Evaluation of Further Training Programmes with an Optimal Matching Algorithm

– Preliminary Version –

February 2004

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Questions, comments and suggestions are welcome.

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Abstract

This paper 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.

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/Steiner (1999) use parametric models and consider observable heterogeneity. Fitzenberger/Prey (1998, 2000) additionally use a non-parametric difference-in-difference method to correct for unobservable heterogeneity. Other studies apply matching methods with difference-in-difference or parametric models (see Hübler 1998, Fitzenberger/Prey 1998, Hujer/Wellner 2000, Lechner 1998, Bergemann et al. 2000).

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/Calindo/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 organisational design of training measures. Therefore, the aim of this paper 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. This conclusion also holds for all sub-samples.

The paper is organised as follows. Section 2 gives an overview of the legal basis of further training programmes in Germany and the development of participation in East Germany and Saxony. Section 3 theoretically describes the fundamental problem of microeconomic evaluation and lists assumptions on the matching process and the resulting requirements for the data. Following the description of the data in section 4, 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

Active labour market programmes have been implemented in East Germany as early as in 1990. The implementation was a result of structural changes and associated strong increases in unemployment following German reunification. Registered unemployment rose from almost zero in 1989/1990 to about 20% in end 2003. Without the

[1] For an overview of evaluation studies in East Germany see also Hujer/Callindo (2000).

implementation of active labour market programmes the unemployment rate would have been close to 30%. Thus, in the first years of transition active labour market policy was mainly used as a means of social policy: it eased the pressure on the labour market and therefore avoided extremely high unemployment rates. Nevertheless, the main function of active labour market policy is still the improvement of individual employment chances and the participants' integration into regular employment.

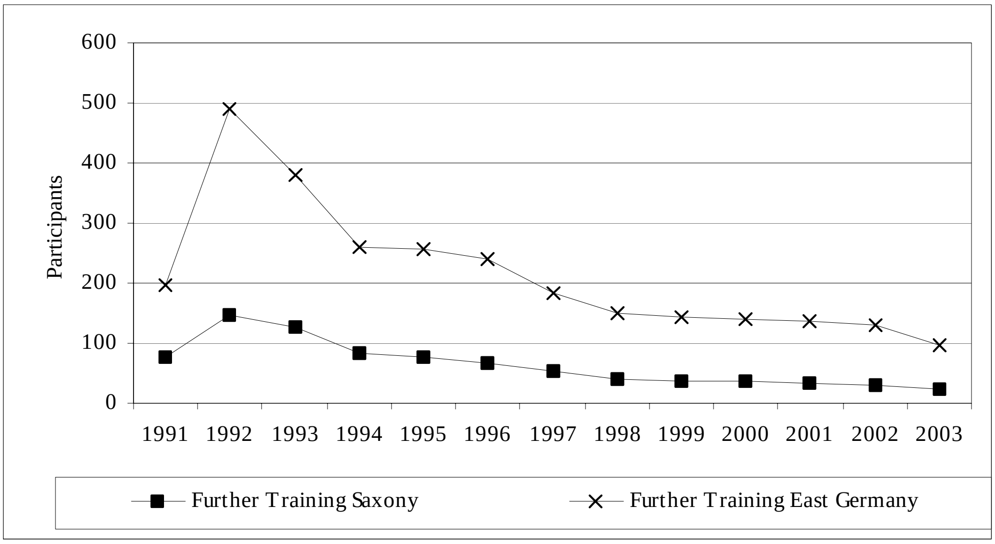
Further training programmes belong to the most important programmes of active labour market policy in East Germany. They intend to integrate unemployed persons into the labour market by promoting vocational qualifications. Further training programmes include vocational re-training measures and the extension 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. The level of the subsistence allowance is based on the unemployment allowance. The participation in further training measures created a new entitlement to unemployment benefits until 1997. In 1998 the legal basis changed so that participation does not entitle participants to unemployment benefits. Additionally, with the reform of the labour promotion law (Arbeitsförderungsgesetz) the so called 'target group focussing' (Zielgruppenorientierung) was established. It states that especially persons with low employment opportunities (e.g. long-term unemployed, disabled persons, older persons) should be selected for such programmes according to their share in total unemployment[2].

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. We do not consider the effects of newly implemented unemployment legislation (Hartz I and II) since 2003 because of the lack of available data.

The participation in further training programmes (Figure 1) in East Germany and Saxony shows a peak 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.

[2] Refer to § 7 SGB III Arbeitsförderungs-Reformgesetz (AFRG).

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



Source: Bundesanstalt für Arbeit

3. 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 :

$$\alpha_{it} = Y_{it}^{T} - Y_{it}^{C},$$

where α_{it} is the individual treatment effect at time *t*. The symbols Y_{it}^{T} and Y_{it}^{C} indicate the potential outcomes in the treatment and non-treatment case and can be defined in different ways, for instance as personal income, unemployment duration or duration of future employment.

Estimating α_{it} directly is impossible because the treatment outcome and the non-treatment outcome cannot be observed for a person simultaneously:

$$Y_{it} = D_i \cdot Y_{it}^{T} + (1 - D_i) Y_{it}^{C}.$$

[3] This model is also known as *Roy-Rubin-model.* For a detailed description see Heckman/LaLonde/Smith (1999), pp. 1877-1879.

