Evaluation of Further Training Programmes in Saxony from 1989 to 2001

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1. INTRODUCTION

Microeconomic evaluation studies try to assess the effectiveness of a country's active labour market policy. The proclaimed objective of labour market programmes is the improvement of the chances of individuals to find regular employment. However, the outcome of such programmes is uncertain. Basically, participation in a labour market programme can have three possible outcomes: the probability of employment can either increase, decrease or remain unchanged. Evaluation studies aim at quantifying the effect of participation in a labour market programme on the probability of employment.

Previous studies on the impact of labour market programmes in Germany established different effects depending on the data used, the period observed, and the methods applied. Most studies are based on the East German Labour Market Monitor from 1990 to 1994, the Labour Market Monitor Saxony-Anhalt and the German Socio-Economic Panel. The problem of selection bias is approached by applying different methods: PANNENBERG (1996), HÜBLER (1997, 1998) and KRAUS, PUHANI and STEINER (1999) use parametric models and consider observable heterogeneity. FITZENBERGER and PREY (1998, 2000) additionally use a non-parametric difference-in-difference method to correct for unobservable heterogeneity. HUJER and WELLNER, 2000 evaluate the effect of further training by means of a hazard rate model for matched samples. Other studies apply matching methods with difference-in-difference or parametric models (see BERGEMANN et al., 2000, 2001, 2004, EICHLER and LECHNER, 2000, 2001 HÜBLER, 1998, LECHNER, 1998). Simulation studies using different methods show that matching and the difference-in-difference method yield best results with regard to removing observable and unobservable heterogeneity (HUJER, CALIENDO and RADIĆ, 2001). Recent studies based on matching methods tend to result in negative or insignificant effects of further training programmes.[1]

However, the literature rarely analyses whether the effect of participation in a programme is influenced by individual characteristics, economic environment or the

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[1] For an overview of evaluation studies in East Germany see also HUJER and CALIENDO (2000).

organisational design of training measures. Therefore, the aim of this study is to evaluate the employment effects of further training programmes for Saxony between 1990 and 2001 for different subgroups representing individual characteristics as well as some aspects of the economic environment.

Our methodological approach differs in three aspects from other studies. First, we follow the concept of perforated unemployment, that means the unemployment spell of participants includes the further training episode. Second, we use the pre-history of the employment status as an indicator of the employment probability before the start of the programme, in order to eliminate Ashenfelter's Dip. Third, we employ a matching algorithm which provides an optimal full assignment. The results of our evaluation study show a negative effect of participation in further training programmes.

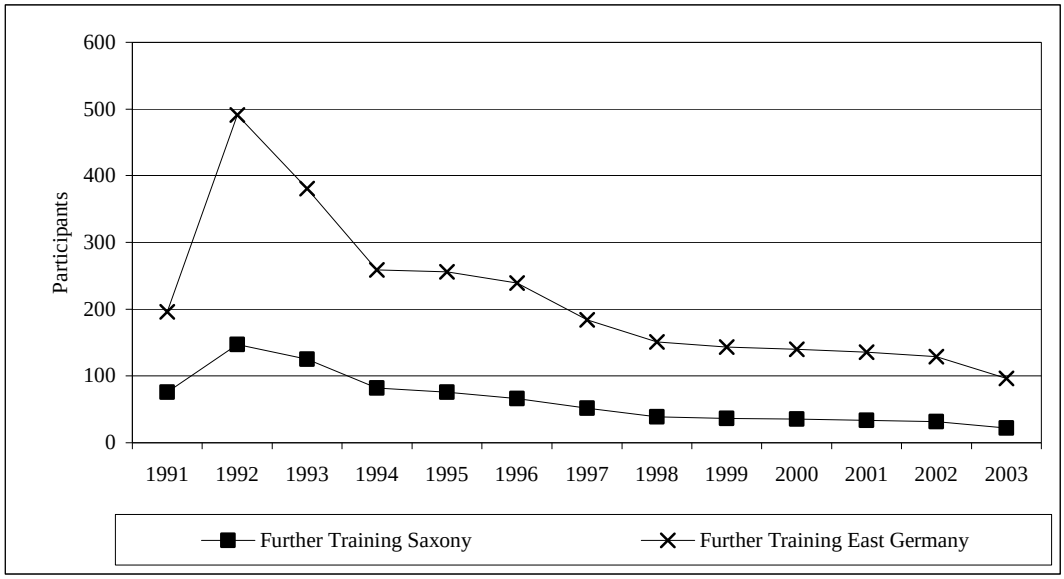
The paper is organised as follows. Sections 2 and 3 give a short overview of the legal basis of further training programmes in Germany and the development of participation in East Germany and Saxony as well as the description of the data. Section 4 theoretically describes the fundamental problem of microeconomic evaluation and lists assumptions on the matching process and the resulting requirements for the data. Following we explain our selection of variables (section 5) and spells (section 6). Sections 7 and 8 present the matching approach and the model of duration analysis we employ for our empirical study. Results are presented in section 9 and section 10 concludes our paper.

2. FURTHER TRAINING IN EAST GERMANY - ESPECIALLY IN SAXONY

Further training programmes belong to the most important programmes of active labour market policy in East Germany. They intend to integrate unemployed persons into the labour market by promoting vocational qualifications. Further training programmes include vocational re-training measures and the extension or adaptation of vocational skills. Such further training measures can last up to 24 months for re-training in a new profession and three to eight months for extension or adaptation programmes. Participants can get a subsistence allowance (Unterhaltsgeld) if they are entitled to unemployment benefits or assistance. Local employment offices assign private training centres or schools to carry out further training programmes. The local employment office also selects the unemployed persons to take part in further training measures.

The importance of further training programmes in East Germany and Saxony can be seen from the number of participants (Figure 1). The maximum is in 1992 with an annual average of about 500,000 persons and 150,000 persons, respectively. In the following years the number of participating persons steadily declined to currently about 96,300 in East Germany.

Figure 1: Participants in further training programmes in East Germany and Saxony from 1991 to 2003 (in thousands)



Source: Bundesanstalt für Arbeit

3. DATA DESCRIPTION

We base our evaluation of active labour market programmes on the Micro Census of Saxony in January 2000, January 2001 and January 2002. The Census offers the required data to satisfy the first assumption: it includes demographic characteristics as well as information on the employment history.[2] The Saxon data base is linked with the German Micro Census in as much as it is carried out three times per year with the similar questions and the similar procedure as the German one. A fraction of 0.5% of all households in Saxony are committed to participate, resulting in 10,000 households per census. All persons in these households (approx. 15,000 participants) are interviewed. It is obligatory to answer the questions of the Micro Census. A household can participate at most three times in the census, implying partial rotation of the participants.

In contrast to the German Micro Census, the Saxon Census includes quarterly information on participants' employment history since 1989. Due to the partial rotation, this information is available only once per person. The complete individual employment history can be reconstructed using quarterly information from the three censuses used. Our sample covers the period from the first quarter of 1989 until the fourth quarter of 2001. It includes spells of unemployment and participation in active labour market policies (ALMP), where it is possible to have more than one spell per person. There are no similar datasets for other East German federal states.

[2] Heckman/Smith (1999) show, that including employment history in addition to demographic characteristics is very important to control for selection bias.

There are three possible sources of inaccuracies in our information on unemployment spells. First, since interviewed persons have to report retrospective information, they might give an incorrect sequence of their various spells or a wrong classification of their employment status, especially when the survey period extends far back into the past. Second, since the data frequency is quarterly, there is no information available on the exact time of a status change. The status change could have occurred in the same quarter it is reported or in the quarter before. Finally, short spells within a quarter cannot be observed.

4. THE MICROECONOMIC EVALUATION PROBLEM

Microeconomic evaluation is based on the model of potential outcomes.[3] It identifies the impact of labour market programmes on individual employment opportunities by comparing the outcome of a treated person with the probable outcome for the hypothetical case of non-treatment. The potential outcome can be defined for instance as personal income, unemployment duration or duration of future employment.

A direct estimation is impossible because the treatment outcome and the non-treatment outcome cannot be observed for a person simultaneously. In this sense, the fundamental evaluation problem is a missing data problem.

For a causal interpretation of the individual treatment effects it is necessary to satisfy the *SUTVA* (stable unit treatment assumption). It requires independence of individual treatment effects, i.e. the programme effect for each participant must not be affected by the treatment of other persons. This excludes indirect effects on the regional labour market or the whole economy[4] and permits the estimation of average treatment effects to overcome the fundamental evaluation problem independent of size and composition of the treated population group. The average effect of treatment on the treated indicates the expected outcome for persons who received treatment compared to the hypothetical situation of non-treatment. Therefore, a group of non-treated persons with – on average – the same relevant observable and unobservable characteristics as the participation group has to be found. If this is not exactly possible the estimation results will be distorted by a selection bias.

One of the most popular methods to overcome the problem of selection bias is a matching procedure. The basic idea is that the outcome of a well chosen group of non-

[3] This model is also known as *Roy-Rubin-model.* For a detailed description see HECKMAN, LALONDE and SMITH (1999), pp. 1877-1879.

[4] See FRÖHLICH (2002), pp. 4-5 for a detailed discussion of this assumption and possible indirect effects.

treated persons is a good proxy for the counterfactual outcome as long as the persons in both groups have the same observable characteristics.

The simplicity of this idea as well as the important fact that matching leaves the individual treatment effects completely unrestricted – that means robustness to heterogeneous treatment effects in the population – are the main reasons for its popularity. On the other hand, matching is highly demanding on the data at hand. The identifying assumption, the conditional independence assumption, requires that conditional on characteristics X the assignment to the treatment and the non-treatment group is independent of the potential outcomes. It is satisfied only if all variables that influence both the selection process and the potential outcome are used for matching. This also implies that all relevant characteristics must be observable. Since this is seldom the case, many studies use the difference-in-difference approach to handle heterogeneity in unobservable characteristics. The problems associated with this approach[5] can be avoided by using adequate proxy variables for the unobserved characteristics.

A further necessary condition for identifying an unbiased treatment effect is the common support condition,[6] which states that for each chosen X it must be possible to find both participants and non-participants. Both assumptions together are sometimes referred to as strongly ignorable treatment assignment.[7]

5. CHOICE OF VARIABLES

The selection of relevant variables for the analysis is derived from human capital theory and recent empirical studies.[8] Theory suggests decreasing investment into human capital with age, and labour market statistics show a negative influence of age on labour demand.[9] Another important factor for labour market behaviour is gender as it is obvious from the employment structure.[10] For the selection process gender may be

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[5] One of the most important problems is the choice of the reference time before the measure starts – it should be unaffected by the future participation and temporary heterogeneity of participants and non-participants. Furthermore, short-run results cannot be interpreted due to Ashenfelter's dip, the decrease of the employment probability before an ALMP-measure, and the mean reversion afterwards.

[6] HECKMAN, ICHIMURA and TODD (1997) decompose the conventional bias measure into different components and show that failure of the common support condition (one component of the bias) results in a substantial increase of the bias.

[7] See ROSENBAUM and RUBIN (1983), p. 43.

[8] This variable selection procedure is also used e.g. in HUJER, MAURER and WELLNER (1997), p. 13 or CHRISTENSEN (2001), pp.25-27.

[9] The unemployment rate of persons of 55 to 60 years is 16.7%, in contrast to 11.5% for persons in the age bracket of 30 to 40. See Bundesanstalt für Arbeit (2004a), overview I/5.

[10] The share of women in the total number of part time and low paid employment is 84.4% and 69.7%, respectively. See Bundesanstalt für Arbeit (2004b, 2004c).

important too, because the assignment to training measures depends on the fraction of men and women among the unemployed[11]. Therefore, gender and age are included into the matching process.

Furthermore, we expect human capital to have a positive influence on the selection process for training[12] and on employment opportunities. To get quasi time-invariant information about formal education levels all persons who were younger than 25 at the beginning of the observation period (1989) were excluded from further analysis, because education is usually completed at the age of 25. If not, persons are not unemployed and hence not included in the sample. A problem could arise if persons continue their education after an unemployment period. If a previous participant has a higher qualification at the interview date than at the beginning of the considered unemployment period, it is possible that this person is matched with a – at matching time – higher qualified person. If a non-treated person continues education during unemployment, the person could be matched with a better-educated participant. Due to the selected sample we expect this problem will rarely occur and thus will not bias the estimation results in a systematic way.

Since other time-variant information, like income and family background, is not available for the matching time the estimated treatment effect will probably be biased. Moreover, these characteristics could follow different paths in the treatment and the non-treatment group. However, we assume that employment history can be used as a proxy for the time-variant characteristics in the matching process. Therefore, we generate the following employment history variables: the share of time spent in employment, non-employment and unemployment, as well as the frequency of changes into and the mean duration of employment, 'non-employment' and unemployment. Moreover, the labour market statuses for six quarters before matching are included.

Besides demographic characteristics and employment history, a similar economic environment of the compared persons is important for unbiased estimation results.[13] Therefore, information about the place of residence and the start of the considered unemployment spell are included additionally. The latter is necessary because of various changes of labour market policy and other economic factors during the observation time.

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[11] See §8 SGB III.

[12] According to recent empirical studies, persons who completed an apprenticeship or any higher education are more likely to participate in vocational training. See e. g. HUJER, MAURER and WELLNER (1997), p. 13 and CHRISTENSEN (2001), p. 27.

[13] HECKMAN, ICHIMURA and TODD (1997) analyse possible sources of biased estimation results. They identify a mismatch of labour market conditions across treatment group members and comparison-group members as one major source of bias.

6. SELECTION OF SPELLS

Our aim is to compare the outcome of a treated person with the person's hypothetical outcome in case of non-treatment to answer the question whether participation can increase the probability to find employment, or whether participation does not influence employability, or whether participation even affects it negatively. In order to eliminate potential biases in the estimation of the treatment effect which cannot be handled by matching, it is necessary to select spells carefully.

We define our spells according to the concept of perforated unemployment[14], which means that the unemployment spell of participants includes the further training episode. A typical participation spell starts with the entry in unemployment in a specific quarter. After a few quarters unemployment is discontinued by a change into further training. Following the measure unemployment is continued. We regard the three periods as a whole. Thus, the only way to end a spell successfully is to change into employment. Not applying the concept of perforated unemployment would induce a selection bias. In this case spells of participation would start with the end of the measure and focus on unemployment duration after the training. At the beginning of the evaluation period most participants are already out of regular employment for a relatively long period of time. Accordingly, they have disadvantages on the labour market. If they would be compared with unemployment spells of non-participants whose unemployment period started recently the participation effect would be overestimated.

We only select unemployment spells for the group of non-participants. For both groups, only spells of persons who have never participated in any ALMP-measure before the observation time are included. We also exclude all spells for persons older than 55 years, because these persons could probably use the policy to smooth their transition to retirement.

Two other sources of bias are an anticipation effect and a cohort effect, which make it difficult to find the correct treatment effect. Therefore, it is necessary to eliminate or to measure these effects.

Many studies observe a decrease in the probability of employment before participation in ALMP-measures. This effect was first observed by Ashenfelter[15] and is therefore referred to as Ashenfelter's Dip. The most popular explanation for this effect is that future participants anticipate their participation and therefore reduce their job search intensity.

In Germany the legal requirements of taking part in an ALMP-measure could be a more important explanation of the dip, because only persons who are unemployed and entitled

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[14] BÜCHEL (1992).

[15] ASHENFELTER (1978).

to unemployment benefits are allowed to participate in an ALMP-measure. The entitlement to unemployment benefits requires a minimum length of employment. This means most of the participants change from employment to unemployment and start a training measure after a few quarters. In our data, 92% of participants are employed one quarter before they change into unemployment and 80% of participants are unemployed less than four quarters before the start of the measure. Therefore, the cohort effect is a result of the selection of participants with specific labour market histories who are compared to a non-selected group of non-participants. This implies that participants and non-participants follow different employment paths. The employment quota of participants declines substantially before the start of the programme, whereas non-participants can have different employment histories. The only criterion is the registration of unemployment, a possible entitlement of unemployment benefits or an allowance to participate in an ALMP-measure are unknown.

A possibility to deal with both, the cohort and anticipation effect, is to match partners with similar employment histories so that participants and non-participants have the same employment probability before the ALMP-measure. In order to eliminate the effects, we only select non-participants as potential matching partners for every participant whose unemployment period is at least as long as the one of the participant before entering training. This selection procedure ensures that participants and non-participant follow similar employment paths until the start of the programme.

With this rules we select 850 participation spells for the matching procedure. In the cases of non-participation 3,726 spells are available.

