching without replacement. 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.

[6]When there are many covariates, it is impractical to match directly on covariates because of the curse of dimensionality. See e.g. Zhao (2005) for some comments on this problem.

[7]See e.g. Caliendo and Kopeinig (2006) for an overview.

We avoid an increased variance of the estimator as we match without replacement (Smith and Todd, 2005). Hence, the constructed counterfactual outcome is based only on distinct non-participants.

For the variance of the estimated treatment effects, we apply the approximation suggested by Lechner (2001, 2002). The following formula applies for nearest neighbor matching without replacement:

$$Var(\hat{\Delta}_{ATT}) = \frac{1}{N} \cdot \Big(Var(Y^1|D=1) + Var(Y^0|D=0) \Big) \ , \tag{4}$$

where N is the number of matched pairs.

The probability of treatment in the two program types under consideration is estimated conditional on a number of observable characteristics using binary probit models with participation as the dependent variable.[8] We run these regressions separately for different sub-samples of participants and non-participants according to program type, gender, and level of vocational education. After estimating the propensity score we match each participant with a distinct non-participant by exact covariate matching plus propensity score matching. The variables used for exact matching are previous duration of unemployment and quarter of (fictitious) program entry.[9] 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 (i) are previously unemployed for the same duration at the (fictitious) program entry, and (ii) are (fictitiously) entering the program in the same quarter. While the latter condition simply makes sure that seasonal influences are held constant and

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

[9]Of course, this matching algorithm is performed only within the different sub-samples the estimated propensity scores are based on.

that the observation period is the same for matched pairs, the former condition builds on similar arguments as e.g. Sianesi (2004) or Fitzenberger *et al.* (2006) put forward. However, we use program entry as our point of reference rather than following entrants into unemployment over time (inflow sample into unemployment). Our approach thus allows us to estimate the ATT for average participants in given program types in 2000 and 2001 as opposed to the ATT for participants in given program types after a certain period of 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.[10]

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

$$SB^b = \frac{(\overline{X}_1 - \overline{X}_0)}{\sqrt{0.5 \cdot (V_1(X) + V_0(X))}} \quad ; \quad SB^a = \frac{(\overline{X}_{1M} - \overline{X}_{0M})}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{0M}(X))}} \quad , \tag{5}$$

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.

These measures suggest that the quality of our matching procedures is quite satisfactory. The percentage bias of a number of covariates are appreciably reduced and any significant differences in these covariates disappear after matching. Moreover, the mean standardized bias of the matched samples are noticeably smaller than that of the unmatched sample. Likewise, the pseudo-R^2 after matching are fairly low and decrease substantially compared to before matching. This is what

[10]In particular, non-participants can potentially participate in the given program type *after* the (fictitious) program entry.

we should expect considering that after matching there should not be any systematic differences in the distribution of covariates between participants and matched non-participants. This test of the matching quality makes us confident to estimate meaningful treatment effects on the basis of nearest neighbor matching without replacement.

4 Results

After applying the matching approach as described, 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, unemployment, and support probabilities for a period of 48 month after the (fictitious) program entry, calculated every fortnight. We thus follow the prevailing approach in the recent evaluation literature.[11]

By doing so, we have to take into account the possible occurrence of lock-in effects for the group of participants. While participating—or being 'locked-in' in the program—individuals probably reduce their search activities for new jobs. But we also expect an opposing effect: an increased employment probability through the program. Therefore, the net program effect consists of these two components (van Ours, 2004) which generally cannot be disentangled.

As displayed in Figure 3 (upper left), participation in type 1 generally has a positive impact on the probability of being employed starting in month 12 after the program entry. In previous months, the impact of being locked-in in the program leads to significantly negative estimated ATT. In subsequent months, the observed positive treatment effect is usually statistically significant with a point estimate of about 5 percentage points. However, looking at sub-groups with respect to gender

[11] 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 (2006).

and vocational education, some heterogeneity in program effects becomes apparent. The program effect is consistently larger for women and for individuals without a vocational degree (Figure 3, lower left and upper right). Therefore, the largest estimated ATT on the probability of being employed can be observed for women without a vocational degree (Figure 3, lower right).

A rather similar picture arises in Figure 4. Although the impacts of type 1 on unemployment probabilities are in general smaller than on employment probabilities, the estimated ATT again appear to be larger for women and for individuals without a vocational degree. Moreover, the estimated ATT on the probability of receiving any kind of support confirm these findings. In fact, Figure 5 virtually mirrors the effects that can be observed with respect to employment probabilities.

The estimated ATT on employment probabilities for type 2 are displayed in Figure 6. In general (upper left), participation in this program reduces the probability of being employed after entering the program by a sizeable amount and a rather long period. This is obviously due to the lock-in effect that is usually more important for longer-term programs. Only about 36 months after program entry, a positive impact of participating in this program can be observed. But 4 years after entering the program, participants are about 10 percentage points more likely to be employed than without doing so. This effect is moreover statistically significant.

Comparing this general effect with the estimated ATT for sub-groups in the same fashion as before, heterogeneous effects can be observed also for type 2. While the lock-in effect is of about the same duration and magnitude for all sub-groups, the positive (long-run) impact on employment probabilities seems to be mainly due to female participants. While a consistent picture arises for women irrespective of their level of vocational education, this is not the case for men. In particular, for male participants without a vocational degree statistically significant positive program effects cannot be observed.

The program effects of type 2 on unemployment and support probabilities (Figures 7 and 8) basically mirror the effects on employment probabilities for this program type. Again, the effects on unemployment probabilities seem to be generally smaller than on support probabilities.

5 Conclusion

This paper studies the effects of participation in publicly financed training programs for the unemployed in Germany. Thereby we focus on the average treatment effect on the treated as well as on treatment effects for different sub-groups of participants with respect to vocational education. Considering two program types—the most important short-term and long-term types in terms of the number of participants—we present evidence for heterogeneous effects of program participation on employment, unemployment and support probabilities.