Here Y_{it} denotes the observed outcome, while Y_{it}^T and Y_{it}^C are the potential outcomes in case of treatment and non-treatment. The dummy variable D_i indicates if person i participates in a programme $(D_i=1)$ or not $(D_i=0)$. 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 so-called *stable unit treatment value assumption (SUTVA).* This assumption requires independence of individual treatment effects, i.e. the programme effect for each participant must not be affected by the treatment of other persons. It excludes indirect effects on the regional labour market or the whole economy.[4]

Satisfying SUTVA 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 most often used is referred to as *average effect of treatment on the treated*. It indicates the expected outcome for persons who received treatment compared to the hypothetical situation of non-treatment:

$$E(\alpha_t \mid D=1) = E(Y_t^T \mid D=1) - E(Y_t^C \mid D=1).$$

The second term on the right hand side, the so-called *counterfactual*, is not observable and has to be replaced by an adequate (observable) substitute. It is possible to use a participant's outcome before treatment or the outcome of a control group of non-participants who meet the condition

$$E(Y_t^C \mid D=1) - E(Y_t^C \mid D=0) = 0.$$

Thus, 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 difference on the left hand side will be nonzero and 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-treated persons is a good proxy for the counterfactual outcome as long as the persons in both groups have the same observable characteristics X:

$$E(Y_t^C \mid X, D=1) = E(Y_t^C \mid X, D=0).$$

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

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. Further advantages for empirical application, especially compared to parametric approaches, are the independence from the functional form of the conditional expectations and from assumptions about the distribution of X.

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:

$$Y_t^T, Y_t^C \perp D \mid X.$$

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:

$$0 < \Pr(D = 1 \mid X) < 1.$$

Both assumptions together are sometimes referred to as *strongly ignorable treatment assignment*.[7]

[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/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 extension of the bias.

[7] See Rosenbaum/Rubin (1983), p. 43.

4. 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.[8] 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.

There are usually three sources of inaccuracies in data 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.

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

5. Choice of Variables

The selection of relevant variables for the analysis is derived from human capital theory and recent empirical studies.[9] Theory suggests decreasing investment into human capital with age, and labour market statistics show a negative influence of age on labour demand.[10] Another important factor for labour market behaviour is gender as it is obvious from the employment structure.[11] For the selection process gender may be important too, because the assignment to training measures depends on the fraction of men and women among the unemployed[12]. 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[13] 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 an instrument for the time-variant characteristics in the matching process. Therefore, we

[9] This variable selection procedure is also used e.g. in Hujer/Maurer/Wellner (1997), p. 13 or Christensen (2001), pp.25-27.

[10] 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.

[11] 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).

[12] See §8 SGB III.

[13] 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/Wellner (1997), p. 13 and Christensen (2001), p. 27.

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.[14] 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.

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*[15], which means that the unemployment spell of participants includes the further training episode. Thus, we do not regard the further training measure as a new spell but as a continuation of unemployment.

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 the *anticipation effect* and the *cohort effect*, which make it difficult to find the correct treatment effect. Therefore, it is necessary to eliminate or to measure these effects.

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[14] Heckman/Ichimura/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.

[15] Büchel, F. (1992).

Many studies observe a decrease in the probability of employment before participation in ALMP-measures. This effect was first observed by Ashenfelter[16] 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 to unemployment benefits are allowed to participate in an ALMP-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 and that the employment quota of participants declines substantially before the start of the programme. 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.

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 employment quotas are the same for both groups at the start of the programme.

7. Application of the Matching Approach

The matching control group consists of individual counterfactual outcomes for each participant. These counterfactual outcomes are determined either as a weighted average of several non-participants or as the outcome of one special non-participant who has similar relevant observed characteristics. The first technique is known as *kernel matching*[17], the second is commonly referred to as *nearest neighbour matching.*[18] or *nearest available pair matching*.

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[16] Ashenfelter, O. (1978).

[17] See e.g. Bergemann et al. (2001), p. 6 for further details.

[18] For a short overview over different nearest neighbour matching approaches see Heckman/LaLonde/ Smith (1999), pp. 1953-1954.

When using the second 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 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 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.[19]

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/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 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.[20]

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

[19] See Lechner (2000), p. 9.

[20] For applications see e. g. Christensen (2001) or Gerfin/Lechner (2002).

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 metric, matching by use of the propensity score would lead to an undesirable asymmetry, when the propensity score is close to 0 or 1, see Lechner (1998), p. 115. Therefore, in this study we apply a one-step balancing-score matching. Our balancing score uses the *participation tendency* instead of the propensity score and additionally includes personal characteristics because of the finite sample size of sub-samples.

We estimate the participation tendency by using a probit model:

$$I_i = \beta X_i + \varepsilon_i,$$

with $\varepsilon_i \sim N(0,\sigma^2)$, and

$$D_i = \begin{cases} 1 & \text{if } I_i > 0 \\ 0 & \text{otherwise.} \end{cases}$$

The first equation is the index function, where I_i denotes the unobservable latent variable, the participation tendency. The second part is the observed participation decision.[21] The estimate of the participation tendency is obtained as

$$\hat{I}_i = \hat{\beta} X_i.$$

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

$$MD_{ij} = \left[(\hat{I}_i, Z_i) - (\hat{I}_j, Z_j)\right]' \Sigma^{-1} \left[(\hat{I}_i, Z_i) - (\hat{I}_j, Z_j)\right],$$

[21] For a detailed description of the probit model see Greene (1997), chapter 19. The estimation results are given in table A1.1 in Appendix 1.

[22] The participation tendency is treated as a metric variable because it can be assumed to be normally distributed. See Lechner (1998), p. 115.

where Z_i and Z_j are the $n \times 1$-vectors of the considered covariates and Σ^{-1} indicates the inverse covariance matrix of $(\hat{I}, Z_i)$. The Mahalanobis distance has the advantages that the covariates are standardised and potential correlations between the covariates are accounted for by including the inverse of their covariance matrix.[23]

The *generalised matching coefficient*[24]

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

with

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

is applied to measure similarity in nominally scaled variables. 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.

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

$$M_{ij} = \frac{1}{m+n} \left[m\left(1 - MC_{ij}\right) + \alpha n MD_{ij} \right],$$

where α is a factor which ensures that the medians of both distance measures are equal.

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. It is an iterative improvement of an initial partial minimum cost assignment. The result is an optimal full assignment with a minimum total sum of squared distances. Obviously, 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.

[23] See Fahrmeir/Hamerle (1984), p. 384.

[24] See Fahrmeir/Hamerle (1984), p. 380 for a detailed description.

To check the quality of the matching result, we conducted tests for differences in the means and distributions of the characteristics in the treatment and the non-treatment group. As can be seen in table A1.2**,** all (sub-) samples show no significant differences in their characteristics in the treatment group and non-treatment group.