7. APPLICATION OF THE MATCHING APPROACH

The matching control group consists of individual counterfactual outcomes for each participant. These counterfactual outcomes are determined in this study as the outcome of one special non-participant who has similar relevant observed characteristics. This technique is commonly referred to as nearest neighbour matching[16] or nearest available pair matching.

When using this approach, two central questions have to be answered: how to define similarity between participants and non-participants and how to make sure that every participant is assigned to a best non-participant?

One possible procedure is matching with replacement, where every participant is assigned to the closest non-participant irrespective of how often one non-participant is

[16] For a short overview over different nearest neighbour matching approaches see HECKMAN, LALONDE and SMITH (1999), pp. 1953-1954.

used as partner for participants. This technique contains the potential problem that only a few non-participants are used very often while other very similar non-participants are not considered. This may result in a rise of the variance of the estimated treatment effect.[17]

When the number of non-participants markedly exceeds the number of participants – which is the case in our study – matching without replacement is usually applied. LECHNER (1998) improves a two-step procedure by ROSENBAUM and RUBIN (1985) by defining variable callipers for the so-called participation tendency. In the first step this single aggregated measure of similarity is used for pre-selection. In the second step additional characteristics for measuring similarity between a participant and possible partners are included. The deviation of these characteristics is not restricted.

LECHNER'S (1998) assignment process is to randomly order the participants, successively find the closest non-participant from the particular sub-sample and remove the matched pair from the pool of considered persons. Each participant for which no similar non-participant can be found is excluded from further analysis. This is a standard procedure in the empirical literature.[18]

The application of any matching procedure without replacement raises several questions if one non-participant is the best partner for more than one participant. Who should be assigned to this non-participant: the first drawn participant, the closest, or the participant who has no alternative partners? The standard procedure assigns the first drawn participant. The disadvantages of this random choice are the risk of not finding adequate partners for the later drawn participants and therefore losing observations, and additionally it cannot be ensured that the best possible assignment is found. The former problem may not be important if the sample size is sufficiently large. Since we divide the sample of participants into various sub-samples in this study, we however cannot ignore this problem. Thus, a procedure is desirable that guarantees not to lose observations due to the design of the assignment process and simultaneously ensures to find the best possible assignment result.

In finite samples the importance of some characteristics for the participation decision and employment prospects may differ, i.e. persons with identical propensity scores may have dissimilar labour market prospects due to the fact that characteristics affect their participation decision and employment chances not to the same degree. FRÖHLICH (2002) recommends to use the principal covariates affecting the outcome or a so-called augmented propensity score for matching. Furthermore, using a symmetric

[17] See LECHNER (2000), p. 9.

[18] For applications see e. g. CHRISTENSEN (2001) or GERFIN and LECHNER (2002).

metric, matching by use of the propensity score would lead to an undesirable asymmetry, when the propensity score is close to 0 or 1.[19]

Because of the finite sample size of the sub-samples we cannot use the propensity score as the only distance measure. Therefore, in this study we apply a one-step balancing-score matching, that uses personal characteristics as well as the participation tendency. The included characteristics are differently scaled. It is pointed out in statistical literature that to measure different scaled covariates with one and the same distance measure is inappropriate.[20] Regarding e.g. quantitative covariates as qualitative ones or vice versa, results in loss of information from the data or an overvaluation of the qualitative variables. The most common way to construct aggregated distance measures is a two step procedure. In a first step scale-specific distance measures are quantified. Then, after a suitable standardisation of the specific distances, the distances are weighted with the number of the included variables in each distance measure.[21]

Similarity between participant *i* and non-participant *j* in participation tendency and metric variables is measured by the Mahalanobis distance[22]

$$MD_{ij} = \left[(\hat{I}_i, X_i) - (\hat{I}_j, X_j)\right]' \Sigma^{-1} \left[(\hat{I}_i, X_i) - (\hat{I}_j, X_j)\right], \qquad (11)$$

where X_i and X_j are the $n \times 1$-vectors of the considered covariates, $\hat{I}_i$ denotes the estimated participation tendency and Σ^{-1} the inverse of the covariance matrix of $(\hat{I}, X_i)$. The Mahalanobis distance has the advantage that potential correlations between the covariates are accounted for by including the inverse of their covariance matrix.[23]

This distance measure contains the following variables (included in vector *X*): age, start of the unemployment spell, share of time spent in employment and unemployment as well as mean duration of employment and unemployment.

We estimate the participation tendency $\hat{I}_i$ as the latent variable of the index function of a probit model. In this estimation we include demographic variables (gender, age and human capital) by default. Indicators for the economic environment (start of the considered unemployment spell and place of residence) and for the employment history (share of time spent in employment/ unemployment, mean duration of employment/ unemployment and labour market statuses for six quarters before matching) enter the

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[19] See LECHNER (1998), p. 115.

[20] See e. g. OPITZ (1980), pp. 50-51 for further details.

[21] See e. g. KAUFMANN and PAPE (1996), p. 453.

[22] The participation tendency is treated as a metric variable because normal distribution can be assumed. See LECHNER (1998), p. 115.

[23] See KAUFMANN and PAPE (1996), p. 450.

estimation only in the case they improve the model.[24] To measure similarity in nominally scaled variables the generalised matching coefficient:[25]

$$MC_{ij} = \frac{1}{m}\sum_{p=1}^{P} m_p \sigma(z_{pi}, z_{pj}) \tag{12}$$

with

$$\sigma(z_{pi}, z_{pj}) = \begin{cases} 1 & \text{if } z_{pi} = z_{pj} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

is applied. The number of covariates under consideration is denoted by P. Covariate z_p has m_p different values. The total sum of values over all covariates is given by $m = \sum_{p=1}^{P} m_p$. Having this type of matching coefficient it is possible to measure similarity allowing for different numbers of values in the covariates.

The included variables (covariates z) are: gender, human capital, place of residence and labour market status for each of six quarters before matching.

Our aggregate distance measure is constructed as a weighted average of the Mahalanobis distance and the generalised matching coefficient:

$$M_{ij} = \frac{1}{a+b}\left[a\left(1 - MC_{ij}\right) + \alpha b MD_{ij} \right], \tag{14}$$

where a and b denote the number of metrically and nominally scaled covariates, respectively. The factor α ensures that the medians of both distance measures, $\left(1 - MC_{ij}\right)$ and MD_{ij}, are equal. In our study it proved inappropriate to use the number of the included variables as the only weighting factors, because in this case the impact of the nominally scaled variables on the aggregate measure is dominated by that of the metric variables. This results in significant differences between matched participants and non-participants in the nominally scaled covariates. Therefore, we extended the standard procedure by including the weighting factor α. Thus, we achieve the desired similarity between participants and non-participants in all considered covariates.[26]

For the assignment process we use the Hungarian algorithm, which is known from graph theory and linear optimisation. The algorithm was introduced by KUHN (1955) to solve the classical assignment problem. The basic idea is to update the edge weights of a

[24] The coefficients of the included covariates are presented in Table A.1 in the appendix.

[25] See KAUFMANN and PAPE (1996), p. 446 for a detailed description.

[26] As can be observed in Table A.2, no significant differences in means and distributions of the covariates between participants and non-participants are found for all (sub-) samples.

bipartite graph with appropriate vertex potentials[27] so that a complete Matching with zero weight exists in the resulting sub-graph.

This iterative process requires a complete bipartite graph with left and right vertices of the same size and nonnegative edge weights. The solution process is as follows: The first step is to construct a sub-graph by choosing a potential for the left vertices so that edges with zero weight arise. In the second step a Matching with maximum number of edges is searched for in this sub-graph. This is done by an iterative improvement of an initial Matching along a prior labelled path. If the result of this improvement process is a complete Matching this is an optimal Matching with minimum overall weight.

If the Matching is incomplete, the minimum weight of all edges with labels on the left side and no labels on the right side is the new vertex potential. The edge weights are updated with this potential and a new sub-graph results, where a new search for a Matching with maximum number of edges starts until an optimal Matching with minimum overall weight is found.[28]

To implement this algorithm for our data we have to fit the distance matrix. The requirement of nonnegative edge weights is fulfilled by the choice of the aggregate distance measure, which has exclusively positive distance values. Obviously, implementing this algorithm avoids the problem of losing observations due to the design of the assignment process and yields an optimal result.

To check the quality of the matching result, we test if differences in the means and distributions of the characteristics in the treatment and the non-treatment group arise.[29] As can be seen in Table A.2 in the Appendix**,** no significant differences – neither of the means nor the distributions of the covariates – between both groups are found for all (sub-) samples.

8. DURATION ANALYSIS

One possible indicator for the impact of labour market programmes is the change in the duration a person is unemployed. Usually it is adequate to compare the means of the matched participation and the non-participation outcome. However, a simple comparison of average participants' and non-participants' unemployment durations is not the appropriate approach for three reasons: the main reason is the existence of censored spells, i.e. unemployment durations that are not finished at the interview time.

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[27] A vertex potential is the valuation of the vertices with real numbers to allow for manipulations of the edge weight without changing the optimal solution.

[28] For a detailed description of this assignment algorithm see e. g. BAZARAA et al. (1990), pp. 499–508.

[29] Differences in means are checked by t-tests, for the distributions we applied KS-tests (for metrical variables) and chi-square-tests (nominally scaled variables), respectively.

Second, the unemployment spells start in different periods. Thus, labour market conditions may vary between different persons. The third problem is the change in the composition of the groups, because some persons take up employment and are not considered for the whole observation period. This is why the distribution of characteristics in the participants' and the non-participants' groups may differ over time.

One possible approach to deal with this kind of problems is to apply a survival analysis. The outcome variable here is the unemployment duration until an observed person changes into employment. Specifically, we employ the semi-parametric proportional hazards model developed by COX (1972). It is called proportional hazards model because of the fundamental assumption that the ratio of the hazard rates of two persons is constant over time.[30] The model requires no distribution assumption for the hazard rate, which is an advantage compared to the application of parametric failure time models.

The hazard rate depends on two factors, time and personal characteristics. The influence of time on the hazard rate, the baseline hazard rate, does not need to be specified. The influence of personal characteristics is assumed to be constant over time and mostly specified as a log linear function[31]. The possibility to consider individual characteristics is a virtue, e. g. compared to the Kaplan-Meier-approach, in the sense of an information gain: Beyond the treatment effect, the coefficients of the estimation give additional information about the influence of the considered characteristics on the hazard rate.[32] COX (1975) showed that the partial likelihood estimates are consistent and asymptotically normally distributed.

When using microeconomic data, information is often only available for time intervals. Then ties, i.e. equal durations until failure for several persons, may bias the estimated results of a continuous hazards model. To account for this problem, a discrete-time logistic hazards model as proposed by COX (1972) is commonly applied. But the distortion can be neglected, if – as is the case in this study – solely time invariant covariates are included.[33] For this reason we apply a modification of the continuous-time Cox model suggested by BRESLOW (1974). In order to take into account ties the

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[30] This assumption can be tested with the Wald-test on the significance of interaction terms for the used covariates and time.

[31] See COX and OAKES (1984), p.91.

[32] When comparing the covariate-adjusted survival functions and the results of the Kaplan-Meier-estimation in our study very similar slopes can be observed. For example see Figure A.1.

[33] See ALLISON (1984), p. 22. GALLER (1986) established by use of Monte-Carlo-Simulations that the interval width should not exceed one quarter of the average spell. In this analysis quarterly data is used and the average spell duration is 21 quarters for participants and 8 for non-participants.

conditional probability h_{g_f} that a group of d_f persons fail at time t_f instead of the failure probability of one person is analysed:[34]

$$\frac{h_{g_f}\left(t_f \mid s_f\right)}{\sum_{j \in R\left(t_f\right)} h_j\left(t_f \mid c_j\right)} = \frac{exp\left(\beta' s_f\right)}{\left(\sum_{j \in R(t_f)} exp\left(\beta' c_j\right)\right)^{d_f}}. \tag{15}$$

The group of failed persons is denoted by g_f , the sum of their individual covariate vectors c_i is $s_f = \sum_{i \in g_f} c_i$, while β denotes the parameter vector and $R\left(t_f\right)$ the risk pool. The index f gives the ordered failure times. The resulting partial likelihood function is the product of all failure times:

$$L(\beta) = \prod_{f=1}^{F} \frac{exp\left(\beta' s_f\right)}{\left(\sum_{j \in R(t_f)} exp\left(\beta' c_j\right)\right)^{d_f}}. \tag{16}$$

In our study only the change of the initial status of unemployment to employment is defined as a failure (and thus, the unemployment spell is completed). All other unemployment spells are considered as censored.

We use a stratified estimation of the hazard rate, where "treatment" is the stratification variable.[35] This specification allows for different baseline hazard rates in both groups, but the influence of the included covariates is equal for participants and non-participants.

The Breslow model is implemented as a partial stepwise model. Theoretically important variables like gender, age, and professional education are included by default. Variables for schooling, economic environment and of employment history enter the model only if they have a significant effect on the shape of the survival function. For all variables, we conducted Wald-tests to test for constant hazard ratios. As can be seen in Table A.3 for all analysed sub-samples, the proportionality assumption cannot be rejected for these variables.

To answer the question if both, a matching procedure and Cox proportional survival analysis are necessary, we compare the estimation results before and after matching. The survival functions in Figures A.2 to A.6 show a noticeable difference between the non-participation curve before and after the matching procedure. Especially in the sub-sample of long-term unemployed persons (Figure A.3) we find a distinctive difference

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[34] For details see e. g. KLEIN and MOESCHBERGER (1997), pp. 237-238.

[35] A test of the proportionality assumption for the covariate "treatment" shows that the ratio of the hazard rates of participants and non-participants differs over time. That means, the (baseline) hazard rates are different for both groups.

in the slopes of the survival functions. This can be explained by the heterogeneity between participants and non-participants before matching in this sub-sample. When comparing the means of the personal characteristics of non-participants before and after matching in Table A.2 we can observe conformance to the characteristics of participants after matching.

The comparison of different beginnings of unemployment spells (Figures A.4 to A.6) show an interesting matching effect. In the first sub-sample non-participants with better labour market chances are matched to the participants. In contrast, in later periods the matching procedure chooses non-participants with a higher unemployment risk. This can be explained by the above mentioned changing assignment practice of participants in training measures by the local employment offices: At the beginning of the 1990s participants often changed directly from employment to training measures. Therefore, a part of the group had good employment prospects before the measure. In this case non-participants with better employment chances are selected. Due to the target group focussing at the end of the 1990s the participants were persons with comparatively low employment probability. Here, the matching procedure chooses similar non-participants.

9. RESULTS

The estimated coefficients of the Cox model for all sub-samples are presented in Table A.3 in the Appendix. It is observed, that gender has a significant influence for almost all sub-samples: men generally leave unemployment faster than women. Age is only significant for some sub-samples and the estimations reveal a negative influence on the hazard rate.

The educational variables, which are significant for only a few sub-samples, show the expected signs. A grammar school degree has a negative influence on the hazard rate, whereas a secondary school degree and a university or college degree have a positive influence.

A high frequency of changes into unemployment generally indicates a short duration of unemployment spells in the past and therefore accelerates the present change into employment. The negative influence of the mean duration of unemployment can be explained likewise. Furthermore, the labour market status variables generally indicate the expected positive influence of former employment on the hazard rate.

Finally, the start of unemployment spells has a significant negative influence on the hazard rate in most of the sub-samples. Persons who were unemployed at the beginning of the 1990s changed back into employment faster than persons whose unemployment spells started later.

At first sight this may seem a startling result. It could possibly be explained by the labour market's development itself. At the beginning of the 1990s the East German labour market was undergoing institutional and statutory changes and was very flexible. After these changes were accomplished, however, the labour market in East Germany was increasingly characterised by inflexibility associated with persistent underemployment. The rise of the long-term unemployment rate in our data can be seen as an indicator for this development.

The aim of the study is to evaluate the effects of further training on the individual unemployment duration of different groups of persons representing individual characteristics and some aspects of the economic environment. We analyse the whole sample as well as the sub-sample of long-term unemployed persons. Additionally, we divide our sample in different sub-samples by gender, education, age, beginning of the unemployment period and duration of the measures.