In particular, treatment effects for program type 1 appear to be consistently larger for women and for individuals without a vocational degree—leading to particularly positive effects for women without a vocational degree. In contrast to that, women independently of their level of vocational education are the driving force behind the generally positive long-term impact of program type 2.

Our results are thus—at least in part—conflicting with the strategy of the reform in 2003. While the aim was to increase the effectiveness of publicly financed training programs in Germany, actually the opposite of what was intended could occur by increasingly selecting individuals with comparatively good employment prospects into programs. The heterogeneity in treatment effects we observe for the most important program type—type 1—calls for a rather different strategy: individuals with comparatively bad labor market prospects, namely low-educated persons and especially low-educated women, *should* represent the target group. According to our results, this strategy could enhance the effectiveness of this particular program type.[12]

However, our results are based on entrants into programs in 2000 and 2001. Therefore, they can only give a hint about what actually happened by introducing the different elements of the reform in 2003—among others, the elements that affected the selection into programs. It thus remains an open question for future research to present evidence on how the changes in the composition of participants precisely affected the effectiveness of publicly financed training in Germany.

[12]On the other hand, the results for type 2 support the strategy of the reform as participants without any vocational degree—i.e. persons which one would consider to represent the particular target group—do not notably benefit from participating in this program type.

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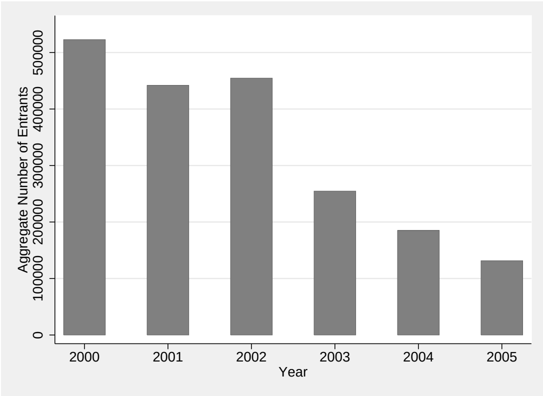
Figure 1: Entrants in Publicly Financed Training Programs (2000–2005).

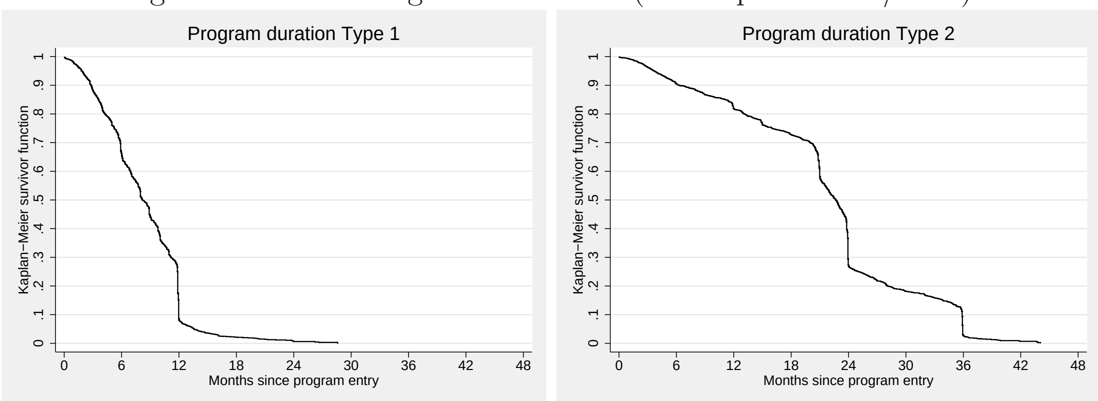


Source: Federal Employment Agency (FEA).

Table 1: Sub-Samples of Participants by Program Type.

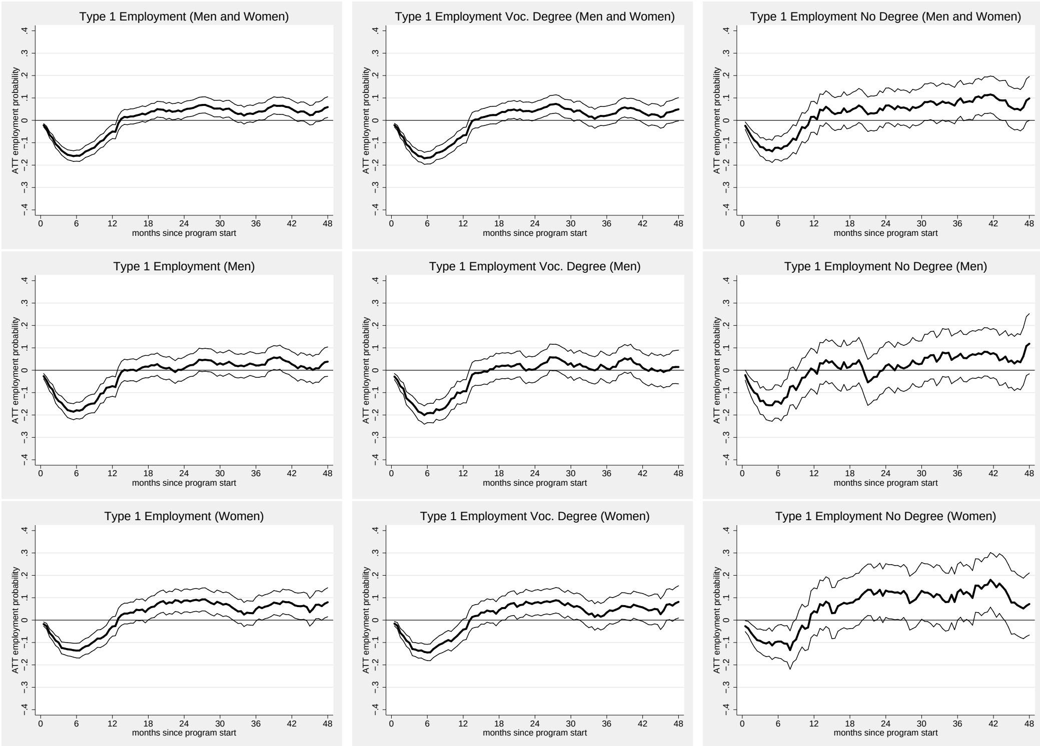
Variable	Type 1	Type 2
Male	0.4976	0.5344
Female	0.5024	0.4656
No vocational degree	0.2151	0.4292
Any vocational degree	0.7849	0.5708
Male × No vocational degree	0.1247	0.2555
Female × No vocational degree	0.0903	0.1737
Male × Any vocational degree	0.3729	0.2789
Female × Any vocational degree	0.4121	0.2919
# observations	2,269	2,309

Figure 2: Actual Program Durations (Participants 2000/2001).