8. Duration Analysis

One possible indicator for the impact of labour market programmes is the change in the duration a person is unemployed. 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. 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 s*urvival analysis*. The outcome variable of this approach is the duration until an observed person changes initial status. 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. This assumption can be tested with the Wald-test on the significance of interaction terms for the used covariates and time.[25]

When using microeconomic data, information is often only available for time intervals. Then *ties* 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. The distortion can be neglected, if – as is the case in this study – solely time invariant covariates are included.[26] For this reason we apply a modification of the Cox model suggested by Breslow (1974). In order to take into account ties the

[25] The underlying proportionality condition cannot be rejected for all variables we used in the different sub-samples, see table A2.2.

[26] 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 that a group of d_f persons fail at time t_f instead of the failure probability of one person is analysed:[27]

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

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

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

We only define a spell as completed if the initial status of unemployment changes to employment. All other spells are considered as censored. The Breslow method 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.

9. Results

The estimation results are presented in Appendix 2. Table A2.1 provides the estimated coefficients of the Cox model for all sub-samples.

The table shows that gender has a significant influence for almost all sub-samples and that 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 an university or college degree have a positive influence.

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[27] For details see Klein/Moeschberger (1997).

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. In our data the rise of the long-term unemployment rate can be seen as an indicator for this development.

Figures 2 to 4 and A2.1 to A2.14 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.[28] The figures reveal that the influence of participation differs across our sub-samples.

As can be seen in Figure A2.1, 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%.

The sub-sample of long-term unemployed persons (Figure A2.2) shows less than 30% employed participants in the twelfth quarter, while non-participation would result in an employment rate of nearly 50%. With increasing time the survival functions of participation and non-participation decrease slowly while the difference between both

[28] The confidence intervals should not be used to draw inferential conclusions about the equality of median survival times for both groups, see Hosmer/Lemeshow (1999), p. 156.

curves remains nearly constant). In the long run (after twenty-eight quarters) 50% of the participants are still not employed, whereas only 30% would not be employed in case of non-participation.

Comparing Figures A2.3 and A2.4 demonstrates that the participation effect is negative particularly for women. While the non-participation curve of men and women is similar,[29] 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).

A similar effect can be found when comparing persons who are older and younger than 40 years, respectively (Figures A2.5 and A2.6). Besides anyway worse labour market prospects due to age[30], participation in further training additionally hampers transition to employment. The survival function of participants older than 40 years decreases slower, and the distance between the survival curves in case of participation and non-participation is larger than for younger persons in the long run.

The influence of education on labour market prospects can be observed when comparing the non-participation survival functions in Figures A2.7 and A2.8. A higher qualification level increases the probability of a person to change into employment. In the third quarter 85% of high-skilled persons are employed, increasing to 98% after ten quarters. The fraction of employed skilled persons is 62% and 78% after three and after twenty quarters, respectively. For both groups the transition is delayed by participation in further training. After three quarters only 15% of the high skilled participants are employed, increasing to only 64% after ten quarters. The effect on skilled persons is similar: after three quarters only 8% of the participants are employed; after twenty quarters 38% are still not employed.

[29] 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.

[30] After the third quarter the fraction of employed younger non-participants is approximately 10% higher.

Regional differences cannot be observed. The curves in Figures A2.9 to A2.11 for districts of Leipzig, Dresden and Chemnitz are similar in the participation case as well as in the non-participation case.

The duration of a further training measure, however, seems to have an influence on the participants' employment prospects in the long run. As can be seen in Figures A2.12 to A2.14, the share of employed former participants in training measures lasting longer than four quarters is about 7% higher than that of participants in short measures, while the non-participation success for the three groups is similar. The non-participation survival functions are similar in all three Figures. In case of participation, however, the fraction of not employed persons after measures shorter than four quarters is constant at 42% after twelve quarters whereas 36% of former participants in measures between four and seven quarters and longer than seven quarters, respectively are not employed after twenty quarters.

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 2 to 4). 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.

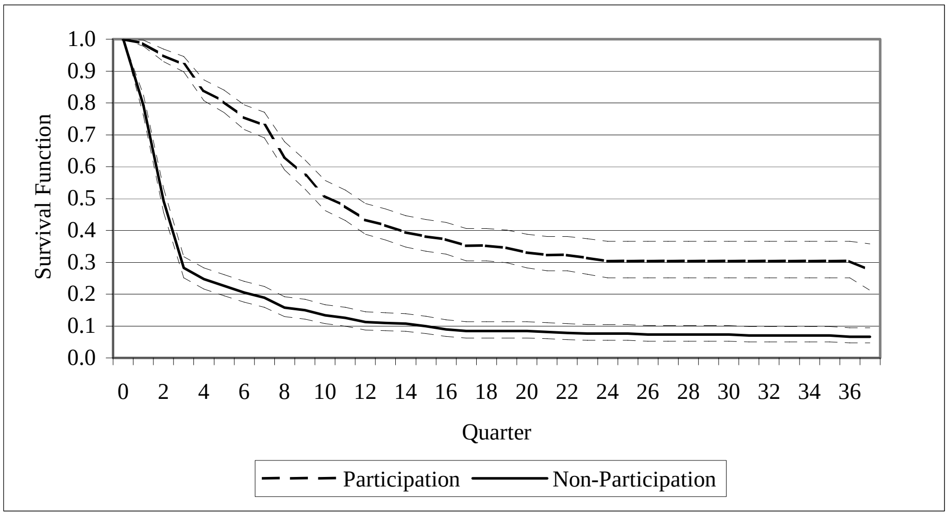
The second period begins around 1993 and ends about 1996. Practice in the Federal Employment Office and Training Agencies began to change which led to a decreasing number of participants in training programmes. Therefore, it could have been easier to adjust the programmes to the labour demand requirements 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.

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 2). 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%.