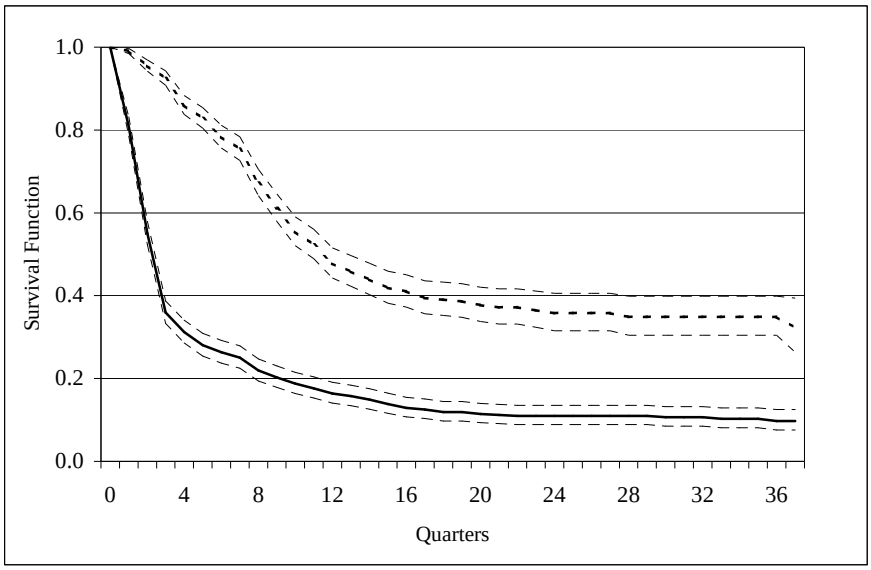
The results show a negative influence of further training on employment chances, with gradual differences in the analysed groups. For lack of space we present only the results for the whole sample and the gender sub-samples. When distinguishing between different times for the beginning of the unemployment period, we find interesting results. Therefore, we present especially these results in detail. The other sub-samples can be seen in Figures A.7 to A.14 in the Appendix.

The Figures show the estimated covariate-adjusted survival function, i.e. the probability of being unemployed for each quarter after the beginning of the unemployment spell. The dashed line identifies participation, the solid line the situation of non-participation. Fine lines show the 95% confidence interval for both cases, participation and non-participation.[36] The Figures reveal that the influence of participation differs across our sub-samples.

As can be seen in Figure 2, over the whole sample the participation in further training has a negative influence on the employment probability. In case of non-participation 65% of the persons find a job within three quarters while in case of participation only 7% do. After twelve quarters nearly 50% of the participants are still not employed. In case they had not participated in the measure the rate of persons not employed would only be 13%.

[36] The confidence intervals should not be used to draw inferential conclusions about the equality of median survival times for both groups, see HOSMER and LEMESHOW (1999), p. 156.

Figure 2: Covariate-adjusted survival functions in participation and non-participation
–Whole Sample –



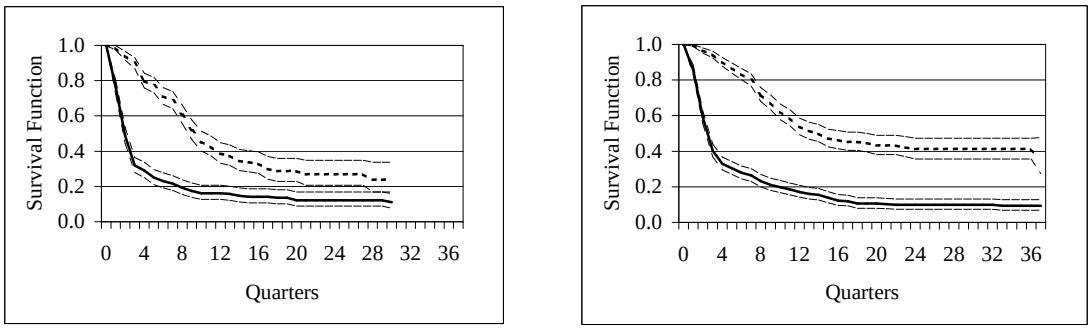
- - - Participation —— Non-Participation – – – 95%-Confidence Interval

Source: Micro Census Saxony, own calculations.

Comparing Figures 3 and 4 demonstrates that the participation effect is negative particularly for women. While the non-participation curve of men and women is similar,[37] the participation in further training noticeably delays women's transition to employment compared to men. After four quarters 20% of male participants and 10% of female participants are employed. The ratio increases to about 55% and 40% for men and women, respectively after ten quarters. Over a longer time horizon the share of not employed female participants exceeds that of male participants (43% and 25%, respectively after twenty quarters).

Figures 3 to 4: Covariate-adjusted survival functions in participation and non-participation

– Men – – Women –



- - - Participation —— Non-Participation – – – 95%-Confidence Interval

Source: Micro Census Saxony, own calculations.

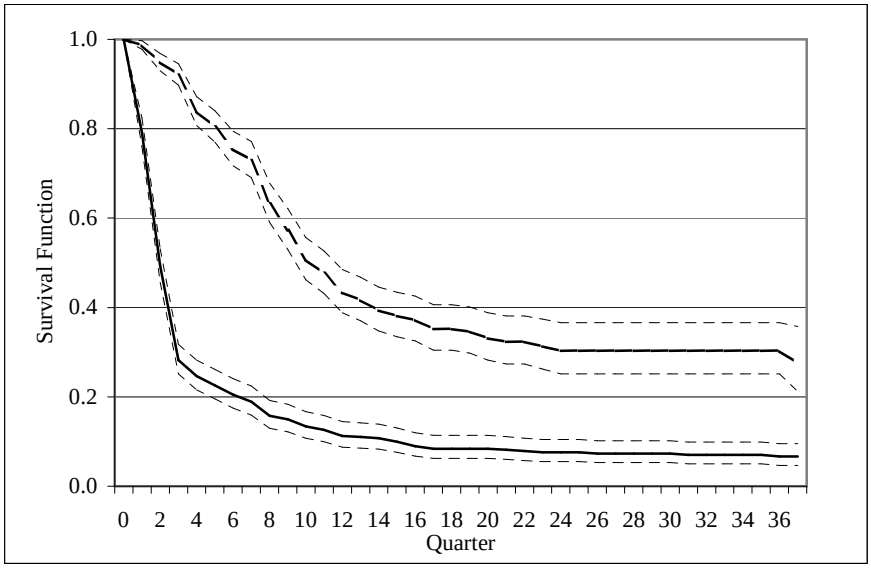
[37] After four quarters 70% of the observed men and 60% of the observed women are employed; after 10 quarters the share is 85% and 80%, respectively.

Our results for three sub-samples, which describe different beginnings of unemployment spells, show a very interesting drift of participation effects with respect to the effectiveness of further training (Figures 5 to 7). This drift can be explained by a changing economic and legal basis during our observational period. Three different periods can be identified: the first period starts in 1989 and ends about 1992. This period is characterised by the transformation process in East Germany. One political answer to the changing conditions on the labour market was a large implementation of further training (see also Figure 1) which was mainly used to ease the pressure on the labour market. The implemented programmes were not differentiated regarding personal, regional or economic requirements.

The second period begins around 1993 and ends about 1996. Practice in the Federal Employment Office and Training Agencies began to change which led to a decreasing number of participants in training programmes. Therefore, it could have been easier to adjust the programmes to the labour demand requirements but de facto there was no major focus on integration of participants into regular employment. Instead Further Training was mainly used to extend the duration of unemployment benefits.

In the third period which starts around 1997 the training policy was modified by introducing the so called ‘target group focussing’. Now subsidies on further training measures were primarily granted to specific target groups like long-term unemployed and older or younger persons without professional skills. Local employment offices continued to plan training programmes but regional labour demand was not part of the consideration.

Figure 5: Covariate-adjusted survival functions in participation and non-participation
– Start of the unemployment spell until 1992 –



- - - Participation —— Non-Participation – – – 95%-Confidence Interval

Source: Micro Census Saxony, own calculations.

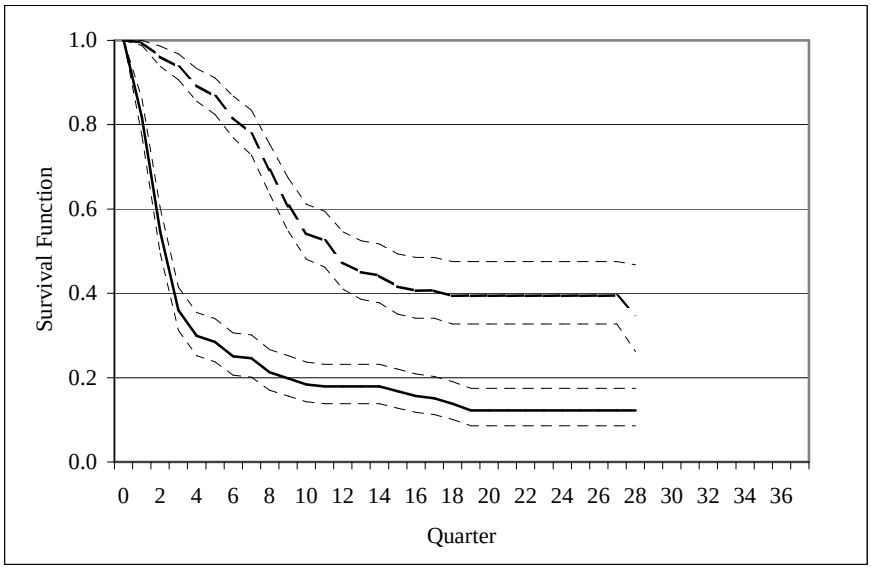
In all three periods participation in further training results in a prolongation of unemployment duration compared to the situation of non-participation. But there are some remarkable changes in the shape of the curves.

Especially during the first period until 1992 a very fast drop out of unemployment for non-participation can be observed (see Figure 5). A large divergence between the survival curves can already be noticed after three quarters. The survival curves begin to converge afterwards but in the long run the difference between the two remains at about 20%.

The shape of the curves can be explained by the developments in the first period described above. Since the participants in further training programmes had a large share in the total number of unemployed persons in this period, it is possible that programmes affected the regular labour market. Thus, the fundamental assumption for microeconomic evaluation, the SUTVA, may be violated. In this case an additional macroeconomic analysis would be appropriate, but this is beyond the scope of this paper.

As can be seen in Figure 6, in the second period from 1993 to 1996 effects of further training are similar to those in the first period. Participants and their hypothetical counterparts changed slightly slower into employment. A possible explanation for this difference is that target group focussing was gradually implemented then. Therefore, persons with lower employment chances often participated in training programmes. In the long run, the gap between both survival curves is nearly the same as in the first period.

Figure 6: Covariate-adjusted survival functions in participation and non-participation
– Start of the unemployment spell between 1993 and 1996 –

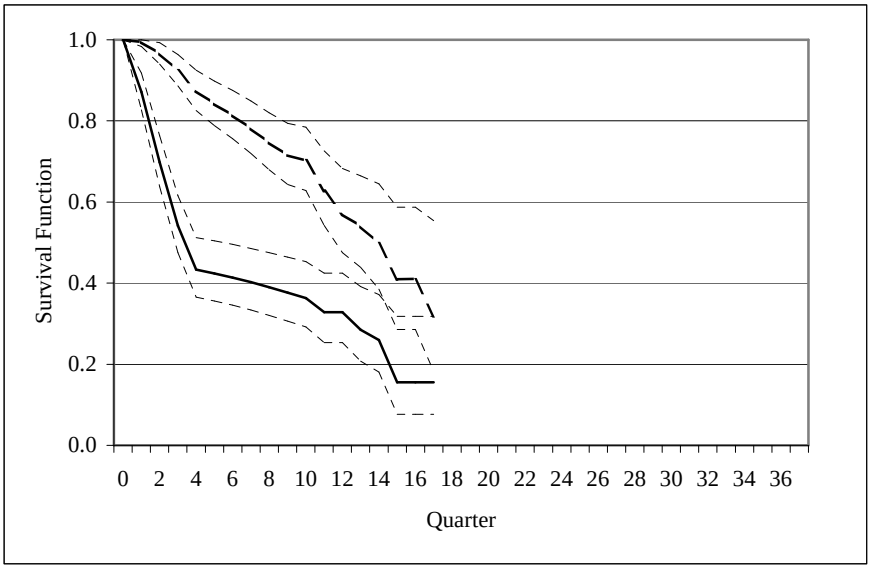


- - - Participation —— Non-Participation – – – 95%-Confidence Interval
Source: Micro Census Saxony, own calculations.

Figure 7 shows that the survival functions changed considerably in the third period since 1997. The survival curve of participants is relatively linear, unlike the respective curve for the second period. Instead of a fading out, the participants' survival function becomes even steeper after the tenth quarter. Moreover, the non-participation survival curve shows a slower decline from the third quarter than in the period before and has a concave instead of a convex shape afterwards. The shape of both curves implies a smaller difference between the participation and non-participation outcome. We cannot observe the further development of the survival functions, because the observation time ends already after 17 quarters.

This change relative to the previous period may be a result of a more rigid implementation of target group focussing. We can also observe this trend in our data, e.g. the share of long-term unemployed persons changed from 24% in the first period to nearly 33% in the third period. In other target groups we cannot identify changes due to our selection of spells.

Figure 7: Covariate-adjusted survival functions in participation and non-participation
– Start of the unemployment spell from 1997 –



- - - Participation —— Non-Participation – – – 95%-Confidence Interval
Source: Micro Census Saxony, own calculations.

The results for the third group could be taken as a hint that further training is more successful if policy is focussed on specific target groups. This may indicate the direction to improve the effectiveness of training programmes.

In our analysis of the whole sample and the above described sub-samples we find a negative influence of further training on employment chances, with gradual differences in the analysed groups. These results are slightly worse than those of other recent evaluation studies which find insignificant effects (FITZENBERGER, 2001, 2004, LECHNER, 2000).

10. CONCLUSIONS

In this study we have evaluated the employment effects of further training programmes for Saxony between 1990 and 2001. Our methodological approach differs in three aspects from other studies in the literature. First, we follow the concept of perforated unemployment which implies that the duration of the programme is included in the total time of unemployment. This approach improves the comparability of the situation of participation and the hypothetical situation of non-participation. Second, we use the prehistory of the employment status. The structure and duration of employment and unemployment periods is used as an indicator of the probability of changing into employment before the start of the programme. Thereby we avoid heterogeneity between participants and non-participants and at the same time we eliminate Ashenfelter's Dip. Third, we employ the Hungarian algorithm for matching, which provides an optimal full assignment. This technique avoids the problem of losing observations due to the design of the assignment process and yields an optimal result as is required for an appropriate assignment procedure.

Since in the literature analyses of whether the effect of participation in a programme is influenced by individual characteristics or economic environment are rarely found, we evaluated the employment effects of further training programmes for different sub-samples representing individual characteristics as well as some aspects of the economic environment. The results of our evaluation show a negative effect of participation in further training programmes – with gradual differences in the sub-samples. These results are similar to the findings of other evaluation studies.

This can be interpreted as a first indication that the employment prospects of the participants are influenced by personal characteristics, economic environment and the organisational design of training measures. Further research should focus on institutional factors like entrance requirements, the subjects of the courses, their adjustment to regional demand, practical work experience during the measure. With this information it would be possible to detect potentially successful measures.

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SUMMARY

This study evaluates the effects of further training on the individual unemployment duration of different groups of persons representing individual characteristics and some aspects of the economic environment. The Micro Census Saxony enables us to include additional information about a person's employment history to eliminate the bias resulting from unobservable characteristics and to avoid Ashenfelter's Dip. To solve the sample selection problem we employ an optimal full matching assignment, the Hungarian algorithm, using an aggregate distance measure. This procedure is superior to greedy pair matching in the sense that it avoids the loss of observations due to the design of the algorithm and yields the optimal assignment result, i.e. the minimum total sum of squared distances. The impact of participation in further training is evaluated by comparing the unemployment duration between participants and non-participants using the Cox Proportional Hazard Model.

Overall, we find empirical evidence that participation in further training programmes results in even longer unemployment duration – with only gradual differences in the analysed groups.