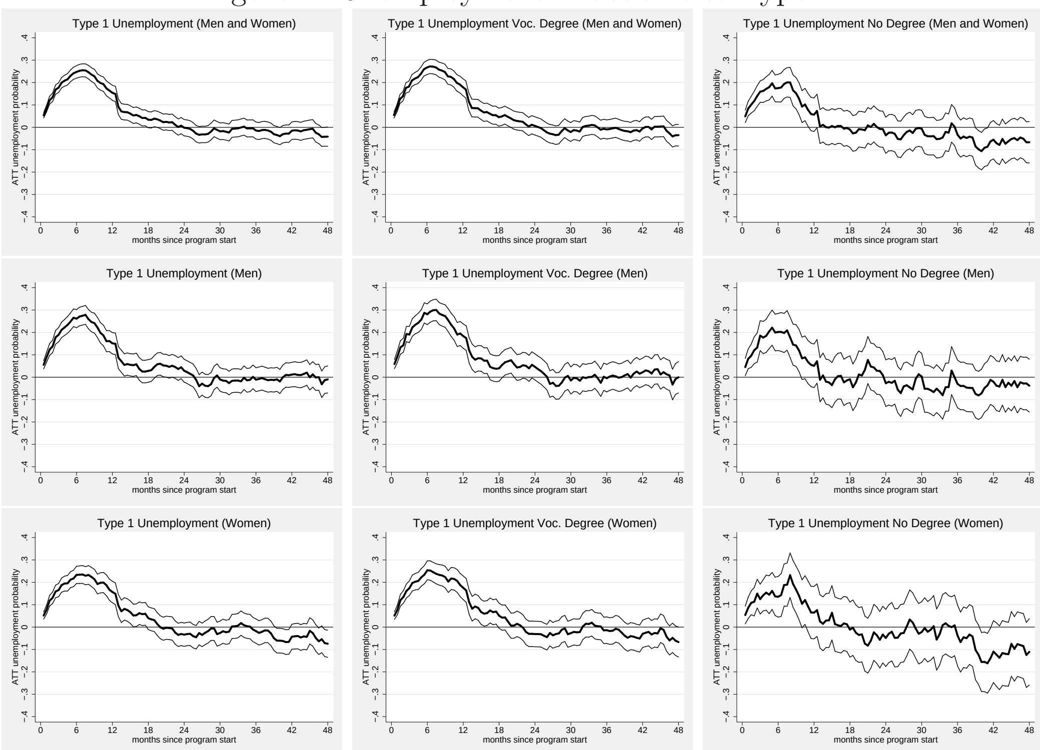
Source: IEB, own calculations.

Figure 3: Employment Probabilities Type 1.



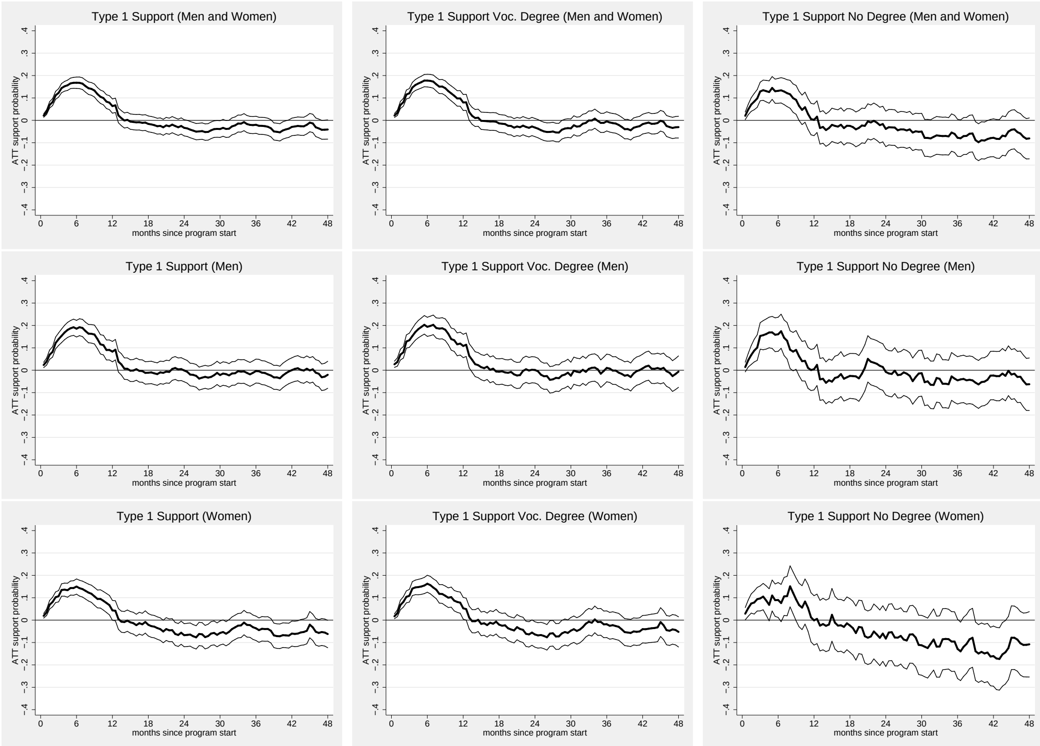
Source: IEB, own calcualations.