Figure 2: Covariate-adjusted survival functions in participation and non-participation
– Start of the unemployment spell until 1992 –

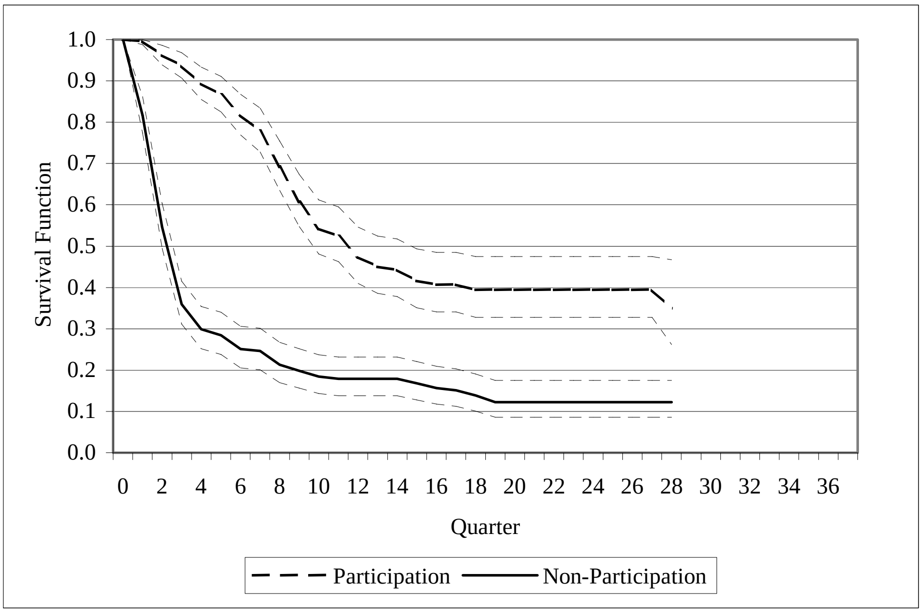


Source: Micro Census Saxony, own calculations

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 3, 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 3: Covariate-adjusted survival functions in participation and non-participation – Start of the unemployment spell between 1993 and 1996 –

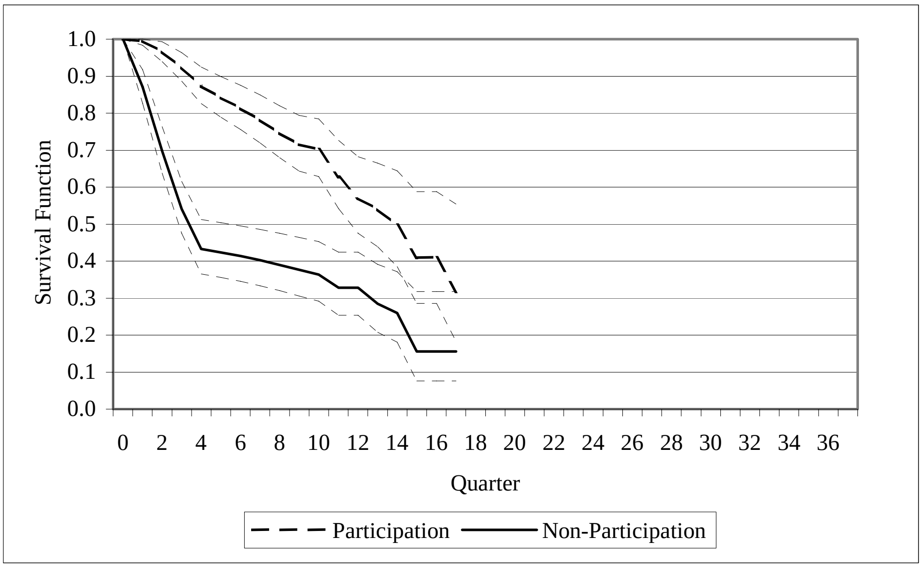


Source: Micro Census Saxony, own calculations

Figure 4 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 in the first four quarters 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.

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. We cannot identify changes in other target groups due to our selection of spells.

Figure 4: Covariate-adjusted survival functions in participation and non-participation
– Start of the unemployment spell from 1997 –



Source: Micro Census Saxony, own calculations

The 'least bad effect' of further training can be found if policy is focussed on specific target groups. This may indicate the direction to improve the effectiveness of training programmes. Because the observation time ends already after 16 quarters in the third period conclusions for long run effects can only be speculative.

10. Summary

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 for our sub-samples.

The results for the sub-samples can be interpreted as a first indication that the employment prospects of the participants are influenced by 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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Appendix 1

Table A1.1: 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		
				Women	Men	Younger than 40	40 and older	Skilled	High Skilled	Chemnitz	Dresden	Leipzig	Until 1992	Between 1993 and 1996	From 1997	Shorter than 4 quarters	4 to 7 quarters	Longer than 7 quarters
Demographic Characteristics	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 Apprenticeship/	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)
Economic Environment	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)	-	-	-	-	-	-	-	-	-	-
Employment History	Share of Time in 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***	-6.976*** (-5.550)	-3.960*** (-6.123)	-2.699*** (-4.948)	-4.121*** (-6.560)	-3.406*** (-5.080)
	Share of Time in 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[2]	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[2]	-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[3] (Employment=1)	-	0.613*** (2.705)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Labour Market Status t-2[3] (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[3] (Employment=1)	-	-	-	-0.882*** (-3.286)	-	-	-	-	-	-0.392* (-1.940)	-	-	-	-	-	-	-
	Labour Market Status t-4[3] (Employment=1)	-	-	-	0.529** (1.992)	-	-	-	-	-	-	0.570** (2.192)	-	-	-	-	0.412** (2.195)	-
	Labour Market Status t-5[3] (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[3] (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] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] "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 A1.2: Tests of mean and distribution for selected characteristics in the groups of participants (P) and non-participants (NP) for the sub-samples