Table A.1: Parameter estimates of the probit model for the sub-samples

Variable	Whole Sample	Long Term Unemployed	Gender		Age		Human Capital		Residence			Start of the Unemployment Spell			Duration of the Measure (in Quarters)		
			Women	Men	Younger than 40	40 and older	Skilled	High Skilled	Chemnitz	Dresden	Leipzig	Until 1992	1993 to 1996	From 1997	Shorter than 4	4 to 7	Longer than 7
Constant	0.210 (0.993)	-1.187*** (-3.443)	0.258 (0.986)	0.132 (0.310)	0.391 (1.270)	0.200 (0.278)	0.288 (1.293)	-0.224 (-0.411)	-0.076 (-0.209)	0.665** (2.062)	-0.539 (-1.291)	0.081 (0.264)	0.223 (0.496)	-0.483 (-0.972)	-1.459*** (-4.516)	-0.743*** (-2.656)	0.675** (2.240)
Gender (male = 1)	-0.322*** (-6.627)	-0.009 (-0.107)	-	-	-0.300*** (-4.904)	-0.371*** (-4.582)	-0.329*** (-6.075)	-0.210 (-1.439)	-0.297*** (-3.813)	-0.339*** (-4.264)	-0.323*** (-3.154)	-0.396*** (-5.316)	-0.215** (-2.337)	-0.298*** (-3.130)	-0.275*** (-3.849)	-0.246*** (-3.868)	-0.374*** (-5.186)
Age	-0.013*** (-2.687)	-0.013* (-1.661)	-0.008 (-1.232)	-0.021*** (-3.051)	-0.022 (-2.480)	-0.006 (-0.404)	-0.018*** (-3.511)	0.010 (0.608)	-0.013 (-1.625)	-0.023*** (-2.797)	0.002 (0.244)	-0.015** (-1.988)	-0.019** (-2.045)	0.000 (0.024)	0.007 (1.053)	-0.006 (-0.934)	-0.036*** (-4.898)
Completed Apprentice-ship/Technician	0.077 (0.883)	0.434*** (2.831)	0.100 (0.874)	0.116 (0.855)	0.162 (1.415)	-0.022 (-0.163)	-	-	-0.165 (-1.107)	0.065 (0.494)	0.543*** (2.735)	0.293** (2.117)	0.071 (0.429)	-0.222 (-1.403)	0.199 (1.409)	-0.109 (-1.029)	0.225* (1.664)
University/College Degree	0.188* (1.696)	0.349* (1.650)	0.106 (0.704)	0.313* (1.854)	0.249* (1.743)	0.142 (0.799)	-	-	-0.096 (-0.504)	0.327* (1.912)	0.516** (2.138)	0.453*** (2.637)	0.054 (0.250)	-0.159 (-0.757)	0.313* (1.820)	0.208 (1.571)	-0.062 (-0.335)
Start of Unemployment-Spell	-0.007** (-2.010)	-	-0.015*** (-4.502)	-	-0.015*** (-4.637)	-	-	-0.023*** (-3.223)	-	-0.011*** (-2.821)	-	-	-	-	-	-	-0.025*** (-6.476)
Residence Chemnitz	-	-	-	-	-	-	-0.117** (-2.250)	-	-	-	-	-	-	-	-	-	-
Frequency of Changes into Unemployment[1]	-3.906*** (-8.781)	-3.532*** (-4.770)	-3.118*** (-6.245)	-4.971*** (-6.686)	-4.333*** (-6.738)	-4.128*** (-6.449)	-4.541*** (-9.548)	-3.796** (-2.258)	-4.046*** (-5.711)	-3.829*** (-5.509)	-5.655*** (-5.437)	- 13.105*** (-3.378)	-6.976*** (-5.550)	-3.960*** (-6.123)	-2.699*** (-4.948)	-4.121*** (-6.560)	-3.406*** (-5.080)
Frequency of Changes into Employment[1]	1.005*** (4.333)	0.548 (1.485)	0.720*** (3.053)	1.312*** (2.886)	1.060*** (4.262)	0.995** (2.338)	1.170*** (5.040)	-	1.844*** (4.626)	1.102*** (3.167)	-	-	1.619*** (3.359)	1.062** (2.576)	1.028*** (3.047)	0.896*** (2.972)	0.563** (2.070)
Mean Duration of Unemployment	0.175*** (9.290)	0.150*** (4.415)	0.138*** (5.936)	0.222*** (6.801)	0.239*** (7.162)	0.151*** (6.330)	0.198*** (9.034)	0.179** (2.146)	0.192*** (6.020)	0.194*** (5.550)	-	1.167*** (3.618)	0.405*** (6.675)	0.140*** (6.042)	0.119*** (5.105)	0.159*** (6.287)	0.162*** (5.831)
Mean Duration of Employment	-0.009*** (-2.597)	-0.011 (-2.407)	-	-0.014*** (-3.861)	-	-0.015*** (-3.713)	-0.016*** (-5.583)	-	-0.021*** (-4.597)	-	0.175*** (4.719)	-	-0.015** (-2.085)	-0.016*** (-3.696)	-0.006* (-1.785)	-0.014*** (-3.986)	-
Labour Market Status t-1[2] (Employment=1)	-	0.613*** (2.705)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Labour Market Status t-2[2] (Employment=1)	-0.293** (-2.282)	-	-	-	-	-0.373* (-1.747)	-	-	-0.417* (-1.862)	-	-0.022*** (-4.021)	0.413** (2.245)	-0.810*** (-2.994)	-	-0.343* (-1.870)	-	-
Labour Market Status t-3[2] (Employment=1)	-	-	-	-0.882*** (-3.286)	-	-	-	-	-	-0.392* (-1.940)	-	-	-	-	-	-	-
Labour Market Status t-4[2] (Employment=1)	-	-	-	0.529** (1.992)	-	-	-	-	-	-	0.570** (2.192)	-	-	-	-	0.412** (2.195)	-
Labour Market Status t-5[2] (Employment=1)	-	-	-0.435** (-2.032)	-1.062*** (-4.677)	-0.566*** (-2.756)	-0.831*** (-3.947)	-0.930*** (-6.611)	-	-	-0.742*** (-3.429)	-0.685*** (-2.626)	-	-0.639** (-2.483)	-0.775*** (-4.139)	-0.781*** (-4.275)	-0.532** (-2.331)	-
Labour Market Status t-6[2] (Employment=1)	-0.656*** (-5.511)	-0.786*** (-3.808)	-0.362* (-1.789)	-	-0.415** (-2.142)	-	-	-	-0.948*** (-4.904)	-	-	-0.443** (-2.523)	-	-	-	-0.553*** (-2.715)	-0.592*** (-3.217)
Long Term Unemployment	-0.534*** (-10.872)	-	-0.754*** (-11.904)	-0.223*** (-2.924)	-0.569*** (-9.279)	-0.482*** (-5.862)	-0.477*** (-8.870)	-0.635*** (-3.712)	-0.446*** (-5.635)	-0.656*** (-8.184)	-0.486*** (-4.717)	-0.745*** (-9.999)	-0.494*** (-5.336)	-0.187* (-1.952)	-0.503*** (-6.766)	-0.357*** (-5.609)	-0.650*** (-8.761)

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell.
– [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell
*,**,*** Significance on the10%-, 5%-, and 1%-level respectively – standard error in brackets

Table A.2: Comparison of means and distributions of selected characteristics in the groups of participants (P) and non-participants (NP) in selected sub-samples before and after Matching

Variable	Whole Sample								Long Term Unemployed							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	0.382	0.534	-0.151	63.294	0.382	0.376	0.006	0.062	0.340	0.377	-0.037	1.224	0.340	0.319	0.021	0.238
	(0.486)	(0.499)	(0.000)	(0.000)	(0.486)	(0.485)	(0.803)	(0.803)	(0.474)	(0.485)	(0.269)	(0.269)	(0.474)	(0.466)	(0.627)	(0.626)
Start of Unemployment-Spell	20.168	25.284	-5.115	5.736	20.168	20.272	-0.104	0.655	20.861	23.481	-2.620	1.741	20.861	20.508	0.353	0.779
	(11.348)	(12.421)	(0.000)	(0.000)	(11.348)	(11.509)	(0.852)	(0.784)	(11.053)	(11.958)	(0.001)	(0.005)	(11.053)	(11.185)	(0.730)	(0.578)
Completed Apprenticeship/ Technician	0.816	0.835	-0.018	1.636	0.816	0.834	-0.018	0.918	0.891	0.828	0.063	6.026	0.891	0.895	-0.004	0.220
	(0.387)	(0.371)	(0.201)	(0.201)	(0.387)	(0.372)	(0.338)	(0.338)	(0.312)	(0.378)	(0.014)	(0.014)	(0.312)	(0.307)	(0.883)	(0.882)
University/College Degree	0.114	0.080	0.034	10.044	0.114	0.108	0.006	0.149	0.059	0.068	-0.009	0.314	0.059	0.059	0.000	0.000
	(0.318)	(0.272)	(0.002)	(0.002)	(0.318)	(0.311)	(0.699)	(0.700)	(0.235)	(0.253)	(0.575)	(0.575)	(0.235)	(0.235)	(1.000)	(1.000)
Age	36.425	38.344	-1.920	3.850	36.425	36.431	-0.006	0.461	36.807	38.090	-1.283	1.558	36.807	36.853	-0.046	0.275
	(5.448)	(5.546)	(0.000)	(0.000)	(5.448)	(5.332)	(0.984)	(0.982)	(5.578)	(5.390)	(0.001)	(0.016)	(5.579)	(5.578)	(0.928)	(1.000)
Residence Chemnitz	0.362	0.417	-0.055	8.669	0.362	0.369	-0.007	0.91	0.395	0.405	-0.010	0.083	0.395	0.387	0.008	0.035
	(0.481)	(0.493)	(0.003)	(0.003)	(0.481)	(0.482)	(0.763)	(0.763)	(0.489)	(0.491)	(0.774)	(0.774)	(0.489)	(0.487)	(0.851)	(0.851)
Residence Dresden	0.404	0.362	0.041	5.110	0.404	0.400	0.004	0.610	0.370	0.376	-0.006	0.037	0.370	0.370	0.000	0.000
	(0.491)	(0.481)	(0.024)	(0.24)	(0.491)	(0.489)	(0.805)	(0.805)	(0.483)	(0.484)	(0.847)	(0.847)	(0.483)	(0.483)	(1.000)	(1.000)
Share of Time in Unemployment[1]	0.031	0.094	-0.064	3.624	0.031	0.039	-0.008	0.946	0.038	0.074	-0.036	1.047	0.038	0.044	-0.006	0.485
	(0.090)	(0.194)	(0.000)	(0.000)	(0.090)	(0.100)	(0.923)	(0.333)	(0.106)	(0.187)	(0.003)	(0.223)	(0.106)	(0.135)	(0.624)	(0.985)
Share of Time in Employment[1]	0.905	0.865	0.040	2.317	0.905	0.909	-0.004	0.970	0.898	0.862	0.036	0.845	0.898	0.892	0.006	0.413
	(0.212)	(0.245)	(0.000)	(0.000)	(0.212)	(0.217)	(0.674)	(0.303)	(0.220)	(0.263)	(0.072)	(0.473)	(0.219)	(0.891)	(0.753)	(0.996)
Share of Time in Non-Employment[1]	0.064	0.040	0.023	1.889	0.064	0.059	0.005	0.703	0.063	0.059	0.004	0.614	0.063	0.065	-0.002	0.367
	(0.188)	(0.159)	(0.000)	(0.002)	(0.188)	(0.188)	(0.595)	(0.706)	(0.186)	(0.192)	(0.756)	(0.846)	(0.186)	(0.064)	(0.946)	(0.999)
Mean Duration of Unemployment	0.640	0.958	-0.317	2.666	0.640	0.505	0.135	0.946	0.786	0.972	-0.186	0.285	0.786	0.714	0.072	0.458
	(1.830)	(2.595)	(0.001)	(0.000)	(1.830)	(1.866)	(0.127)	(0.333)	(2.190)	(2.863)	(0.335)	(1.000)	(2.191)	(2.465)	(0.739)	(0.985)
Mean Duration of Employment	13.747	15.564	-1.817	3.076	13.747	14.133	-0.386	0.800	14.385	16.125	-1.740	1.279	14.385	14.334	0.051	0.367
	(9.566)	(12.131)	(0.000)	(0.000)	(9.566)	(9.504)	(0.405)	(0.544)	(9.874)	(11.803)	(0.030)	(0.076)	(9.874)	(9.973)	(0.956)	(0.999)
Mean Duration of Non-Employment	0.955	0.602	0.353	1.889	0.955	0.94	0.015	0.703	0.846	0.850	-0.004	0.570	0.846	0.758	0.088	0.321
	(2.862)	(2.633)	(0.001)	(0.000)	(2.862)	3.432)	(0.922)	(0.706)	(2.497)	(3.113)	(0.984)	(0.901)	(2.497)	(2.479)	(0.702)	(1.000)
Labour Market Status t-1[2] (Employment=1)	0.924	0.943	-0.020	4.807	0.924	0.926	-0.002	0.340	0.950	0.912	0.038	3.846	0.950	0.950	0.000	0.000
	(0.266)	(0.231)	(0.028)	(0.028)	(0.266)	(0.262)	(0.854)	(0.854)	(0.219)	(0.283)	(0.050)	(0.050)	(0.219)	(0.218)	(1.000)	(1.000)
Labour Market Status t-2[2] (Employment=1)	0.908	0.922	-0.014	1.892	0.908	0.921	-0.013	0.912	0.932	0.899	0.033	2.677	0.933	0.929	0.004	0.033
	(0.289)	(0.267)	(0.169)	(0.169)	(0.289)	(0.269)	(0.340)	(0.340)	(0.250)	(0.300)	(0.102)	(0.102)	(0.250)	(0.257)	(0.857)	(0.857)
Labour Market Status t-3[2] (Employment=1)	0.898	0.888	0.010	0.718	0.898	0.909	-0.011	0.675	0.912	0.884	0.028	1.595	0.912	0.912	0.000	0.000
	(0.303)	(0.316)	(0.397)	(0.397)	(0.303)	(0.287)	(0.265)	(0.411)	(0.284)	(0.320)	(0.207)	(0.207)	(0.283)	(0.283)	(1.000)	(1.000)
Labour Market Status t-4[2] (Employment=1)	0.888	0.847	0.041	9.354	0.888	0.905	-0.017	1.242	0.891	0.874	0.017	0.514	0.891	0.899	-0.008	0.890
	(0.315)	(0.360)	(0.002)	(0.002)	(0.315)	0.293)	(0.265)	(0.265)	(0.312)	(0.331)	(0.474)	(0.473)	(0.312)	(0.301)	(0.766)	(0.765)
Labour Market Status t-5[2] (Employment=1)	0.879	0.903	-0.024	4.269	0.879	0.893	-0.014	0.838	0.870	0.889	-0.019	0.763	0.870	0.895	-0.025	0.729
	(0.326)	(0.297)	(0.039)	(0.039)	(0.326)	(0.309)	(0.360)	(0.360)	(0.337)	(0.314)	(0.383)	(0.382)	(0.336)	(0.307)	(0.394)	(0.393)
Labour Market Status t-6[2] (Employment=1)	0.878	0.895	-0.017	2.036	0.878	0.888	-0.01	0.461	0.866	0.884	-0.018	0.687	0.866	0.866	0.000	0.000
	(0.328)	(0.307)	(0.154)	(0.154)	(0.328)	(0.315)	(0.497)	(0.497)	(0.341)	(0.320)	(0.407)	(0.407)	(0.341)	(0.341)	(1.000)	(1.000)
Long Term Unemployed	0.280	0.442	-0.162	75.245	0.280	0.303	-0.023	1.139	-	-	-	-	-	-	-	-
	(0.449)	(0.497)	(0.000)	(0.000)	(0.449)	(0.460)	(0.286)	(0.286)	-	-	-	-	-	-	-	-