Figure 4: Unemployment Probabilities Type 1.



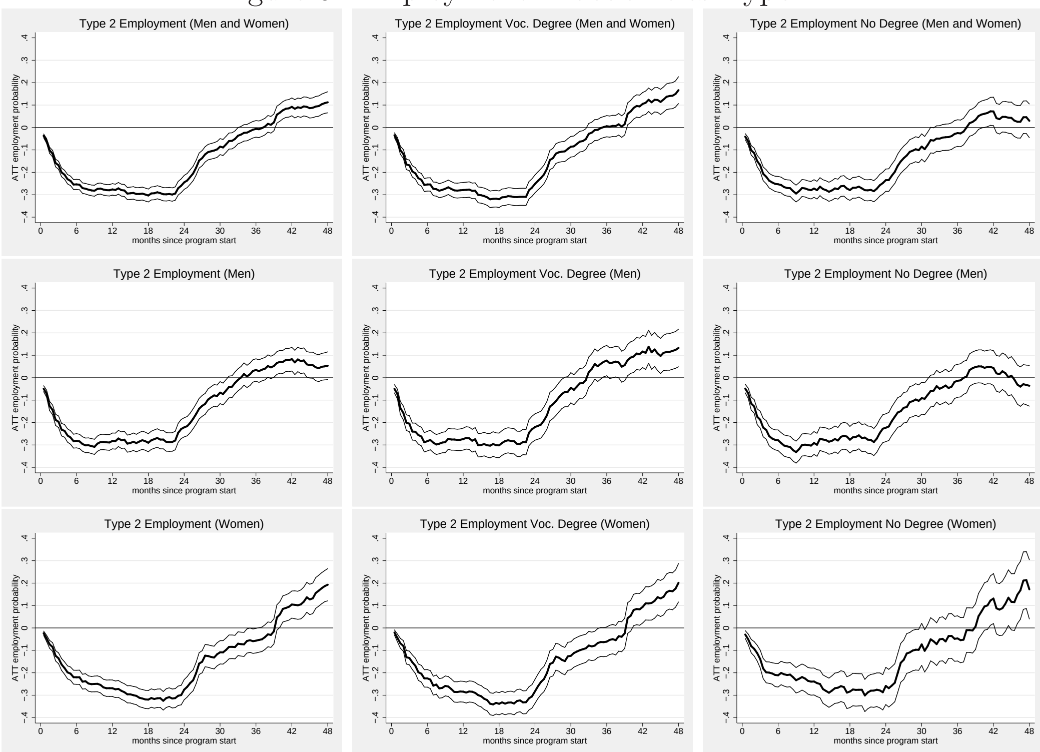
Source: IEB, own calcualations.

Figure 5: Support Probabilities Type 1.



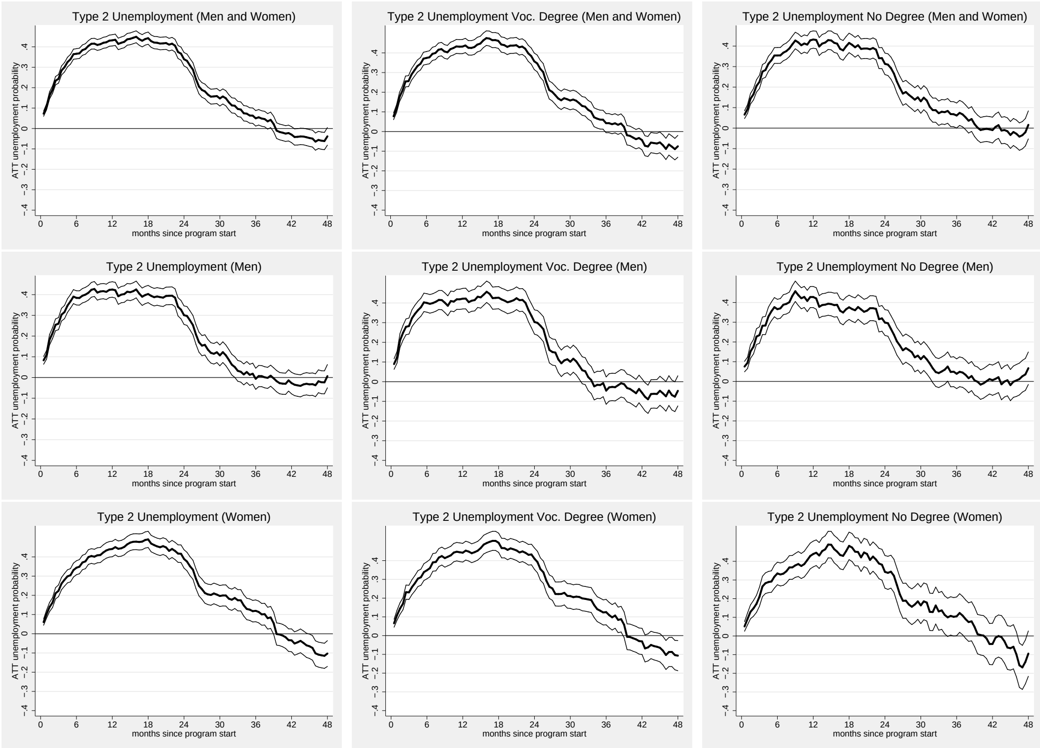
Source: IEB, own calcualations.

Figure 6: Employment Probabilities Type 2.