Variable	Whole Sample				Long Term Unemployed				Gender							
									Women				Men			
	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]
	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]
Gender	0.382	0.376	0.006	0.062	0.340	0.319	0.021	0.238	-	-	-	-	-	-	-	-
(male = 1)	(0.486)	(0.485)	(0.803)	(0.803)	(0.474)	(0.466)	(0.627)	(0.626)	-	-	-	-	-	-	-	-
Start of	20.168	20.272	-0.104	0.655	20.861	20.508	0.353	0.779	18.566	18.512	0.054	0.555	22.757	22.794	-0.037	0.353
Unemployment-Spell	(11.348)	(11.509)	(0.852)	(0.784)	(11.053)	(11.185)	(0.730)	(0.578)	(10.529)	(10.734)	(0.935)	(0.917)	(12.118)	(12.017)	(0.969)	(1.000)
Completed Apprentice-	0.816	0.834	-0.018	0.918	0.891	0.895	-0.004	0.220	0.821	0.84	-0.019	0.676	0.809	0.834	-0.025	0.672
ship/Technician	(0.387)	(0.372)	(0.338)	(0.338)	(0.312)	(0.307)	(0.883)	(0.882)	(0.383)	(0.366)	(0.411)	(0.411)	(0.392)	(0.372)	(0.413)	(0.413)
University/College	0.114	0.108	0.006	0.149	0.059	0.059	0.000	0.000	0.107	0.097	0.010	0.260	0.126	0.114	0.012	0.233
Degree	(0.318)	(0.311)	(0.699)	(0.700)	(0.235)	(0.235)	(1.000)	(1.000)	(0.308)	(0.296)	(0.610)	(0.610)	(0.332)	(0.317)	(0.630)	(0.629)
Age	36.425	36.431	-0.006	0.461	36.807	36.853	-0.046	0.275	36.208	36.211	-0.003	0.309	36.775	36.846	-0.071	0.353
	(5.448)	(5.332)	(0.984)	(0.982)	(5.579)	(5.578)	(0.928)	(1.000)	(5.376)	(5.265)	(0.991)	(1.000)	(5.542)	(5.359)	(0.869)	(1.000)
Residence Chemnitz	0.362	0.369	-0.007	0.91	0.395	0.387	0.008	0.035	0.350	0.362	-0.012	0.150	0.382	0.369	0.013	0.105
	(0.481)	(0.482)	(0.763)	(0.763)	(0.489)	(0.487)	(0.851)	(0.851)	(0.477)	(0.480)	(0.699)	(0.699)	(0.485)	(0.482)	(0.746)	(0.746)
Residence Dresden	0.404	0.400	0.004	0.610	0.370	0.370	0.000	0.000	0.408	0.404	0.004	0.016	0.397	0.400	-0.003	0.006
	(0.491)	(0.489)	(0.805)	(0.805)	(0.483)	(0.483)	(1.000)	(1.000)	(0.491)	(0.491)	(0.900)	(0.900)	(0.489)	(0.489)	(0.936)	(0.936)
Frequency of Changes into	0.031	0.039	-0.008	0.946	0.038	0.044	-0.006	0.485	0.034	0.035	-0.001	0.586	0.026	0.032	-0.006	0.431
Unemployment[1]	(0.090)	(0.100)	(0.923)	(0.333)	(0.106)	(0.135)	(0.624)	(0.985)	(0.096)	(0.116)	(0.846)	(0.882)	(0.077)	(0.097)	(0.427)	(0.992)
Frequency of Changes into	0.905	0.909	-0.004	0.970	0.898	0.892	0.006	0.413	0.878	0.878	0.000	0.401	0.950	0.945	0.005	0.510
Employment[1]	(0.212)	(0.217)	(0.674)	(0.303)	(0.219)	(0.891)	(0.753)	(0.996)	(0.244)	(0.258)	(0.991)	(0.997)	(0.135)	(0.152)	(0.687)	(0.957)
Frequency of Changes into	0.064	0.059	0.005	0.703	0.063	0.065	-0.002	0.367	0.088	0.087	0.001	0.432	0.024	0.023	0.001	0.235
Non-Employment[1]	(0.188)	(0.188)	(0.595)	(0.706)	(0.186)	(0.064)	(0.946)	(0.999)	(0.219)	(0.228)	(0.936)	(0.992)	(0.110)	(0.115)	(0.917)	(1.000)
Mean Duration of	0.640	0.505	0.135	0.946	0.786	0.714	0.072	0.458	0.689	0.583	0.106	0.586	0.562	0.382	0.180	0.586
Unemployment[2]	(1.830)	(1.866)	(0.127)	(0.333)	(2.191)	(2.465)	(0.739)	(0.985)	(1.955)	(2.061)	(0.393)	(0.882)	(1.602)	(1.265)	(0.112)	(0.8882)
Mean Duration of	13.747	14.133	-0.386	0.800	14.385	14.334	0.051	0.367	12.181	12.287	-0.106	0.494	16.278	16.431	-0.153	0.494
Employment[2]	(9.566)	(9.504)	(0.405)	(0.544)	(9.874)	(9.973)	(0.956)	(0.999)	(8.602)	(8.338)	(0.840)	(0.968)	(10.461)	(10.632)	(0.853)	(0.968)
Mean Duration of Non-	0.955	0.94	0.015	0.703	0.846	0.758	0.088	0.321	1.218	1.138	0.080	0.401	0.531	0.498	0.033	0.401
Employment[2]	(2.862)	3.432)	(0.922)	(0.706)	(2.497)	(2.479)	(0.702)	(1.000)	(3.047)	(3.105)	(0.677)	(0.997)	(2.473)	(3.022)	(0.882)	(0.997)
Labour Market Status t-1[3]	0.924	0.926	-0.002	0.340	0.950	0.950	0.000	0.000	0.903	0.901	0.002	0.011	0.957	0.957	0.000	0.000
(Employment=1)	(0.266)	(0.262)	(0.854)	(0.854)	(0.219)	(0.218)	(1.000)	(1.000)	(0.296)	(0.298)	(0.917)	(0.917)	(0.203)	0.203)	(1.000)	(1.000)
Labour Market Status t-2[3]	0.908	0.921	-0.013	0.912	0.933	0.929	0.004	0.033	0.886	0.891	-0.005	0.087	0.945	0.957	-0.012	0.526
(Employment=1)	(0.289)	(0.269)	(0.340)	(0.340)	(0.250)	(0.257)	(0.857)	(0.857)	(0.318)	(0.311)	(0.769)	(0.769)	(0.228)	(0.203)	(0.469)	0.468)
Labour Market Status t-3[3]	0.898	0.909	-0.011	0.675	0.912	0.912	0.000	0.000	0.876	0.878	-0.002	0.009	0.932	0.948	-0.016	0.682
(Employment=1)	(0.303)	(0.287)	(0.265)	(0.411)	(0.283)	(0.283)	(1.000)	(1.000)	(0.329)	(0.327)	(0.925)	(0.925)	(0.251)	(0.222)	(0.410)	(0.409)
Labour Market Status t-4[3]	0.888	0.905	-0.017	1.242	0.891	0.899	-0.008	0.890	0.861	0.872	-0.011	0.297	0.932	0.951	-0.019	1.006
(Employment=1)	(0.315)	0.293)	(0.265)	(0.265)	(0.312)	(0.301)	(0.766)	(0.765)	(0.345)	(0.333)	(0.586)	(0.586)	(0.251)	(0.216)	(0.317)	(0.316)
Labour Market Status t-5[3]	0.879	0.893	-0.014	0.838	0.870	0.895	-0.025	0.729	0.851	0.859	-0.008	0.123	0.923	0.929	-0.006	0.090
(Employment=1)	(0.326)	(0.309)	(0.360)	(0.360)	(0.336)	(0.307)	(0.394)	(0.393)	(0.355)	(0.347)	(0.726)	(0.726)	(0.266)	(0.256)	(0.765)	(0.764)
Labour Market Status t-6[3]	0.878	0.888	-0.01	0.461	0.866	0.866	0.000	0.000	0.846	0.857	-0.011	0.271	0.929	0.945	-0.016	0.651
(Employment=1)	(0.328)	(0.315)	(0.497)	(0.497)	(0.341)	(0.341)	(1.000)	(1.000)	(0.361)	(0.349)	(0.603)	(0.603)	(0.256)	(0.229)	(0.421)	(0.420)
Long Term Unemployed	0.280	0.303	-0.023	1.139	-	-	-	-	0.299	0.318	-0.019	0.446	0.249	0.271	-0.022	0.392
	(0.449)	(0.460)	(0.286)	(0.286)	-	-	-	-	(0.458)	(0.465)	(0.505)	(0.504)	(0.432)	(0.444)	(0.532)	(0.531)