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Gender															
	Woman								Man							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Start of Unemployment-Spell	18.566	22.584	-4.018	3.727	18.566	18.512	0.054	0.555	22.757	27.644	-4.887	3.609	22.757	22.794	-0.037	0.353
	(10.539)	(12.228)	(0.000)	(0.000)	(10.529)	(10.734)	(0.935)	(0.917)	(12.138)	(12.110)	(0.000)	(0.000)	(12.118)	(12.017)	(0.969)	(1.000)
Completed Apprenticeship/ Technician	0.821	0.831	-0.010	0.311	0.821	0.84	-0.019	0.676	0.809	0.838	-0.029	1.612	0.809	0.834	-0.025	0.672
	(0.384)	(0.374)	(0.577)	(0.577)	(0.383)	(0.366)	(0.411)	(0.411)	(0.394)	(0.369)	(0.204)	(0.204)	(0.392)	(0.372)	(0.413)	(0.413)
University/College Degree	0.107	0.079	0.028	3.824	0.107	0.097	0.010	0.260	0.126	0.081	0.045	7.150	0.126	0.114	0.012	0.233
	(0.309)	(0.270)	(0.051)	(0.051)	(0.308)	(0.296)	(0.610)	(0.610)	(0.333)	(0.273)	(0.007)	(0.007)	(0.332)	(0.317)	(0.630)	(0.629)
Age	36.208	37.695	-1.487	2.299	36.208	36.211	-0.003	0.309	36.775	38.913	-2.138	2.847	36.775	36.846	-0.071	0.353
	(5.382)	(5.532)	(0.000)	(0.000)	(5.376)	(5.265)	(0.991)	(1.000)	(5.551)	(5.497)	(0.000)	(0.000)	(5.542)	(5.359)	(0.869)	(1.000)
Residence Chemnitz	0.350	0.407	-0.057	5.464	0.350	0.362	-0.012	0.150	0.382	0.426	-0.044	2.273	0.382	0.369	0.013	0.105
	(0.478)	(0.491)	(0.019)	(0.019)	(0.477)	(0.480)	(0.699)	(0.699)	(0.487)	(0.495)	(0.132)	(0.132)	(0.485)	(0.482)	(0.746)	(0.746)
Residence Dresden	0.408	0.376	0.032	1.673	0.408	0.404	0.004	0.016	0.397	0.350	0.047	2.728	0.397	0.400	-0.003	0.006
	(0.492)	(0.485)	(0.196)	(0.196)	(0.491)	(0.491)	(0.900)	(0.900)	(0.490)	(0.477)	(0.099)	(0.099)	(0.489)	(0.489)	(0.936)	(0.936)
Share of Time in Unemployment[1]	0.034	0.090	-0.056	2.103	0.034	0.035	-0.001	0.586	0.026	0.098	-0.072	3.122	0.026	0.032	-0.006	0.431
	(0.097)	(0.201)	(0.000)	(0.000)	(0.096)	(0.116)	(0.846)	(0.882)	(0.077)	(0.187)	(0.000)	(0.000)	(0.077)	(0.097)	(0.427)	(0.992)
Share of Time in Employment[1]	0.878	0.836	0.042	1.336	0.878	0.878	0.000	0.401	0.950	0.891	0.059	2.508	0.950	0.945	0.005	0.510
	(0.245)	(0.283)	(0.002)	(0.056)	(0.244)	(0.258)	(0.991)	(0.997)	(0.135)	(0.203)	(0.000)	(0.000)	(0.135)	(0.152)	(0.687)	(0.957)
Share of Time in Non-Employment[1]	0.088	0.074	0.014	1.177	0.088	0.087	0.001	0.432	0.024	0.011	0.013	0.826	0.024	0.023	0.001	0.235
	(0.220)	(0.210)	(0.178)	(0.125)	(0.219)	(0.228)	(0.936)	(0.992)	(0.110)	(0.829)	(0.011)	(0.502)	(0.110)	(0.115)	(0.917)	(1.000)
Mean Duration of Unemployment	0.689	1.125	-0.436	1.274	0.689	0.583	0.106	0.586	0.562	0.811	-0.249	2.206	0.562	0.382	0.180	0.586
	(1.957)	(3.090)	(0.002)	(0.078)	(1.955)	(2.061)	(0.393)	(0.882)	(1.605)	(2.057)	(0.037)	(0.000)	(1.602)	(1.265)	(0.112)	(0.888)
Mean Duration of Employment	12.181	13.758	-1.577	2.133	12.181	12.287	-0.106	0.494	16.278	17.143	-0.865	2.304	16.278	16.431	-0.153	0.494
	(8.611)	(10.726)	(0.002)	(0.000)	(8.602)	(8.338)	(0.840)	(0.968)	(10.478)	(13.040)	(0.255)	(0.000)	(10.461)	(10.632)	(0.853)	(0.968)
Mean Duration of Non-Employment	1.218	1.065	0.153	1.165	1.218	1.138	0.080	0.401	0.531	0.197	0.334	0.826	0.531	0.498	0.033	0.401
	(3.051)	(3.347)	(0.351)	(0.132)	(3.047)	(3.105)	(0.677)	(0.997)	(2.478)	(1.690)	(0.002)	(0.502)	(2.473)	(3.022)	(0.882)	(0.997)
Labour Market Status t-1[2] (Employment=1)	0.903	0.909	-0.006	0.187	0.903	0.901	0.002	0.011	0.957	0.973	-0.016	2.677	0.957	0.957	0.000	0.000
	(0.296)	(0.288)	(0.666)	(0.665)	(0.296)	(0.298)	(0.917)	(0.917)	(0.203)	(0.161)	(0.102)	(0.102)	(0.203)	(0.203)	(1.000)	(1.000)
Labour Market Status t-2[2] (Employment=1)	0.886	0.889	-0.003	0.043	0.886	0.891	-0.005	0.087	0.945	0.952	-0.007	0.300	0.945	0.957	-0.012	0.526
	(0.318)	(0.314)	(0.837)	(0.837)	(0.318)	(0.311)	(0.769)	(0.769)	(0.229)	(0.214)	(0.584)	(0.584)	(0.228)	(0.203)	(0.469)	(0.468)
Labour Market Status t-3[2] (Employment=1)	0.876	0.860	0.016	0.879	0.876	0.878	-0.002	0.009	0.932	0.912	0.020	1.550	0.932	0.948	-0.016	0.682
	(0.330)	(0.347)	(0.349)	(0.349)	(0.329)	(0.327)	(0.925)	(0.925)	(0.252)	(0.284)	(0.213)	(0.213)	(0.251)	(0.222)	(0.410)	(0.409)
Labour Market Status t-4[2] (Employment=1)	0.861	0.845	0.016	0.833	0.861	0.872	-0.011	0.297	0.932	0.850	0.082	15.988	0.932	0.951	-0.019	1.006
	(0.346)	(0.362)	(0.362)	(0.361)	(0.345)	(0.333)	(0.586)	(0.586)	(0.252)	(0.358)	(0.000)	(0.000)	(0.251)	(0.216)	(0.317)	(0.316)
Labour Market Status t-5[2] (Employment=1)	0.851	0.869	-0.018	1.042	0.851	0.859	-0.008	0.123	0.923	0.932	-0.009	0.353	0.923	0.929	-0.006	0.090
	(0.356)	(0.338)	(0.308)	(0.307)	(0.355)	(0.347)	(0.726)	(0.726)	(0.267)	(0.252)	(0.553)	(0.553)	(0.266)	(0.256)	(0.765)	(0.764)
Labour Market Status t-6[2] (Employment=1)	0.846	0.859	-0.013	0.530	0.846	0.857	-0.011	0.271	0.929	0.926	0.003	0.041	0.929	0.945	-0.016	0.651
	(0.362)	(0.349)	(0.467)	(0.467)	(0.361)	(0.349)	(0.603)	(0.603)	(0.257)	(0.262)	(0.839)	(0.839)	(0.256)	(0.229)	(0.421)	(0.420)
Long Term Unemployed	0.299	0.590	-0.291	137.128	0.299	0.318	-0.019	0.446	0.249	0.313	-0.064	5.349	0.249	0.271	-0.022	0.392
	(0.458)	(0.492)	(0.000)	(0.000)	(0.458)	(0.465)	(0.505)	(0.504)	(0.433)	(0.464)	(0.021)	(0.021)	(0.432)	(0.444)	(0.532)	(0.531)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Age															
	Younger than 40								40 and older							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	0.369	0.498	-0.129	31.102	0.369	0.372	-0.003	0.015	0.413	0.580	-0.167	25.158	0.413	0.405	0.008	0.032
	(0.483)	(0.500)	(0.000)	(0.000)	(0.482)	(0.483)	(0.904)	(0.904)	(0.493)	(0.494)	(0.000)	(0.000)	(0.492)	(0.490)	(0.859)	(0.858)
Start of Unemployment-Spell	17.401	21.230	3.829	4.080	17.401	17.330	0.071	0.756	26.483	30.623	-4.140	2.364	26.483	26.876	-0.393	0.439
	(9.656)	(11.451)	(0.000)	(0.000)	(9.648)	(9.672)	(0.899)	(0.617)	(12.387)	(11.609)	(0.000)	(0.000)	(12.363)	(12.423)	(0.718)	(0.990)
Completed Apprentice-ship/Technician	0.829	0.834	-0.005	0.076	0.829	0.844	-0.015	0.502	0.788	0.836	-0.048	3.637	0.788	0.826	-0.038	1.239
	(0.377)	(0.373)	(0.738)	(0.783)	(0.376)	(0.362)	(0.479)	(0.479)	(0.409)	(0.371)	(0.057)	(0.057)	(0.408)	(0.378)	(0.266)	(0.266)
University/College Degree	0.112	0.082	0.030	5.003	0.112	0.108	0.004	0.035	0.120	0.078	0.041	5.113	0.120	0.097	0.023	0.721
	(0.315)	(0.275)	(0.025)	(0.025)	(0.314)	(0.311)	(0.853)	(0.852)	(0.325)	(0.268)	(0.024)	(0.024)	(0.325)	(0.295)	(0.397)	(0.396)
Age	33.580	34.419	-0.839	2.199	33.580	33.643	-0.063	0.378	42.915	43.519	-0.675	1.793	42.915	42.992	-0.077	0.747
	(3.614)	(3.498)	(0.000)	(0.000)	(3.610)	(3.575)	(0.765)	(0.999)	(2.662)	(2.845)	(0.001)	(0.003)	(2.626)	(2.508)	(0.734)	(0.632)
Residence Chemnitz	0.350	0.403	0.053	5.307	0.350	0.342	0.008	0.093	0.390	0.437	-0.047	1.999	0.390	0.417	-0.027	0.393
	(0.477)	(0.491)	(0.021)	(0.021)	(0.477)	(0.474)	(0.760)	(0.76)	(0.489)	(0.496)	(0.158)	(0.157)	(0.487)	(0.493)	(0.532)	(0.531)
Residence Dresden	0.425	0.371	0.054	5.657	0.425	0.425	0.000	0.000	0.355	0.350	0.005	0.023	0.355	0.367	-0.012	0.075
	(0.495)	(0.483)	(0.017)	(0.017)	(0.494)	(0.494)	(1.000)	(1.000)	(0.479)	(0.477)	(0.879)	(0.879)	(0.478)	(0.481)	(0.784)	(0.784)
Share of Time in Unemployment[1]	0.024	0.077	0.053	2.479	0.024	0.023	0.001	0.669	0.046	0.117	-0.071	2.317	0.046	0.052	-0.006	0.308
	(0.079)	(0.179)	(0.000)	(0.000)	(0.079)	(0.091)	(0.881)	(0.762)	(0.108)	(0.209)	(0.000)	(0.000)	(0.108)	(0.128)	(0.575)	(1.000)
Share of Time in Employment[1]	0.904	0.866	0.038	1.622	0.904	0.908	-0.004	0.727	0.909	0.864	0.045	1.678	0.909	0.907	0.002	0.527
	(0.219)	(0.251)	(0.001)	(0.010)	(0.219)	(0.223)	(0.717)	(0.666)	(0.196)	(0.236)	(0.004)	(0.007)	(0.195)	(0.221)	(0.898)	(0.944)
Share of Time in Non-Employment[1]	0.072	0.056	0.016	1.129	0.072	0.068	0.004	0.553	0.045	0.019	0.026	1.399	0.045	0.041	0.004	0.659
	(0.199)	(0.186)	(0.072)	(0.156)	(0.198)	(0.203)	(0.738)	(0.920)	(0.161)	(0.109)	(0.001)	(0.040)	(0.160)	(0.166)	(0.808)	(0.778)
Mean Duration of Unemployment	0.486	0.758	-0.272	1.736	0.486	0.367	0.119	0.669	0.993	1.220	-0.227	1.414	0.993	0.792	0.201	0.615
	(1.523)	(2.201)	(0.005)	(0.004)	(1.521)	(1.530)	(0.182)	(0.762)	(2.355)	(3.013)	(0.247)	(0.037)	(2.350)	(2.261)	(0.321)	(0.844)
Mean Duration of Employment	12.111	13.341	-1.230	1.929	12.111	12.462	-0.351	0.785	17.482	18.496	-1.014	2.151	17.482	18.003	-0.521	0.967
	(7.836)	(10.228)	(0.007)	(0.001)	(7.828)	(7.665)	(0.437)	(0.568)	(11.873)	(13.724)	(0.261)	(0.000)	(11.85)	(11.734)	(0.616)	(0.308)
Mean Duration of Non-Employment	0.951	0.766	0.185	1.149	0.951	0.920	0.031	0.553	0.963	0.385	0.578	1.390	0.963	0.757	0.206	0.659
	(2.661)	(2.723)	(0.142)	(0.143)	(2.659)	(2.828)	(0.842)	(0.920)	(3.283)	(2.496)	(0.001)	(0.042)	(3.277)	(3.686)	(0.501)	(0.778)
Labour Market Status t-1[2] (Employment=1)	0.922	0.929	-0.007	0.391	0.922	0.929	-0.007	0.196	0.927	0.964	-0.037	6.497	0.927	0.931	-0.004	0.029
	(0.268)	(0.256)	(0.532)	(0.532)	(0.268)	(0.256)	(0.658)	(0.658)	(0.261)	(0.193)	(0.011)	(0.011)	(0.260)	(0.254)	(0.865)	(0.865)
Labour Market Status t-2[2] (Employment=1)	0.907	0.907	0.000	0.000	0.907	0.920	-0.013	0.687	0.911	0.943	-0.032	3.840	0.911	0.931	-0.020	0.662
	(0.291)	(0.290)	(0.994)	(0.994)	(0.290)	(0.270)	(0.408)	(0.407)	(0.285)	(0.232)	(0.050)	(0.050)	(0.284)	(0.254)	(0.417)	(0.416)
Labour Market Status t-3[2] (Employment=1)	0.898	0.881	0.017	1.374	0.898	0.909	-0.011	0.349	0.896	0.896	0.000	0.000	0.896	0.919	-0.023	0.827
	(0.302)	(0.324)	(0.241)	(0.241)	(0.302)	(0.288)	(0.555)	(0.554)	(0.306)	(0.305)	(0.987)	(0.987)	(0.305)	(0.272)	(0.364)	(0.363)
Labour Market Status t-4[2] (Employment=1)	0.892	0.857	0.035	4.635	0.892	0.904	-0.012	0.451	0.880	0.834	0.046	3.587	0.880	0.911	-0.031	1.323
	(0.311)	(0.349)	(0.031)	(0.031)	(0.311)	(0.295)	(0.502)	(0.502)	(0.325)	(0.372)	(0.058)	(0.058)	(0.324)	(0.284)	(0.251)	(0.250)
Labour Market Status t-5[2] (Employment=1)	0.876	0.901	-0.025	2.946	0.876	0.887	-0.011	0.292	0.884	0.905	-0.021	1.072	0.884	0.903	-0.019	0.509
	(0.329)	(0.299)	(0.086)	(0.086)	(0.329)	(0.317)	(0.590)	(0.589)	(0.321)	(0.294)	(0.301)	(0.300)	(0.320)	(0.295)	(0.477)	(0.476)
Labour Market Status t-6[2] (Employment=1)	0.873	0.892	-0.019	1.560	0.873	0.885	-0.012	0.390	0.888	0.899	-0.011	0.268	0.888	0.919	-0.031	1.417
	(0.333)	(0.311)	(0.212)	(0.212)	(0.332)	(0.319)	(0.533)	(0.532)	(0.316)	(0.302)	(0.605)	(0.604)	(0.315)	(0.272)	(0.235)	(0.234)
Long Term Unemployed	0.269	0.443	-0.174	57.820	0.269	0.291	-0.022	0.709	0.305	0.442	-0.137	17.104	0.305	0.344	-0.039	0.881
	(0.444)	(0.497)	(0.000)	(0.000)	(0.443)	(0.454)	(0.400)	(0.400)	(0.461)	(0.497)	(0.000)	(0.000)	(0.460)	(0.474)	(0.349)	(0.348)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Human Capital															
	Skilled								High skilled							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender	0.379	0.535	-0.156	55.531	0.379	0.370	0.009	0.111	0.423	0.536	-0.113	3.929	0.423	0.495	-0.072	1.017
(male = 1)	(0.485)	(0.499)	(0.000)	(0.000)	(0.485)	(0.482)	(0.740)	(0.739)	(0.496)	(0.499)	(0.048)	(0.047)	(0.493)	(0.499)	(0.316)	(0.313)
Start of Unemployment-Spell	20.059	25.443	-5.384	5.548	20.059	20.182	-0.123	0.698	18.949	25.124	-6.179	2.281	18.949	19.711	-0.762	0.574
	(11.248)	(12.392)	(0.000)	(0.000)	(11.24)	(11.279)	(0.840)	(0.715)	(11.195)	(12.411)	(0.000)	(0.000)	(11.136)	(11.533)	(0.642)	(0.896)
Completed Apprentice-ship/Technician	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-		-	-	-	-	-	-	-	-	-	-	-
University/College Degree	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Age	36.233	38.366	-2.133	3.866	36.233	36.249	-0.016	0.537	37.021	38.256	-1.235	0.972	37.021	36.979	0.042	0.431
	(5.472)	(5.565)	(0.000)	(0.000)	(5.468)	(5.335)	(0.956)	(0.935)	(5.192)	(5.493)	(0.052)	(0.302)	(5.162)	(4.803)	(0.954)	(0.992)
Residence Chemnitz	0.372	0.429	-0.057	7.539	0.372	0.373	-0.001	0.003	0.289	0.408	-0.120	4.435	0.289	0.330	-0.041	0.386
	(0.484)	(0.495)	(0.006)	(0.006)	(0.483)	(0.483)	(0.956)	(0.956)	(0.455)	(0.492)	(0.035)	(0.035)	(0.453)	(0.470)	(0.537)	(0.534)
Residence Dresden	0.388	0.358	0.029	2.121	0.388	0.386	0.002	0.003	0.464	0.355	0.109	3.716	0.464	0.474	-0.010	0.021
	(0.487)	(0.479)	(0.145)	(0.145)	(0.487)	(0.486)	(0.956)	(0.956)	(0.501)	(0.479)	(0.054)	(0.054)	(0.498)	(0.499)	(0.886)	(0.886)
Share of Time in Unemployment[1]	0.030	0.095	-0.066	3.372	0.030	0.034	-0.004	0.698	0.019	0.058	-0.039	0.883	0.019	0.020	-0.001	0.431
	(0.088)	(0.192)	(0.000)	(0.000)	(0.088)	(0.110)	(0.482)	(0.715)	(0.596)	(0.157)	(0.017)	(0.417)	(0.059)	(0.091)	(0.979)	(0.992)
Share of Time in Employment[1]	0.913	0.869	0.044	2.278	0.913	0.910	0.003	0.564	0.876	0.851	0.025	0.733	0.876	0.894	-0.018	0.790
	(0.198)	(0.240)	(0.000)	(0.000)	(0.198)	(0.211)	(0.803)	(0.908)	(0.251)	(0.267)	(0.418)	(0.656)	(0.249)	(0.253)	(0.618)	(0.561)
Share of Time in Non-Employment[1]	0.057	0.036	0.021	1.678	0.057	0.056	0.001	0.456	0.105	0.091	0.014	0.517	0.105	0.087	0.018	0.718
	(0.174)	(0.151)	(0.001)	(0.007)	(0.173)	(0.178)	(0.913)	(0.985)	(0.247)	(0.229)	(0.607)	(0.952)	(0.245)	(0.243)	(0.603)	(0.681)
Mean Duration of Unemployment	0.637	0.933	-0.296	2.693	0.637	0.535	0.102	0.698	0.402	0.629	-0.227	0.379	0.402	0.309	0.093	0.359
	(1.834)	(2.471)	(0.003)	(0.000)	(1.832)	(1.915)	(0.310)	(0.715)	(1.294)	(1.903)	(0.275)	(0.999)	(1.287)	(1.501)	(0.646)	(1.000)
Mean Duration of Employment	13.777	15.649	-1.872	2.893	13.777	14.116	-0.339	0.752	12.374	15.509	-3.135	1.465	12.374	13.052	-0.678	0.431
	(9.394)	(12.156)	(0.000)	(0.000)	(9.387)	(9.274)	(0.500)	(0.625)	(9.393)	(12.002)	(0.019)	(0.027)	(9.344)	(9.649)	(0.622)	(0.992)
Mean Duration of Non-Employment	0.866	0.536	0.330	1.678	0.866	0.918	-0.052	0.456	1.665	1.273	0.392	0.598	1.665	1.253	0.412	0.79
	(2.743)	(2.535)	(0.002)	(0.007)	(2.741)	(3.431)	(0.755)	(0.985)	(3.675)	(3.296)	(0.324)	(0.867)	(3.655)	(3.765)	(0.442)	(0.561)
Labour Market Status t-1[2] (Employment=1)	0.931	0.945	-0.014	2.209	0.931	0.931	0.000	0.000	0.897	0.916	-0.019	0.345	0.897	0.907	-0.010	0.058
	(0.254)	(0.227)	(0.137)	(0.137)	(0.254)	(0.253)	(1.000)	(1.000)	(0.306)	(0.277)	(0.558)	(0.557)	(0.304)	(0.290)	(0.810)	(0.809)
Labour Market Status t-2[2] (Employment=1)	0.916	0.924	-0.008	0.470	0.916	0.925	-0.009	0.355	0.866	0.896	-0.030	0.683	0.866	0.918	-0.052	1.335
	(0.277)	(0.265)	(0.493)	(0.493)	(0.276)	(0.263)	(0.551)	(0.551)	(0.342)	(0.305)	(0.410)	(0.409)	(0.340)	(0.275)	(0.250)	(0.248)
Labour Market Status t-3[2] (Employment=1)	0.903	0.889	0.015	1.165	0.903	0.914	-0.011	0.425	0.887	0.879	-0.012	0.034	0.887	0.907	-0.020	0.223
	(0.296)	(0.314)	(0.280)	(0.280)	(0.295)	(0.281)	(0.515)	(0.515)	(0.319)	(0.326)	(0.854)	(0.853)	(0.317)	(0.290)	(0.639)	(0.637)
Labour Market Status t-4[2] (Employment=1)	0.892	0.845	0.047	9.870	0.892	0.905	-0.013	0.639	0.887	0.866	0.021	0.271	0.887	0.907	-0.020	0.223
	(0.311)	(0.362)	(0.002)	(0.002)	(0.310)	(0.293)	(0.424)	(0.424)	(0.319)	(0.341)	(0.604)	(0.603)	(0.317)	(0.290)	(0.639)	(0.637)
Labour Market Status t-5[2] (Employment=1)	0.882	0.908	-0.026	4.336	0.882	0.888	-0.006	0.113	0.876	0.879	-0.003	0.008	0.876	0.907	-0.031	0.481