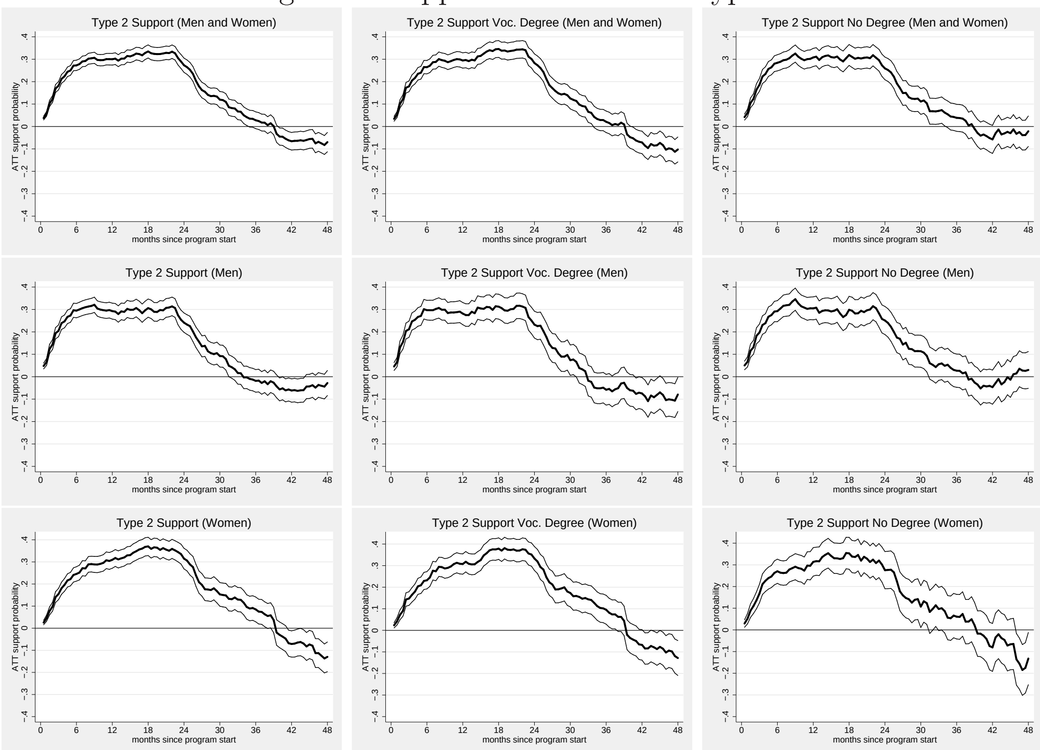
Source: IEB, own calcualations.

Figure 7: Unemployment Probabilities Type 2.



Source: IEB, own calcualations.

Figure 8: Support Probabilities Type 2.



Source: IEB, own calcualations.

Table 2: Matching Quality: Men with Vocational Degree.

Variable		Type 1 Participants	Type 1 Non-Participants	Type 1 % Bias	Type 1 p-Value	Type 2 Participants	Type 2 Non-Participants	Type 2 % Bias	Type 2 p-Value
Socio-demographic characteristics									
Age	Before Matching	37.47	41.94	-40.3	0.000	33.83	41.93	-79.0	0.000
	After Matching	37.47	37.48	- 0.1	0.974	33.83	34.20	- 3.7	0.405
German	Before Matching	0.941	0.950	- 4.3	0.202	0.944	0.950	- 3.0	0.449
	After Matching	0.941	0.938	1.1	0.835	0.944	0.952	- 3.7	0.518
Married	Before Matching	0.428	0.475	- 9.4	0.008	0.375	0.475	-20.3	0.000
	After Matching	0.428	0.421	1.5	0.763	0.375	0.398	- 4.7	0.409
Dependent children: youngest kid 0–3 years old	Before Matching	0.059	0.032	13.2	0.000	0.066	0.032	15.9	0.000
	After Matching	0.059	0.060	- 0.6	0.917	0.066	0.066	0.0	1.000
Dependent children: youngest kid 4–14 years old	Before Matching	0.158	0.124	9.9	0.003	0.198	0.124	20.4	0.000
	After Matching	0.158	0.160	- 0.7	0.892	0.198	0.223	- 6.8	0.291
Educational Attainment									
No graduation	Before Matching	0.016	0.029	- 8.9	0.026	0.015	0.027	- 8.6	0.063
	After Matching	0.016	0.012	2.5	0.529	0.015	0.020	- 3.5	0.509
First stage of secondary level	Before Matching	0.321	0.518	-40.8	0.000	0.375	0.519	-29.2	0.000
	After Matching	0.321	0.309	2.6	0.593	0.375	0.398	- 4.7	0.409
Second stage of secondary level	Before Matching	0.419	0.317	21.1	0.000	0.468	0.318	31.0	0.000
	After Matching	0.419	0.442	- 4.9	0.341	0.468	0.443	5.1	0.387
Advanced technical college entrance qualification	Before Matching	0.072	0.043	12.5	0.000	0.051	0.043	4.0	0.304
	After Matching	0.072	0.067	2.1	0.695	0.051	0.053	- 0.8	0.897
General qualification for university entrance	Before Matching	0.173	0.093	23.7	0.000	0.091	0.093	- 0.8	0.845
	After Matching	0.173	0.170	0.7	0.895	0.091	0.086	1.7	0.762
Vocational Attainment									
No vocational degree	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
In-plant training	Before Matching	0.768	0.851	-21.2	0.000	0.879	0.852	7.9	0.062
	After Matching	0.768	0.773	- 1.3	0.813	0.879	0.884	- 1.5	0.790
Off-the-job training, vocational school, technical school	Before Matching	0.100	0.079	7.5	0.023	0.078	0.077	0.4	0.919
	After Matching	0.100	0.102	- 0.9	0.869	0.078	0.074	1.2	0.828
University, advanced technical college	Before Matching	0.132	0.071	20.4	0.000	0.043	0.071	-12.1	0.007
	After Matching	0.132	0.125	2.5	0.656	0.043	0.041	0.7	0.886
(Un–)Employment History									
Share of unemployment in 1st year before program entry	Before Matching	0.597	0.593	1.4	0.703	0.621	0.593	8.9	0.035
	After Matching	0.597	0.586	3.5	0.475	0.621	0.632	- 3.3	0.551
Share of unemployment in 2nd year before program entry	Before Matching	0.295	0.352	-15.7	0.000	0.287	0.352	-18.6	0.000
	After Matching	0.295	0.288	2.0	0.678	0.287	0.267	5.7	0.282
Share of unemployment in 3rd year before program entry	Before Matching	0.250	0.306	-15.7	0.000	0.216	0.305	-26.1	0.000
	After Matching	0.250	0.250	0.0	0.995	0.216	0.214	0.6	0.902
Share of unemployment in 4th year before program entry	Before Matching	0.217	0.252	-10.4	0.004	0.195	0.252	-17.4	0.000
	After Matching	0.217	0.208	2.8	0.559	0.195	0.199	- 1.2	0.823
Share of employment in 1st year before program entry	Before Matching	0.241	0.230	3.8	0.287	0.205	0.230	- 8.4	0.052
	After Matching	0.241	0.251	- 3.1	0.538	0.205	0.209	- 1.0	0.849
Share of employment in 2nd year before program entry	Before Matching	0.455	0.404	12.1	0.001	0.461	0.405	13.3	0.001
	After Matching	0.455	0.469	- 3.2	0.526	0.461	0.470	- 2.3	0.688
Share of employment in 3rd year before program entry	Before Matching	0.517	0.479	8.9	0.012	0.521	0.479	9.6	0.018
	After Matching	0.517	0.526	- 2.0	0.687	0.521	0.527	- 1.6	0.782
Share of employment in 4th year before program entry	Before Matching	0.533	0.527	1.5	0.680	0.528	0.527	0.1	0.982
	After Matching	0.533	0.528	1.3	0.797	0.528	0.523	1.1	0.845
Joint significance (p-value)	Before Matching		0.000				0.000		
	After Matching		1.000				1.000		
Mean standardized bias	Before Matching		9.991				11.655		
	After Matching		2.218				2.312		