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [4] standard deviation in brackets — [5] p-value in brackets — [6] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A1.2 (continued)

Variable	Age								Human Capital							
	Younger than 40				40 and older				Skilled				High skilled			
	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]
	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]
Gender	0.369	0.372	-0.003	0.015	0.413	0.405	0.008	0.032	0.379	0.370	0.009	0.111	0.423	0.495	-0.072	1.017
(male = 1)	(0.482)	(0.483)	(0.904)	(0.904)	(0.492)	(0.490)	(0.859)	(0.858)	(0.485)	(0.482)	(0.740)	(0.739)	(0.493)	(0.499)	(0.316)	(0.313)
Start of	17.401	17.330	0.071	0.756	26.483	26.876	-0.393	0.439	20.059	20.182	-0.123	0.698	18.949	19.711	-0.762	0.574
Unemployment-Spell	(9.648)	(9.672)	(0.899)	(0.617)	(12.363)	(12.423)	(0.718)	(0.990)	(11.240)	(11.279)	(0.840)	(0.715)	(11.136)	(11.533)	(0.642)	(0.896)
Completed Apprentice-	0.829	0.844	-0.015	0.502	0.788	0.826	-0.038	1.239	-	-	-	-	-	-	-	-
ship/Technician	(0.376)	(0.362)	(0.479)	(0.479)	(0.408)	(0.378)	(0.266)	(0.266)		-	-	-	-	-	-	-
University/College	0.112	0.108	0.004	0.035	0.120	0.097	0.023	0.721	-	-	-	-	-	-	-	-
Degree	(0.314)	(0.311)	(0.853)	(0.852)	(0.325)	(0.295)	(0.397)	(0.396)	-	-	-	-	-	-	-	-
Age	33.580	33.643	-0.063	0.378	42.915	42.992	-0.077	0.747	36.233	36.249	-0.016	0.537	37.021	36.979	0.042	0.431
	(3.610)	(3.575)	(0.765)	(0.999)	(2.626)	(2.508)	(0.734)	(0.632)	(5.468)	(5.335)	(0.956)	(0.935)	(5.162)	(4.803)	(0.954)	(0.992)
Residence Chemnitz	0.350	0.342	0.008	0.093	0.390	0.417	-0.027	0.393	0.372	0.373	-0.001	0.003	0.289	0.330	-0.041	0.386
	(0.477)	(0.474)	(0.760)	(0.760)	(0.487)	(0.493)	(0.532)	(0.531)	(0.483)	(0.483)	(0.956)	(0.956)	(0.453)	(0.470)	(0.537)	(0.534)
Residence Dresden	0.425	0.425	0.000	0.000	0.355	0.367	-0.012	0.075	0.388	0.386	0.002	0.003	0.464	0.474	-0.01	0.021
	(0.494)	(0.494)	(1.000)	(1.000)	(0.478)	(0.481)	(0.784)	(0.784)	(0.487)	(0.486)	(0.956)	(0.956)	(0.498)	(0.499)	(0.886)	(0.886)
Frequency of Changes into	0.024	0.023	0.001	0.669	0.046	0.052	-0.006	0.308	0.030	0.034	-0.004	0.698	0.019	0.020	-0.001	0.431
Unemployment[1]	(0.079)	(0.091)	(0.881)	(0.762)	(0.108)	(0.128)	(0.575)	(1.000)	(0.088)	(0.110)	(0.482)	(0.715)	(0.059)	(0.091)	(0.979)	(0.992)
Frequency of Changes into	0.904	0.908	-0.004	0.727	0.909	0.907	0.002	0.527	0.913	0.910	0.003	0.564	0.876	0.894	-0.018	0.790
Employment[1]	(0.219)	(0.223)	(0.717)	(0.666)	(0.195)	(0.221)	(0.898)	(0.944)	(0.198)	(0.211)	(0.803)	(0.908)	(0.249)	(0.253)	(0.618)	(0.561)
Frequency of Changes into	0.072	0.068	0.004	0.553	0.045	0.041	0.004	0.659	0.057	0.056	0.001	0.456	0.105	0.087	0.018	0.718
Non-Employment[1]	(0.198)	(0.203)	(0.738)	(0.920)	(0.160)	(0.166)	(0.808)	(0.778)	(0.173)	(0.178)	(0.913)	(0.985)	(0.245)	(0.243)	(0.603)	(0.681)