	(0.323)	(0.289)	(0.037)	(0.037)	(0.322)	(0.315)	(0.737)	(0.737)	(0.331)	(0.326)	(0.931)	(0.931)	(0.329)	(0.290)	(0.491)	(0.488)
Labour Market Status t-6[2] (Employment=1)	0.882	0.899	-0.017	1.870	0.882	0.888	-0.006	0.113	0.876	0.859	0.017	0.175	0.876	0.907	-0.031	0.481
	(0.323)	(0.301)	(0.172)	(0.171)	(0.323)	(0.315)	(0.737)	(0.737)	(0.331)	(0.348)	(0.677)	(0.676)	(0.329)	(0.290)	(0.491)	(0.488)
Long Term Unemployed	0.305	0.439	-0.134	41.429	0.305	0.333	-0.028	1.197	0.144	0.378	-0.234	18.345	0.144	0.144	0.000	0.000
	(0.461)	(0.496)	(0.000)	(0.000)	(0.460)	(0.471)	(0.274)	(0.274)	(0.353)	(0.486)	(0.000)	(0.000)	(0.351)	(0.351)	(1.000)	(1.000)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Duration of Measure															
	Shorter than 4 quarters								4 to 7 quarters							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[4]	NP[4]	Difference[4]	Test Result[4]
Gender (male = 1)	0.404	0.533	-0.129	14.504	0.404	0.400	0.004	0.009	0.406	0.534	-0.128	20.053	0.406	0.391	0.015	0.156
	(0.492)	(0.499)	(0.000)	(0.000)	(0.492)	(0.489)	(0.924)	(0.924)	(0.492)	(0.499)	(0.000)	(0.000)	(0.492)	(0.487)	(0.694)	(0.693)
Start of Unemployment-Spell	23.996	25.284	-1.288	1.612	23.996	23.409	0.587	0.513	20.767	25.284	-4.517	3.093	20.767	21.084	-0.317	0.541
	(13.319)	(12.423)	(0.129)	(0.011)	(13.319)	(12.845)	(0.631)	(0.955)	(11.269)	(12.423)	(0.000)	(0.000)	(11.269)	(11.724)	(0.722)	(0.932)
Completed Apprentice-ship/Technician	0.822	0.835	-0.013	0.262	0.822	0.826	-0.004	0.015	0.758	0.835	-0.077	12.641	0.758	0.767	-0.009	0.074
	(0.384)	(0.371)	(0.609)	(0.609)	(0.384)	(0.379)	(0.903)	(0.903)	(0.428)	(0.372)	(0.000)	(0.000)	(0.428)	(0.422)	(0.786)	(0.785)
University/College Degree	0.126	0.080	0.046	5.987	0.126	0.126	0.000	0.000	0.152	0.080	0.072	20.227	0.152	0.155	-0.003	0.011
	(0.333)	(0.272)	(0.014)	(0.014)	(0.333)	(0.332)	(1.000)	(1.000)	(0.359)	(0.272)	(0.000)	(0.000)	(0.359)	(0.362)	(0.915)	(0.915)
Age	37.948	38.344	-0.396	0.827	37.948	37.617	0.331	0.513	36.994	38.344	-1.350	1.712	36.994	37.116	-0.122	0.464
	(5.745)	(5.546)	(0.294)	(0.501)	(5.745)	(5.491)	(0.529)	(0.955)	(5.397)	(5.546)	(0.000)	(0.006)	(5.397)	(5.392)	(0.769)	(0.983)
Residence Chemnitz	0.365	0.417	-0.052	2.425	0.365	0.365	0.000	0.000	0.343	0.417	-0.074	6.962	0.343	0.346	-0.003	0.007
	(0.483)	(0.493)	(0.119)	(0.119)	(0.483)	(0.481)	(1.000)	(1.000)	(0.475)	(0.493)	(0.008)	(0.008)	(0.475)	(0.475)	(0.935)	(0.935)
Residence Dresden	0.391	0.362	0.029	0.801	0.391	0.391	0.000	0.000	0.424	0.362	0.062	5.057	0.424	0.427	-0.003	0.060
	(0.489)	(0.481)	(0.371)	(0.371)	(0.489)	(0.488)	(1.000)	(1.000)	(0.495)	(0.481)	(0.025)	(0.025)	(0.495)	(0.495)	(0.938)	(0.938)
Share of Time in Unemployment[1]	0.038	0.094	-0.056	2.078	0.038	0.034	0.004	0.699	0.031	0.094	-0.063	2.472	0.031	0.034	-0.003	0.618
	(0.108)	(0.194)	(0.000)	(0.000)	(0.108)	(0.111)	(0.703)	(0.712)	(0.084)	(0.194)	(0.000)	(0.000)	(0.084)	(0.105)	(0.642)	(0.839)
Share of Time in Employment[1]	0.893	0.865	0.028	1.111	0.893	0.897	-0.004	0.513	0.913	0.865	0.048	1.800	0.913	0.916	-0.003	0.773
	(0.224)	(0.245)	(0.093)	(0.169)	(0.224)	(0.227)	(0.836)	(0.955)	(0.198)	(0.245)	(0.001)	(0.003)	(0.198)	(0.201)	(0.824)	(0.589)
Share of Time in Non-Employment[1]	0.069	0.040	0.029	1.372	0.069	0.068	0.001	0.280	0.056	0.040	0.016	1.316	0.056	0.049	0.007	0.695
	(0.192)	(0.158)	(0.009)	(0.046)	(0.192)	(0.198)	(0.981)	(1.000)	(0.178)	(0.159)	(0.084)	(0.063)	(0.178)	(0.175)	(0.615)	(0.719)
Mean Duration of Unemployment	0.742	0.958	-0.216	1.006	0.742	0.513	0.229	0.699	0.664	0.957	-0.293	1.408	0.664	0.558	0.106	0.618
	(1.999)	(2.595)	(0.215)	(0.263)	(1.999)	(1.790)	(0.198)	(0.712)	(1.794)	(2.595)	(0.043)	(0.038)	(1.794)	(1.921)	(0.460)	(0.839)
Mean Duration of Employment	15.575	15.564	0.011	1.240	15.575	15.841	-0.266	0.653	14.156	15.564	-1.408	1.882	14.156	14.297	-0.141	0.348
	(11.643)	(12.133)	(0.989)	(0.093)	(11.643)	(11.341)	(0.805)	(0.788)	(9.421)	(12.133)	(0.039)	(0.002)	(9.421)	(9.285)	(0.845)	(1.000)
Mean Duration of Non-Employment	1.158	0.602	0.556	1.372	1.158	1.130	0.028	0.280	0.942	0.602	0.340	1.312	0.942	0.897	0.045	0.657
	(3.254)	(2.634)	(0.002)	(0.046)	(3.254)	(3.870)	(0.934)	(1.000)	(2.959)	(2.634)	(0.025)	(0.064)	(2.959)	(3.750)	(0.864)	(0.781)
Labour Market Status t-1[2] (Employment=1)	0.909	0.943	-0.034	4.718	0.909	0.900	0.009	0.101	0.931	0.943	-0.012	0.819	0.931	0.937	-0.006	0.097
	(0.288)	(0.231)	(0.030)	(0.030)	(0.288)	(0.300)	(0.752)	(0.751)	(0.253)	(0.231)	(0.366)	(0.366)	(0.253)	(0.242)	(0.756)	(0.755)
Labour Market Status t-2[2] (Employment=1)	0.883	0.922	-0.039	4.675	0.883	0.891	-0.008	0.087	0.922	0.922	0.000	0.000	0.922	0.937	-0.015	0.572
	(0.322)	(0.267)	(0.031)	(0.031)	(0.322)	(0.311)	(0.769)	(0.768)	(0.268)	(0.267)	(0.997)	(0.997)	(0.268)	(0.242)	(0.450)	(0.449)
Labour Market Status t-3[2] (Employment=1)	0.852	0.887	-0.035	2.673	0.852	0.878	-0.026	0.671	0.919	0.887	0.032	3.191	0.919	0.931	-0.012	0.346
	(0.356)	(0.316)	(0.102)	(0.102)	(0.356)	(0.326)	(0.414)	(0.413)	(0.273)	(0.316)	(0.074)	(0.074)	(0.273)	(0.252)	(0.557)	(0.556)
Labour Market Status t-4[2] (Employment=1)	0.848	0.847	0.001	0.000	0.848	0.874	-0.026	0.653	0.910	0.847	0.063	9.751	0.910	0.925	-0.015	0.495
	(0.359)	(0.359)	(0.982)	(0.982)	(0.359)	(0.331)	(0.420)	(0.419)	(0.286)	(0.359)	(0.002)	(0.002)	(0.286)	(0.262)	(0.482)	(0.482)
Labour Market Status t-5[2] (Employment=1)	0.852	0.903	-0.051	6.096	0.852	0.857	-0.005	0.017	0.889	0.903	-0.014	0.587	0.889	0.919	-0.029	1.728
	(0.356)	(0.296)	(0.014)	(0.014)	(0.356)	(0.350)	(0.895)	(0.895)	(0.314)	(0.296)	(0.444)	(0.444)	(0.314)	(0.272)	(0.189)	(0.189)
Labour Market Status t-6[2] (Employment=1)	0.865	0.894	-0.029	1.944	0.865	0.874	-0.009	0.077	0.881	0.894	-0.013	0.626	0.881	0.899	-0.018	0.547
	(0.342)	(0.307)	(0.163)	(0.163)	(0.342)	(0.332)	(0.782)	(0.782)	(0.325)	(0.307)	(0.429)	(0.429)	(0.325)	(0.302)	(0.460)	(0.460)
Long Term Unemployed	0.256	0.442	-0.186	30.478	0.256	0.283	-0.026	0.397	0.325	0.442	-0.117	17.119	0.325	0.343	-0.018	0.241
	(0.437)	(0.497)	(0.000)	(0.000)	(0.437)	(0.450)	(0.529)	(0.528)	(0.469)	(0.497)	(0.000)	(0.000)	(0.469)	(0.475)	(0.624)	(0.623)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Duration of Measure: Longer than 7 quarters							
	Before Matching				After Matching			
	Mean			Distribution[6]	Mean	Distribution[6]	Mean	Distribution[6]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	0.337	0.534	-0.197	41.039	0.337	0.337	0.000	0.000
	(0.474)	(0.499)	(0.000)	(0.000)	(0.474)	(0.472)	(1.000)	(1.000)
Start of Unemployment-Spell	16.375	25.284	-8.909	6.001	16.375	16.558	-0.183	0.377
	(8.141)	(12.422)	(0.000)	(0.000)	(8.141)	(8.602)	(0.795)	(0.999)
Completed Apprentice-ship/Technician	0.881	0.835	0.046	4.130	0.881	0.888	-0.007	0.069
	(0.325)	(0.371)	(0.042)	(0.042)	(0.325)	(0.315)	(0.794)	(0.793)
University/College Degree	0.060	0.080	-0.020	1.548	0.060	0.056	0.004	0.032
	(0.237)	(0.272)	(0.214)	(0.213)	(0.237)	(0.230)	(0.858)	(0.858)
Age	34.526	38.344	-3.818	4.686	34.526	34.723	-0.197	0.419
	(4.698)	(5.546)	(0.000)	(0.000)	(4.698)	(4.645)	(0.616)	(0.995)
Residence Chemnitz	0.382	0.417	-0.035	1.327	0.382	0.389	-0.007	0.030
	(0.487)	(0.493)	(0.249)	(0.249)	(0.487)	(0.487)	(0.864)	(0.863)
Residence Dresden	0.389	0.362	0.027	0.860	0.389	0.393	-0.004	0.007
	(0.488)	(0.481)	(0.354)	(0.354)	(0.488)	(0.488)	(0.932)	(0.932)
Share of Time in Unemployment[1]	0.025	0.094	-0.069	2.514	0.025	0.021	0.004	0.461
	(0.077)	(0.194)	(0.000)	(0.000)	(0.077)	(0.079)	(0.610)	(0.984)
Share of Time in Employment[1]	0.906	0.865	0.041	1.883	0.906	0.913	-0.007	0.503
	(0.218)	(0.245)	(0.006)	(0.002)	(0.218)	(0.220)	(0.733)	(0.962)
Share of Time in Non-Employment[1]	0.069	0.040	0.029	1.047	0.069	0.066	0.003	0.251
	(0.197)	(0.159)	(0.004)	(0.223)	(0.197)	(0.198)	(0.860)	(1.000)
Mean Duration of Unemployment	0.530	0.957	-0.427	2.483	0.530	0.375	0.155	0.586
	(1.729)	(2.595)	(0.006)	(0.000)	(1.729)	(1.520)	(0.257)	(0.882)
Mean Duration of Employment	11.793	15.564	-3.771	3.104	11.793	11.925	-0.132	0.670
	(7.312)	(12.133)	(0.000)	(0.000)	(7.312)	(7.086)	(0.827)	(0.760)
Mean Duration of Non-Employment	0.807	0.602	0.205	0.920	0.807	0.911	-0.104	0.209
	(2.369)	(2.634)	(0.203)	(0.365)	(2.369)	(2.963)	(0.645)	(1.000)
Labour Market Status t-1[2] (Employment=1)	0.926	0.943	-0.017	1.413	0.926	0.933	-0.007	0.108
	(0.262)	(0.231)	(0.235)	(0.235)	(0.262)	(0.249)	(0.743)	(0.743)
Labour Market Status t-2[2] (Employment=1)	0.912	0.922	-0.010	0.378	0.912	0.933	-0.021	0.887
	(0.283)	(0.267)	(0.539)	(0.538)	(0.283)	(0.249)	(0.347)	(0.346)
Labour Market Status t-3[2] (Employment=1)	0.909	0.887	0.022	1.209	0.909	0.919	-0.010	0.201
	(0.288)	(0.316)	(0.272)	(0.271)	(0.288)	(0.273)	(0.655)	(0.654)
Labour Market Status t-4[2] (Employment=1)	0.895	0.847	0.048	4.692	0.895	0.916	-0.021	0.736
	(0.307)	(0.360)	(0.030)	(0.030)	(0.307)	(0.277)	(0.392)	(0.391)
Labour Market Status t-5[2] (Employment=1)	0.888	0.903	-0.015	0.658	0.888	0.916	-0.028	1.267
	(0.316)	(0.296)	(0.417)	(0.417)	(0.316)	(0.277)	(0.261)	(0.260)
Labour Market Status t-6[2] (Employment=1)	0.884	0.894	-0.010	0.297	0.884	0.895	-0.011	0.161
	(0.320)	(0.307)	(0.586)	(0.586)	(0.320)	(0.307)	(0.689)	(0.689)
Long Term Unemployed	0.246	0.442	-0.196	41.826	0.246	0.256	-0.010	0.084
	(0.431)	(0.967)	(0.000)	(0.000)	(0.431)	(0.436)	(0.772)	(0.772)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Start of Unemployment Spell until 1992								Start of Unemployment Spell between 1993 and 1996							
	Before Matching				After Matching				Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	0.305	0.408	-0.103	14.903	0.305	0.323	-0.018	0.329	0.448	0.533	-0.085	5.581	0.448	0.452	-0.004	0.009
	(0.460)	(0.491)	(0.000)	(0.000)	(0.460)	(0.467)	(0.567)	(0.566)	(0.497)	(0.499)	(0.018)	(0.018)	(0.497)	(0.497)	(0.926)	(0.925)
Start of Unemployment-Spell	11.509	11.071	0.438	1.890	11.509	11.429	0.08	0.432	23.139	23.826	-0.687	1.384	23.139	23.070	0.069	0.513
	(2.592)	(2.685)	(0.003)	(0.002)	(2.592)	(2.589)	(0.644)	(0.992)	(4.837)	(4.638)	(0.042)	(0.043)	(4.837)	(4.789)	(0.877)	(0.955)
Completed Apprentice-ship/Technician	0.819	0.827	-0.008	0.158	0.819	0.838	-0.019	0.631	0.826	0.831	-0.005	0.033	0.826	0.865	-0.039	1.349
	(0.385)	(0.378)	(0.691)	(0.691)	(0.385)	(0.367)	(0.428)	(0.427)	(0.379)	(0.375)	(0.856)	(0.856)	(0.379)	(0.341)	(0.246)	(0.245)
University/College Degree	0.126	0.079	0.047	8.889	0.126	0.108	0.018	0.684	0.100	0.081	0.019	0.896	0.100	0.087	0.013	0.231
	(0.332)	(0.269)	(0.003)	(0.003)	(0.332)	(0.310)	(0.409)	(0.408)	(0.300)	(0.273)	(0.344)	(0.344)	(0.300)	(0.282)	(0.632)	(0.631)
Age	34.279	34.806	-0.528	1.054	34.279	34.339	-0.06	0.366	36.939	38.0445	-1.106	1.613	36.939	37.104	-0.165	0.513
	(4.727)	(4.759)	(0.044)	(0.217)	(4.727)	(4.537)	(0.847)	(0.999)	(4.593)	(4.713)	(0.001)	(0.011)	(4.593)	(4.363)	(0.693)	(0.955)
Residence Chemnitz	0.374	0.430	-0.056	4.255	0.374	0.374	0.000	0.000	0.348	0.424	-0.076	4.617	0.348	0.374	-0.026	0.339
	(0.483)	(0.495)	(0.039)	(0.039)	(0.483)	(0.483)	(1.000)	(1.000)	(0.476)	(0.494)	(0.032)	(0.032)	(0.476)	(0.483)	(0.561)	(0.560)
Residence Dresden	0.396	0.354	0.042	2.464	0.396	0.396	0.000	0.000	0.413	0.361	0.052	2.184	0.413	0.422	-0.009	0.036
	(0.489)	(0.478)	0.117)	(0.117)	(0.489)	(0.489)	(1.000)	(1.000)	(0.492)	(0.480)	(0.140)	(0.139)	(0.492)	(0.493)	(0.850)	(0.850)
Share of Time in Unemployment1	0.008	0.023	-0.015	0.578	0.008	0.010	-0.002	0.266	0.046	0.107	-0.061	1.871	0.046	0.044	0.002	0.979
	(0.046)	(0.113)	(0.005)	(0.892)	(0.046)	(0.072)	(0.670)	(1.000)	(0.107)	(0.204)	(0.000)	(0.002)	(0.107)	(0.137)	(0.831)	(0.293)
Share of Time in Employment1	0.923	0.919	0.004	0.285	0.923	0.925	-0.002	0.366	0.893	0.858)	0.035	1.210	0.893	0.901	-0.008	0.746
	(0.216)	(0.228)	(0.758)	(1.000)	(0.216)	(0.224)	(0.888)	(0.999)	(0.203)	0.244)	(0.040)	(0.107)	(0.203)	(0.212)	(0.673)	(0.634)
Share of Time in Non-Employment1	0.069	0.057	0.012	0.650	0.069	0.065	0.004	0.432	0.061	0.034	0.026	1.382	0.061	0.055	0.006	0.466
	(0.208)	(0.201)	(0.302)	(0.792)	(0.208)	(0.215)	(0.787)	(0.992)	(0.166)	(0.139)	(0.013)	(0.044)	(0.166)	(0.164)	(0.712)	(0.982)
Mean Duration of Unemployment	0.113	0.126	-0.013	0.130	0.113	0.091	0.022	0.266	0.935	1.000	-0.065	0.621	0.935	0.665	0.270	0.979
	(0.636)	(0.678)	(0.730)	(1.000)	(0.636)	(0.673)	(0.612)	(1.000)	(2.020)	(2.410)	(0.704)	(0.836)	(2.020)	(2.256)	(0.196)	(0.293)
Mean Duration of Employment	8.979	8.603	0.376	01.271	8.979	8.901	0.078	0.399	16.429	15.635	0.793	1.679	16.429	16.938	-0.509	0.886
	(3.909)	(3.671)	(0.068)	(0.079)	(3.909)	(3.627)	(0.758)	(0.997)	(7.782)	(8.970)	(0.211)	(0.007)	(7.782)	(7.283)	(0.470)	(0.413)
Mean Duration of Non-Employment	0.648	0.480	0.168	0.680	0.648	0.579	0.069	0.432	1.187	0.591	0.596	1.358	1.187	1.052	0.135	0.466
	(1.988)	(1.737)	(0.093)	(0,745	(1.988)	(1.970)	(0.601)	(0.992)	(3.317)	(2.452)	(0.002)	(0.050)	(3.317)	(3.205)	(0.659)	(0.982)
Labour Market Status t-12 (Employment=1)	0.940	0.938	0.002	0.018	0.940	0.942	-0.002	0.020	0.904	0.962	-0.057	13.808	0.904	0.922	-0.018	0.438
	(0.236)	(0.240)	(0.892)	(0.892)	(0.236)	(0.232)	(0.888)	(0.887)	(0.294)	(0.191)	(0.000)	(0.000)	(0.294)	(0.268)	(0.509)	(0.508)
Labour Market Status t-22 (Employment=1)	0.934	0.927	0.007	0.220	0.934	0.938	-0.004	0.074	0.878	0.940	-0.062	11.124	0.878	0.909	-0.031	1.119
	(0.248)	(0.260)	(0.639)	(0.639)	(0.248)	(0.241)	(0.786)	(0.786)	(0.326)	(0.238)	(0.001)	(0.001)	(0.326)	(0.288)	(0.291)	(0.290)
Labour Market Status t-32 (Employment=1)	0.925	0.906	0.018	1.368	0.925	0.916	0.009	0.241	0.883	0.904	-0.021	0.996	0.883	0.909	-0.026	0.837
	(0.263)	(0.291)	(0.242)	(0.242)	(0.263)	(0.277)	(0.624)	(0.623)	(0.322)	(0.294)	(0.319)	(0.318)	(0.322)	(0.288)	(0.361)	(0.360)
Labour Market Status t-42 (Employment=1)	0.914	0.902	0.012	0.566	0.914	0.914	0.000	0.000	0.878	0.865	0.013	0.293	0.878	0.9	-0.022	0.551
	(0.280)	(0.298)	(0.452)	(0.452)	(0.280)	(0.280)	(1.000)	(1.000)	(0.327)	(0.342)	(0.588)	(0.588)	(0.327)	(0.300)	(0.459)	(0.458)
Labour Market Status t-52 (Employment=1)	0.907	0.930	-0.023	2.525	0.907	0.916	-0.009	0.219	0.861	0.903	-0.042	3.711	0.861	0.883	-0.022	0.486
	(0.290)	(0.255)	(0.112)	(0.112)	(0.290)	(0.277)	(0.640)	(0.639)	(0.346)	(0.296)	(0.0541)	(0.054)	(0.346)	(0.321)	(0.487)	(0.486)
Labour Market Status t-62 (Employment=1)	0.905	0.934	-0.247	4.210	0.905	0.914	-0.009	0.215	0.857	0.888	-0.031	1.787	0.857	0.878	-0.021	0.472
	(0.293)	(0.247)	(0.040)	(0.040)	(0.293)	(0.280)	(0.644)	(0.643)	(0.350)	(0.312)	(0.181)	(0.181)	(0.350)	(0.327)	(0.493)	(0.492)
Long Term Unemployed	0.241	0.491	-0.250	84.559	0.241	0.261	-0.020	0.476	0.322	0.476	-0.155	18.533	0.322	0.357	-0.035	0.621
	(0.428)	(0.500)	(0.000)	(0.000)	(0.428)	(0.439)	(0.491)	(0.490)	(0.467)	(0.499)	(0.000)	(0.000)	(0.467)	(0.479)	(0.432)	(0.431)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A.2 (continued)