Source: IEB, own calculations.
Note: Only selected variables reported. Specifications include more variables. Mean standardized bias and the test of joint significance refer to 75 variables that are at least included in the specification.

Table 3: Matching Quality: Men without Vocational Degree.

Variable		Type 1 Participants	Type 1 Non-Participants	Type 1 % Bias	Type 1 p-Value	Type 2 Participants	Type 2 Non-Participants	Type 2 % Bias	Type 2 p-Value
Socio-demographic characteristics									
Age	Before Matching	34.94	36.19	-11.6	0.090	30.25	33.99	-42.2	0.000
	After Matching	34.94	34.93	0.2	0.981	30.25	30.31	- 0.8	0.877
German	Before Matching	0.752	0.710	9.4	0.131	0.788	0.717	16.5	0.000
	After Matching	0.752	0.763	- 2.5	0.764	0.788	0.803	- 3.4	0.551
Married	Before Matching	0.444	0.422	4.5	0.456	0.348	0.387	- 8.1	0.059
	After Matching	0.444	0.407	7.5	0.385	0.348	0.339	1.9	0.752
Dependent children: youngest kid 0–3 years old	Before Matching	0.070	0.051	7.9	0.158	0.103	0.056	17.3	0.000
	After Matching	0.070	0.048	9.3	0.275	0.103	0.101	0.7	0.921
Dependent children: youngest kid 4–14 years old	Before Matching	0.219	0.145	19.0	0.001	0.136	0.155	- 5.5	0.208
	After Matching	0.219	0.241	- 5.8	0.540	0.136	0.150	- 4.1	0.492
Educational Attainment									
No graduation	Before Matching	0.296	0.328	- 6.8	0.271	0.158	0.325	-39.9	0.000
	After Matching	0.296	0.304	- 1.6	0.851	0.158	0.165	- 1.7	0.744
First stage of secondary level	Before Matching	0.496	0.523	- 5.3	0.382	0.518	0.510	1.6	0.699
	After Matching	0.496	0.504	- 1.5	0.864	0.518	0.507	2.2	0.718
Second stage of secondary level	Before Matching	0.130	0.099	9.5	0.096	0.205	0.104	28.0	0.000
	After Matching	0.130	0.122	2.3	0.796	0.205	0.232	- 7.6	0.275
Advanced technical college entrance qualification	Before Matching	0.015	0.014	0.7	0.909	0.038	0.015	14.6	0.000
	After Matching	0.015	0.019	- 3.1	0.737	0.038	0.042	- 2.3	0.759
General qualification for university entrance	Before Matching	0.063	0.036	12.4	0.018	0.082	0.046	14.7	0.000
	After Matching	0.063	0.052	5.1	0.580	0.082	0.054	11.2	0.073
Vocational Attainment									
No vocational degree	Before Matching	1.000	1.000	n/a	n/a	1.000	1.000	n/a	n/a
	After Matching	1.000	1.000	n/a	n/a	1.000	1.000	n/a	n/a
In-plant training	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
Off-the-job training, vocational school, technical school	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
University, advanced technical college	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
(Un–)Employment History									
Share of unemployment in 1st year before program entry	Before Matching	0.607	0.598	2.8	0.651	0.553	0.577	- 7.5	0.080
	After Matching	0.607	0.607	- 0.0	0.997	0.553	0.551	0.5	0.934
Share of unemployment in 2nd year before program entry	Before Matching	0.365	0.401	- 9.3	0.136	0.300	0.382	-22.9	0.000
	After Matching	0.365	0.360	1.3	0.874	0.300	0.298	0.6	0.911
Share of unemployment in 3rd year before program entry	Before Matching	0.307	0.363	-14.6	0.021	0.254	0.351	-27.1	0.000
	After Matching	0.307	0.309	- 0.5	0.948	0.254	0.243	2.9	0.593
Share of unemployment in 4th year before program entry	Before Matching	0.301	0.304	- 0.6	0.919	0.244	0.298	-15.3	0.001
	After Matching	0.301	0.322	- 5.3	0.538	0.244	0.236	2.0	0.719
Share of employment in 1st year before program entry	Before Matching	0.221	0.171	17.6	0.003	0.236	0.180	19.5	0.000
	After Matching	0.221	0.230	- 3.0	0.736	0.236	0.241	- 1.5	0.814
Share of employment in 2nd year before program entry	Before Matching	0.388	0.271	30.2	0.000	0.391	0.274	30.4	0.000
	After Matching	0.388	0.407	- 4.9	0.586	0.391	0.394	- 0.9	0.887
Share of employment in 3rd year before program entry	Before Matching	0.377	0.284	23.5	0.000	0.396	0.276	30.5	0.000
	After Matching	0.377	0.370	1.8	0.836	0.396	0.416	- 5.1	0.421
Share of employment in 4th year before program entry	Before Matching	0.357	0.303	13.3	0.024	0.374	0.286	22.3	0.000
	After Matching	0.357	0.353	1.0	0.909	0.374	0.351	5.7	0.356
Joint significance (p-value)	Before Matching		0.000				0.000		
	After Matching		1.000				0.973		
Mean standardized bias	Before Matching		11.623				14.915		
	After Matching		3.374				2.957		