Mean Duration of	0.486	0.367	0.119	0.669	0.993	0.792	0.201	0.615	0.637	0.535	0.102	0.698	0.402	0.309	0.093	0.359
Unemployment[2]	(1.521)	(1.530)	(0.182)	(0.762)	(2.350)	(2.261)	(0.321)	(0.844)	(1.832)	(1.915)	(0.310)	(0.715)	(1.287)	(1.501)	(0.646)	(1.000)
Mean Duration of	12.111	12.462	-0.351	0.785	17.482	18.003	-0.521	0.967	13.777	14.116	-0.339	0.752	12.374	13.052	-0.678	0.431
Employment[2]	(7.828)	(7.665)	(0.437)	(0.568)	(11.850)	(11.734)	(0.616)	(0.308)	(9.387)	(9.274)	(0.500)	(0.625)	(9.344)	(9.649)	(0.622)	(0.992)
Mean Duration of Non-	0.951	0.920	0.031	0.553	0.963	0.757	0.206	0.659	0.866	0.918	-0.052	0.456	1.665	1.253	0.412	0.790
Employment[2]	(2.659)	(2.828)	(0.842)	(0.920)	(3.277)	(3.686)	(0.501)	(0.778)	(2.741)	(3.431)	(0.755)	(0.985)	(3.655)	(3.765)	(0.442)	(0.561)
Labour Market Status t-1[3]	0.922	0.929	-0.007	0.196	0.927	0.931	-0.004	0.029	0.931	0.931	0.000	0.000	0.897	0.907	-0.01	0.058
(Employment=1)	(0.268)	(0.256)	(0.658)	(0.658)	(0.260)	(0.254)	(0.865)	(0.865)	(0.254)	(0.253)	(1.000)	(1.000)	(0.304)	(0.290)	(0.810)	(0.809)
Labour Market Status t-2[3]	0.907	0.920	-0.013	0.687	0.911	0.931	-0.02	0.662	0.916	0.925	-0.009	0.355	0.866	0.918	-0.052	1.335
(Employment=1)	(0.290)	(0.270)	(0.408)	(0.407)	(0.284)	0.254	(0.417)	(0.416)	(0.276)	(0.263)	(0.551)	(0.551)	(0.340)	(0.275)	(0.250)	(0.248)
Labour Market Status t-3[3]	0.898	0.909	-0.011	0.349	0.896	0.919	-0.023	0.827	0.903	0.914	-0.011	0.425	0.887	0.907	-0.02	0.223
(Employment=1)	(0.302)	(0.288)	(0.555)	(0.554)	(0.305)	(0.272)	(0.364)	(0.363)	(0.295)	(0.281)	(0.515)	(0.515)	(0.317)	(0.290)	(0.639)	(0.637)
Labour Market Status t-4[3]	0.892	0.904	-0.012	0.451	0.880	0.911	-0.031	1.323	0.892	0.905	-0.013	0.639	0.887	0.907	-0.02	0.223
(Employment=1)	(0.311)	(0.295)	(0.502)	(0.502)	(0.324)	(0.284)	(0.251)	(0.250)	(0.310)	(0.293)	(0.424)	(0.424)	(0.317)	(0.290)	(0.639)	(0.637)
Labour Market Status t-5[3]	0.876	0.887	-0.011	0.292	0.884	0.903	-0.019	0.509	0.882	0.888	-0.006	0.113	0.876	0.907	-0.031	0.481
(Employment=1)	(0.329)	(0.317)	(0.590)	(0.589)	(0.320)	(0.295)	(0.477)	(0.476)	(0.322)	(0.315)	(0.737)	(0.737)	(0.329)	(0.290)	(0.491)	(0.488)
Labour Market Status t-6[3]	0.873	0.885	-0.012	0.390	0.888	0.919	-0.031	1.417	0.882	0.888	-0.006	0.113	0.876	0.907	-0.031	0.481
(Employment=1)	(0.332)	(0.319)	(0.533)	(0.532)	(0.315)	(0.272)	(0.235)	(0.234)	(0.323)	(0.315)	(0.737)	(0.737)	(0.329)	(0.290)	(0.491)	(0.488)
Long Term Unemployed	0.269	0.291	-0.022	0.709	0.305	0.344	-0.039	0.881	0.305	0.333	-0.028	1.197	0.144	0.144	0.000	0.000
	(0.443)	(0.454)	(0.400)	(0.400)	(0.460)	(0.474)	(0.349)	(0.348)	(0.460)	(0.471)	(0.274)	(0.274)	(0.351)	(0.351)	(1.000)	(1.000)

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [4] standard deviation in brackets — [5] p-value in brackets — [6] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A1.2 (continued)