Variable	Start of Unemployment Spell from 1997							
	Before Matching				After Matching			
	Mean			Distribution[5]	Mean			Distribution[5]
	P[3]	NP[3]	Difference[4]	Test Result[4]	P[3]	NP[3]	Difference[4]	Test Result[4]
Gender (male = 1)	0.500	0.646	-0.146	13.684	0.500	0.464	0.036	0.429
	(0.500)	(0.478)	(0.000)	(0.000)	(0.500)	(0.498)	(0.514)	(0.512)
Start of Unemployment-Spell	39.399	39.264	0.135	0.848	39.399	39.351	0.048	0.655
	(4.216)	(4.463)	(0.710)	(0.468)	(4.216)	(4.172)	(0.917)	(0.785)
Completed Apprentice-ship/Technician	0.798	0.845	-0.047	2.464	0.798	0.810	-0.012	0.075
	(0.401)	(0.362)	(0.117)	(0.116)	(0.401)	(0.392)	(0.784)	(0.784)
University/College Degree	0.101	0.081	0.020	0.804	0.101	0.101	0.000	0.000
	(0.302)	(0273)	(0.370)	(0.370)	(0.302)	(0.301)	(1.000)	(1.000)
Age	41.494	41.770	-0.276	0.795	41.494	41.357	0.137	0.327
	(4.763)	(4.710)	(0.474)	(0.552)	(4.763)	(4.637)	(0.790)	(1.000)
Residence Chemnitz	0.351	0.400	-0.49	1.509	0.351	0.375	-0.024	0.206
	(0.477)	(0.490)	(0.220)	(0.219)	(0.477)	(0.484)	(0.651)	(0.650)
Residence Dresden	0.411	0.369	0.041	1.091	0.411	0.411	0.000	0.000
	(0.492)	(0.483)	(0.270)	(0.296)	(0.492)	(0.492)	(1.000)	(1.000)
Share of Time in Unemployment[1]	0.070	0.146	-0.076	2.272	0.070	0.087	-0.017	0.600
	(0.125)	(0.221)	(0.000)	(0.000)	(0.125)	(0.149)	(0.255)	(0.864)
Share of Time in Employment[1]	0.875	0.823	0.052	1.658	0.875	0.860	0.015	0.546
	(0.208)	(0.251)	(0.010)	(0.008)	(0.208)	(0.223)	(0.518)	(0.927)
Share of Time in Non-Employment[1]	0.055	0.030	0.024	1.723	0.055	0.053	0.002	0.818
	(0.155)	(0.126)	(0.022)	(0.005)	(0.155)	(0.166)	(0.913)	(0.515)
Mean Duration of Unemployment	1.657	1.668	-0.011	1.045	1.657	1.429	0.228	0.655
	(2.705)	(3.465)	(0.967)	(0.225)	(2.705)	(2.532)	(0.432)	(0.785)
Mean Duration of Employment	22.908	21.748	1.159	2.258	22.908	23.664	-0.756	0.655
	(13.567)	(15.547)	(0.356)	(0.000)	(13.567)	(13.682)	(0.612)	(0.785)
Mean Duration of Non-Employment	1.464	0.720	0.744	1.723	1.464	1.446	0.018	0.818
	(3.890)	(3.346)	(0.008)	(0.005)	(3.890)	(4.816)	(0.971)	(0.515)
Labour Market Status t-1[2] (Employment=1)	0.905	0.932	-0.028	1.726	0.905	0.893	0.012	0.131
	(0.293)	(0.251)	(0.189)	(0.189)	(0.293)	(0.309)	(0.718)	(0.718)
Labour Market Status t-2[2] (Employment=1)	0.881	0.904	-0.023	0.861	0.881	0.893	-0.012	0.119
	(0.324)	(0.295)	(0.354)	(0.353)	(0.324)	(0.309)	(0.731)	(0.730)
Labour Market Status t-3[2] (Employment=1)	0.845	0.857	-0.011	0.154	0.845	0.881	-0.036	0.907
	(0.361)	(0.351)	(0.695)	(0.695)	(0.361)	(0.324)	(0.342)	(0.341)
Labour Market Status t-4[2] (Employment=1)	0.833	0.784	0.050	2.217	0.833	0.869	-0.036	0.846
	(0.372)	(0.412)	(0.137)	(0.137)	(0.372)	(0.337)	(0.359)	(0.358)
Labour Market Status t-5[2] (Employment=1)	0.827	0.877	-0.050	3.306	0.827	0.833	-0.006	0.021
	(0.378)	(0.328)	(0.069)	(0.069)	(0.378)	(0.372)	(0.885)	(0.884)
Labour Market Status t-6[2] (Employment=1)	0.833	0.865	-0.031	1.223	0.833	0.839	-0.006	0.022
	(0.372)	(0.342)	(0.269)	(0.269	(0.372)	(0.367)	(0.883)	(0.883)
Long Term Unemployed	0.327	0.369	-0.042	1.139	0.327	0.423	-0.096	3.251
	(0.469)	(0.483)	(0.286)	(0.286)	(0.469)	(0.494)	(0.072)	(0.071)