Source: IEB, own calculations.
Note: Only selected variables reported. Specifications include more variables. Mean standardized bias and the test of joint significance refer to 75 variables that are at least included in the specification.

Table 4: Matching Quality: Women with Vocational Degree.

		Type 1				Type 2			
Variable		Participants	Non-Participants	% Bias	p-Value	Participants	Non-Participants	% Bias	p-Value
Socio-demographic characteristics									
Age	Before Matching	38.35	40.44	-21.4	0.000	34.84	40.46	-61.2	0.000
	After Matching	38.35	38.15	2.0	0.631	34.84	34.56	3.0	0.506
German	Before Matching	0.953	0.961	- 3.9	0.217	0.926	0.962	-15.3	0.000
	After Matching	0.953	0.961	- 3.8	0.415	0.926	0.906	8.9	0.189
Married	Before Matching	0.559	0.599	- 8.0	0.016	0.560	0.599	- 7.8	0.047
	After Matching	0.559	0.537	4.5	0.345	0.560	0.565	- 1.0	0.866
Dependent children: youngest kid 0–3 years old	Before Matching	0.075	0.062	5.2	0.104	0.088	0.062	9.7	0.008
	After Matching	0.075	0.078	- 0.9	0.859	0.088	0.077	4.2	0.476
Dependent children: youngest kid 4–14 years old	Before Matching	0.374	0.293	17.2	0.000	0.495	0.293	42.1	0.000
	After Matching	0.374	0.377	- 0.5	0.923	0.495	0.512	- 3.6	0.539
Educational Attainment									
No graduation	Before Matching	0.007	0.016	- 8.9	0.024	0.008	0.016	- 7.6	0.098
	After Matching	0.007	0.003	3.1	0.316	0.008	0.008	0.0	1.000
First stage of secondary level	Before Matching	0.254	0.381	-27.6	0.000	0.238	0.381	-31.4	0.000
	After Matching	0.254	0.252	0.2	0.957	0.238	0.243	- 1.0	0.844
Second stage of secondary level	Before Matching	0.514	0.454	12.0	0.000	0.565	0.454	22.4	0.000
	After Matching	0.514	0.523	- 1.8	0.707	0.565	0.565	0.0	1.000
Advanced technical college entrance qualification	Before Matching	0.062	0.040	9.8	0.001	0.049	0.040	3.9	0.299
	After Matching	0.062	0.061	0.5	0.922	0.049	0.045	1.5	0.792
General qualification for university entrance	Before Matching	0.164	0.109	16.1	0.000	0.141	0.109	9.8	0.009
	After Matching	0.164	0.161	1.0	0.848	0.141	0.139	0.5	0.936
Vocational Attainment									
No vocational degree	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
In-plant training	Before Matching	0.752	0.808	-13.5	0.000	0.761	0.808	-11.5	0.002
	After Matching	0.752	0.748	1.1	0.828	0.761	0.740	5.0	0.401
Off-the-job training, vocational school, technical school	Before Matching	0.125	0.124	0.4	0.900	0.164	0.124	11.6	0.002
	After Matching	0.125	0.131	- 1.7	0.725	0.164	0.186	- 6.2	0.303
University, advanced technical college	Before Matching	0.123	0.069	18.6	0.000	0.075	0.068	2.6	0.503
	After Matching	0.123	0.122	0.4	0.943	0.075	0.074	0.6	0.915
(Un–)Employment History									
Share of unemployment in 1st year before program entry	Before Matching	0.593	0.606	- 4.0	0.238	0.605	0.606	- 0.3	0.937
	After Matching	0.593	0.598	- 1.6	0.726	0.605	0.593	3.8	0.500
Share of unemployment in 2nd year before program entry	Before Matching	0.274	0.350	-20.3	0.000	0.298	0.351	-14.1	0.001
	After Matching	0.274	0.289	- 3.9	0.389	0.298	0.305	- 2.0	0.717
Share of unemployment in 3rd year before program entry	Before Matching	0.254	0.312	-15.3	0.000	0.232	0.312	-21.8	0.000
	After Matching	0.254	0.258	- 1.2	0.798	0.232	0.257	- 6.8	0.199
Share of unemployment in 4th year before program entry	Before Matching	0.216	0.265	-13.5	0.000	0.212	0.265	-15.0	0.000
	After Matching	0.216	0.233	- 4.7	0.304	0.212	0.207	1.2	0.819
Share of employment in 1st year before program entry	Before Matching	0.199	0.180	6.6	0.043	0.168	0.179	- 4.1	0.306
	After Matching	0.199	0.203	- 1.5	0.755	0.168	0.171	- 1.2	0.820
Share of employment in 2nd year before program entry	Before Matching	0.369	0.322	11.3	0.000	0.327	0.322	1.4	0.729
	After Matching	0.369	0.357	2.8	0.549	0.327	0.330	- 0.6	0.918
Share of employment in 3rd year before program entry	Before Matching	0.394	0.366	6.5	0.045	0.347	0.366	- 4.4	0.275
	After Matching	0.394	0.387	1.7	0.724	0.347	0.347	0.2	0.973
Share of employment in 4th year before program entry	Before Matching	0.413	0.403	2.2	0.509	0.355	0.403	-11.1	0.005
	After Matching	0.413	0.390	5.2	0.271	0.355	0.351	1.1	0.839
Joint significance (p-value)	Before Matching		0.000				0.000		
	After Matching		1.000				1.000		
Mean standardized bias	Before Matching		8.173				10.613		
	After Matching		2.321				2.726		

Source: IEB, own calculations.
Note: Only selected variables reported. Specifications include more variables. Mean standardized bias and the test of joint significance refer to 75 variables that are at least included in the specification.

Table 5: Matching Quality: Women without Vocational Degree.

Variable		Type 1 Participants	Type 1 Non-Participants	Type 1 % Bias	Type 1 p-Value	Type 2 Participants	Type 2 Non-Participants	Type 2 % Bias	Type 2 p-Value
Socio-demographic characteristics									
Age	Before Matching	37.03	39.98	-25.7	0.001	32.57	36.12	-38.5	0.000
	After Matching	37.03	37.33	- 2.7	0.751	32.57	32.51	0.7	0.910
German	Before Matching	0.837	0.796	10.6	0.155	0.849	0.779	17.9	0.001
	After Matching	0.837	0.867	- 7.9	0.395	0.849	0.838	2.7	0.689
Married	Before Matching	0.500	0.551	-10.2	0.150	0.491	0.516	- 5.0	0.333
	After Matching	0.500	0.551	-10.2	0.313	0.491	0.483	1.6	0.827
Dependent children: youngest kid 0–3 years old	Before Matching	0.061	0.045	7.2	0.273	0.106	0.055	18.9	0.000
	After Matching	0.061	0.051	4.5	0.662	0.106	0.103	1.0	0.906
Dependent children: youngest kid 4–14 years old	Before Matching	0.342	0.245	21.3	0.002	0.507	0.297	43.8	0.000
	After Matching	0.342	0.347	- 1.1	0.916	0.507	0.528	- 4.4	0.560
Educational Attainment									
No graduation	Before Matching	0.143	0.233	-23.3	0.003	0.074	0.242	-47.3	0.000
	After Matching	0.143	0.148	- 1.3	0.886	0.074	0.066	2.2	0.670
First stage of secondary level	Before Matching	0.469	0.562	-18.7	0.009	0.419	0.532	-22.7	0.000
	After Matching	0.469	0.454	3.1	0.762	0.419	0.427	- 1.6	0.825
Second stage of secondary level	Before Matching	0.296	0.153	34.8	0.000	0.342	0.167	41.1	0.000
	After Matching	0.296	0.316	- 5.0	0.662	0.342	0.371	- 6.8	0.404
Advanced technical college entrance qualification	Before Matching	0.031	0.014	11.6	0.038	0.061	0.015	23.9	0.000
	After Matching	0.031	0.020	6.9	0.523	0.061	0.048	7.0	0.423
General qualification for university entrance	Before Matching	0.061	0.038	10.6	0.093	0.103	0.044	22.9	0.000
	After Matching	0.061	0.061	0.0	1.000	0.103	0.088	6.1	0.458
Vocational Attainment									
No vocational degree	Before Matching	1.000	1.000	n/a	n/a	1.000	1.000	n/a	n/a
	After Matching	1.000	1.000	n/a	n/a	1.000	1.000	n/a	n/a
In-plant training	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
Off-the-job training, vocational school, technical school	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
University, advanced technical college	Before Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
	After Matching	0.000	0.000	n/a	n/a	0.000	0.000	n/a	n/a
(Un–)Employment History									
Share of unemployment in 1st year before program entry	Before Matching	0.635	0.613	6.4	0.374	0.533	0.578	-13.4	0.011
	After Matching	0.635	0.659	- 7.2	0.474	0.533	0.540	- 2.1	0.770
Share of unemployment in 2nd year before program entry	Before Matching	0.355	0.377	- 5.6	0.442	0.232	0.342	-30.2	0.000
	After Matching	0.355	0.388	- 8.4	0.415	0.232	0.245	- 3.5	0.607
Share of unemployment in 3rd year before program entry	Before Matching	0.294	0.316	- 5.5	0.450	0.184	0.294	-30.9	0.000
	After Matching	0.294	0.333	- 9.8	0.336	0.184	0.183	0.2	0.972
Share of unemployment in 4th year before program entry	Before Matching	0.247	0.255	- 2.3	0.753	0.144	0.241	-29.2	0.000
	After Matching	0.247	0.251	- 1.0	0.919	0.144	0.133	3.3	0.601
Share of employment in 1st year before program entry	Before Matching	0.131	0.144	- 5.1	0.494	0.199	0.151	17.4	0.000
	After Matching	0.131	0.142	- 4.2	0.670	0.199	0.211	- 4.4	0.570
Share of employment in 2nd year before program entry	Before Matching	0.273	0.250	6.2	0.378	0.326	0.242	21.8	0.000
	After Matching	0.273	0.295	- 5.8	0.578	0.326	0.311	3.7	0.620
Share of employment in 3rd year before program entry	Before Matching	0.265	0.272	- 1.8	0.807	0.297	0.243	14.0	0.005
	After Matching	0.265	0.253	3.0	0.764	0.297	0.272	6.4	0.392
Share of employment in 4th year before program entry	Before Matching	0.272	0.296	- 5.8	0.418	0.294	0.253	10.3	0.040
	After Matching	0.272	0.282	- 2.4	0.805	0.294	0.280	3.4	0.649
Joint significance (p-value)	Before Matching		0.000				0.000		
	After Matching		0.999				1.000		
Mean standardized bias	Before Matching		9.275				15.747		
	After Matching		4.188				3.014		

Source: IEB, own calculations.
Note: Only selected variables reported. Specifications include more variables. Mean standardized bias and the test of joint significance refer to 75 variables that are at least included in the specification.