[1] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [3] standard deviation in brackets — [4] p-value in brackets — [5] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

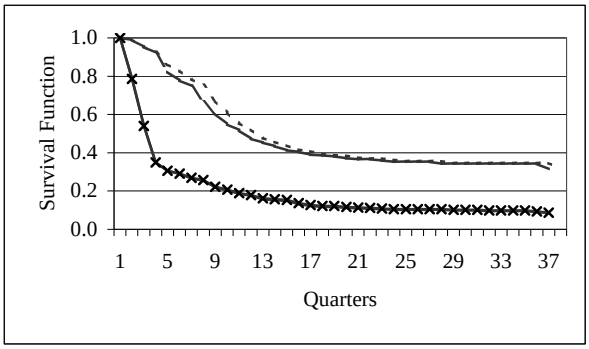
Table A.3: Parameter estimates of the proportional hazards model for the sub-samples

Variable	Whole Sample	Long Term Unemployed	Gender		Age		Human Capital		Start of the Unemployment Spell			Duration of the Measure		
			Men	Women	Younger than 40	40 and older	High skilled	Skilled	Until 1992	Between 1993 and 1996	From 1997	Shorter than 4 quarters	4 to 7 quarters	Longer than 7 quarters
Demographic Characteristics														
Gender (male = 1)	0.303*** (0.063)	-0.100 (0.148)	-	-	0.268*** (0.074)	0.416*** (0.120)	-0.055 (0.169)	0.399*** (0.070)	0.3397*** (0.084)	0.315*** (0.117)	0.459*** (0.163)	0.323*** (0.121)	0.322*** (0.100)	0.380*** (0.104)
Age	-0.011 (0.007)	-0.029** (0.012)	-0.007 (0.010)	-0.015* (0.009)	0.008 (0.010)	-0.036 (0.026)	-0.005 (0.019)	-0.013* (0.007)	-0.004 (0.009)	-0.029** (0.013)	-0.019 (0.018)	0.018 (0.013)	-0.009 (0.010)	-0.027** (0.011)
Grammar School Degree	-	-0.603* (0.338)	-	-	-0.318** (0.158)	-	-	-0.293* (0.159)	-	-	-	-	-	-
Secondary School Degree	0.249* (0.149)	-	-	0.448** (0.180)	-	-	-	-	0.418** (0.179)	-	-	-	-	-
Completed Apprenticeship/ Technician	-0.019 (0.129)	0.361 (0.353)	0.218 (0.220)	-0.255 (0.158)	0.045 (0.163)	-0.024 (0.229)	-	-	-0.178 (0.178)	0.213 (0.270)	-0.169 (0.280)	0.256 (0.310)	-0.158 (0.181)	-0.190 (0.222)
University/College Degree	0.200 (0.199)	0.345 (0.487)	0.392 (0.252)	0.126 (0.251)	0.290 (0.238)	0.106 (0.289)	-	-	0.159 (0.260)	0.600* (0.320)	-0.308 (0.381)	0.718** (0.341)	0.298 (0.207)	0.028 (0.297)
Economic Environment														
Start of Unemployment-Spell	-0.0132*** (0.004)	-	-	-0.021*** (0.006)	-0.013*** (0.004)	-	-0.043*** (0.010)	0.011*** (0.004)	-	-	-	-0.030*** (0.006)	-0.018*** (0.005)	-
Residence Dresden	-	-	-	-	-	-	-	-	-	-	0.412** (0.165)	-	-	-
Employment History														
Frequency of Changes into Unemployment[1]	4.943*** (1.245)	4.586** (2.191)	3.539** (1.574)	4.608** (1.838)	-	-	-	4.787*** (1.356)	-	4.672** (2.058)	4.341*** (1.604)	3.050* (1.825)	-	-
Frequency of Changes into Employment[1]	-	-	-	-	-	2.277** (1.130)	-	-	-	-	-	-	-	-
Mean Duration of Unemployment	-0.050** (0.023)	-	-0.113** (0.049)	-	-	-	-	-0.044* (0.025)	-	-	-	-	-	-
Mean Duration of Employment	-	-	-	0.013* (0.008)	-	-	-	-	-	-	-	-	-	-
Labour Market Status t-1[2]		-	-0.018*** (0.006)	-	-	-	-	-	-	-	-	-	-	-
Labour Market Status t-2[2]	-	-		-	-	-	-	-	-	-	-	-	-	-
Labour Market Status t-3[2]	-	-	-0.963** (0.49)	-	-	-	-	-	-	-	-	-	-	-
Labour Market Status t-4[2]	-	-	-	-	0.282** (0.129)	-	-	-	0.266* (0.151)	-	-	-	-	-
Labour Market Status t-5[2]	-	-	-	-	-	-	-	-	-	0.356* (0.196)	-	-	-	-
Labour Market Status t-6[2]								0.244** (0.120)						
Model Statistics														
Number of Matched Pairs	850	238	325	525	591	259	97	694	452	230	168	230	335	285
LR-Test of Global Null Hypothesis[3]	93.264 (0.000)	15.487 (0.017)	47.541 (0.000)	61.673 (0.000)	63.575 (0.000)	19.809 (0.001)	27.376 (0.000)	67.958 (0.000)	58.984 (0.000)	21.475 (0.002)	22.162 (0.001)	41.793 (0.000)	40.738 (0.000)	19.835 (0.000)
Wald Test of Proportionality[3]	11.707 (0.230)	4.430 (0.619)	8.644 (0.471)	11.034 (0.087)	9.965 (0.191)	4.467 (0.484)	4.031 (0.258)	11.602 (0.114)	4.3604 (0.628)	3.714 (0.715)	7.024 (0.319)	11.513 (0.074)	3.478 (0.627)	1.347 (0.853)

*,**,*** Significance on the 10%-, 5%-, and 1%-level respectively – standard error in brackets

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] "t-n" denotes the number of quarters until the start of the considered unemployment spell; Employment = 1 – [3] p-value in brackets

Figure A.1: Comparison of Kaplan-Meier and Cox proportional hazard survival functions for the whole sample after matching



- - - Participation (Cox) ; – - - – Participation (Kaplan-Meier) ;
—— Non-Participation (Cox) ; –x–x– Non-Participation (Kaplan-Meier)

Figures A.2–A.6: Comparison of covariate-adjusted survival functions in participation and non-participation case before and after matching for selected sub-samples

Figure A.2: Whole Sample

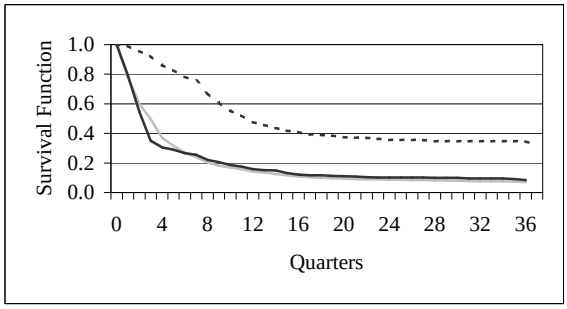


Figure A.3: Long Term Unemployed

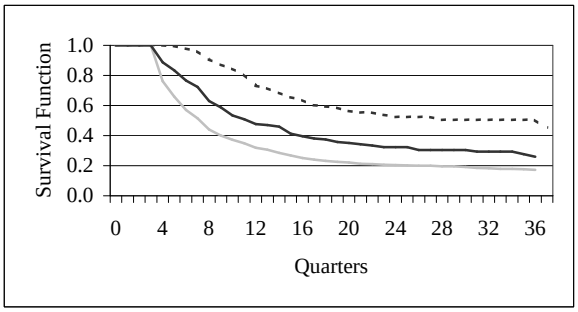


Figure A.4: Start of Unemployment spell until 1992

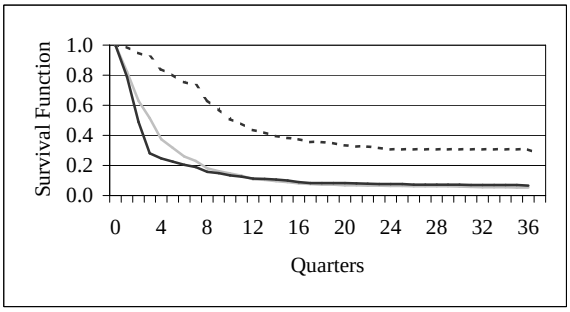


Figure A.5: Start of Unemployment spell between 1993 and 1996

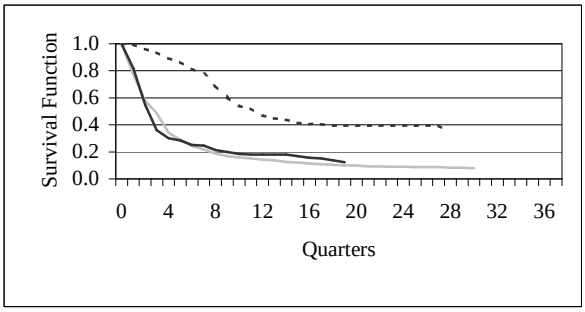
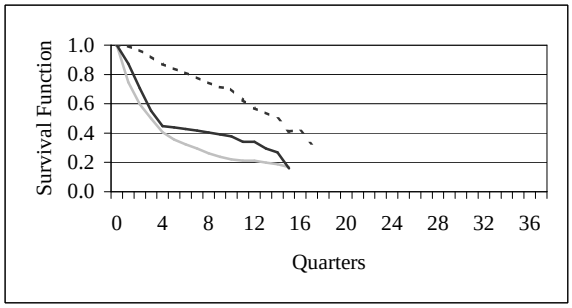


Figure A.6: Start of Unemployment spell from 1997



- - - - - Participation; —— Non-Participation before Matching; —— Non-Participation after Matching

Figures A.7 – A.14: Covariate-adjusted survival functions in participation and non-participation case for the sub-samples

Figure A.7: Younger than 40

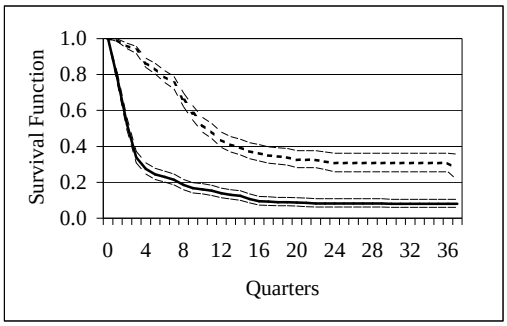


Figure A.8: Older than 40

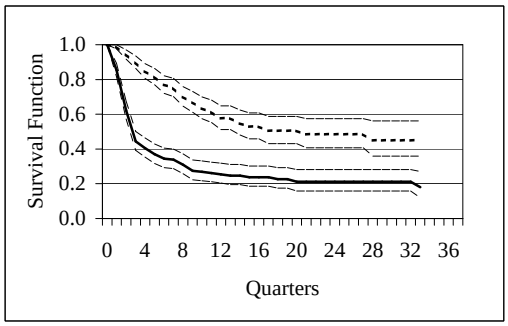


Figure A.9: Skilled

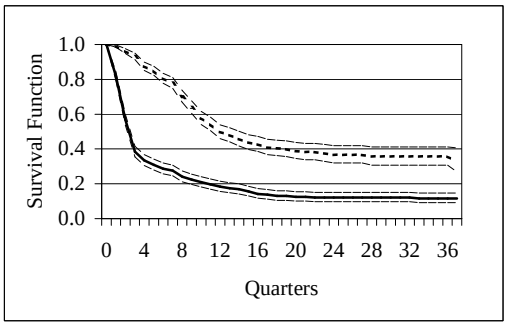


Figure A.10: High Skilled

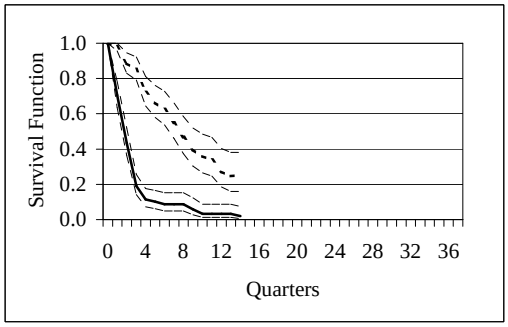


Figure A.11: Measure shorter than 4 quarters

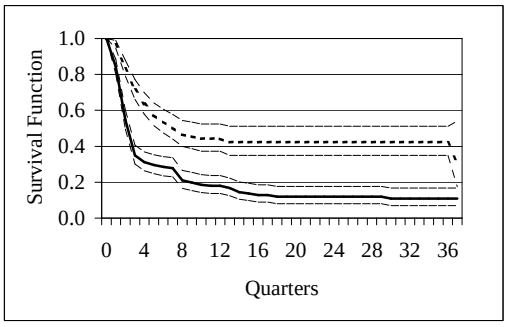


Figure A.12: Measure 4 to 7 quarters

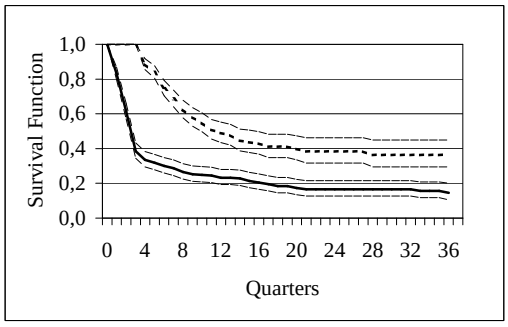


Figure A.13: Measure longer than 7 quarters

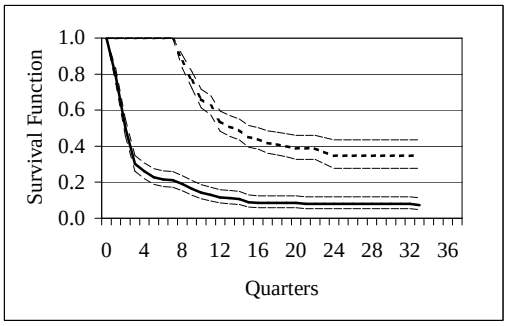
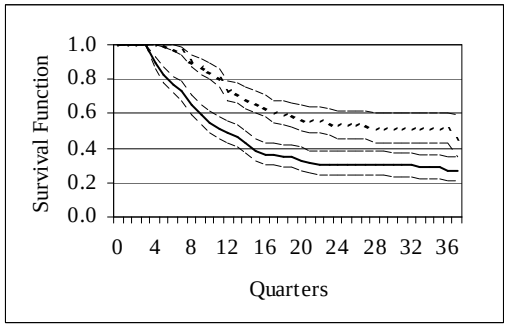


Figure A.14: Long Term Unemployed



- - - Participation —— Non-Participation – – – 95%-Confidence Interval