Variable	Residence												Start of Unemployment Spell Until 1992			
	Chemnitz				Dresden				Leipzig							
	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]
	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]
Gender	0.403	0.403	0.000	0.000	0.376	0.391	-0.015	0.154	0.362	0.377	-0.015	0.970	0.305	0.323	-0.018	0.329
(male = 1)	(0.490)	(0.490)	(1.000)	-1000	(0.484)	(0.487)	(0.695)	(0.695)	(0.480)	(0.484)	(0.756)	(0.755)	(0.460)	(0.467)	(0.567)	(0.566)
Start of	19.753	19.724	0.029	0.483	20.356	20.283	0.073	0.573	20.487	21.377	-0.89	0.451	11.509	11.429	0.08	0.432
Unemployment-Spell	(10.866)	(10.927)	(0.974)	(0.974)	(11.813)	(11.801)	(0.936)	(0.898)	(11.238)	(11.585)	(0.439)	(0.987)	(2.592)	(2.589)	(0.644)	(0.992)
Completed Apprentice-	0.838	0.847	-0.009	0.110	0.784	0.799	-0.015	0.221	0.839	0.859	-0.02	0.314	0.819	0.838	-0.019	0.631
ship/Technician	(0.368)	(0.359)	(0.741)	(0.740)	(0.411)	(0.400)	(0.639)	(0.638)	(0.367)	(0.347)	(0.576)	(0.575)	(0.385)	(0.367)	(0.428)	(0.427)
University/College	0.091	0.088	0.003	0.020	0.131	0.131	0.000	0.000	0.121	0.111	0.010	0.98	0.126	0.108	0.018	0.684
Degree	(0.287)	(0.282)	(0.888)	(0.888)	(0.338)	(0.337)	(1.000)	(1.000)	(0.325)	(0.313)	(0.755)	(0.754)	(0.332)	(0.310)	(0.409)	(0.408)
Age	36.695	36.812	-0.117	0.363	36.003	36.061	-0.058	0.420	36.734	36.628	0.106	0.551	34.279	34.339	-0.06	0.366
	(5.231)	(5.075)	(0.779)	(0.999)	(5.431)	(5.300)	(0.887)	(0.995)	(5.748)	(5.828)	(0.856)	(0.921)	(4.727)	(4.537)	(0.847)	(0.999)
Residence Chemnitz	-	-	-	-	-	-	-	-	-	-	-	-	0.374	0.374	0.000	0.000
	-	-	-	-	-	-	-	-	-	-	-	-	(0.483)	(0.483)	(1.000)	(1.000)
Residence Dresden	-	-	-	-	-	-	-	-	-	-	-	-	0.396	0.396	0.000	0.000
	-	-	-	-	-	-	-	-	-	-	-	-	(0.489)	(0.489)	(1.000)	(1.000)
Frequency of Changes into	0.034	0.036	-0.002	0.645	0.029	0.023	0.006	0.573	0.029	0.028	0.001	0.501	0.008	0.010	-0.002	0.266
Unemployment[1]	(0.094)	(0.112)	(0.840)	(0.800)	(0.091)	(0.087)	(0.441)	(0.898)	(0.0779)	(0.082)	(0.890)	(0.963)	(0.046)	(0.072)	(0.670)	(1.000)
Frequency of Changes into	0.917	0.918	-0.001	0524	0.896	0.907	-0.011	0.802	0.904	0.916	-0.012	0.652	0.923	0.925	-0.002	0.366
Employment[1]	(0.188)	(0.192)	(0.911)	(0.947)	(0.226)	(0.234)	(0.543)	(0.541)	(0.219)	(0.209)	(0.582)	(0.789)	(0.216)	(0.224)	(0.888)	(0.999)
Frequency of Changes into	0.049	0.046	0.003	0.363	0.075	0.070	0.005	0.573	0.067	0.056	0.011	0.602	0.069	0.065	0.004	0.432
Non-Employment[1]	(0.160)	(0.161)	(0.793)	(0.999)	(0.201)	(0.208)	(0.729)	(0.898)	(0.203)	(0.193)	(0.589)	(0.862)	(0.208)	(0.215)	(0.787)	(0.992)
Mean Duration of	0.656	0.494	0.162	0.645	0.564	0.382	0.182	0.611	0.748	0.497	0.251	0.501	0.113	0.091	0.022	0.266
Unemployment[2]	(1.829)	(1.760)	(0.262)	(0.800)	(1.729)	(1.483)	(0.141)	(0.850)	(1.985)	(1.613)	(0.169)	(0.963)	(0.636)	(0.673)	(0.612)	(1.000)
Mean Duration of	13.045	13.211	-0.166	0.322	14.557	14.862	-0.305	0.878	13.440	14.607	-1.167	0.852	8.979	8.901	0.078	0.399
Employment[2]	(8.281)	(8.419)	(0.806)	(1.000)	(11.004)	(10.564)	(0.712)	(0.424)	(8.604)	(8.783)	(0.183)	(0.462)	(3.909)	(3.627)	(0.758)	(0.997)
Mean Duration of Non-	0.848	0.774	0.074	0.322	0.984	0.965	0.019	0.649	1.070	1.033	0.037	0.602	0.648	0.579	0.069	0.432
Employment[2]	(2.863)	(2.666)	(0.740)	(1.000)	(2.485)	(2.945)	(0.928)	(0.793)	(3.407)	(4.948)	(0.930)	(0.862)	(1.988)	(1.970)	(0.601)	(0.992)
Labour Market Status t-1[3]	0.938	0.935	0.003	0.027	0.901	0.910	-0.009	0.153	0.940	0.940	0.000	0.000	0.940	0.942	-0.002	0.020
(Employment=1)	-0.24	-0.246	(0.869)	(0.869)	(0.298)	(0.286)	(0.696)	(0.696)	(0.238)	(0.238)	(1.000)	(1.000)	(0.236)	(0.232)	(0.888)	(0.887)
Labour Market Status t-2[3]	0.919	0.935	-0.016	0.599	0.892	0.904	-0.012	0.255	0.920	0.935	-0.015	0.335	0.934	0.938	-0.004	0.074
(Employment=1)	(0.273)	(0.246)	(0.440)	(0.439)	(0.310)	(0.294)	(0.615)	(0.614)	(0.271)	(0.247)	(0.564)	(0.563)	(0.248)	(0.241)	(0.786)	(0.786)
Labour Market Status t-3[3]	0.916	0.929	-0.013	0.362	0.869	0.886	-0.017	0.488	0.920	0.930	-0.010	0.144	0.925	0.916	0.009	0.241
(Employment=1)	(0.278)	(0.257)	(0.548)	(0.548)	(0.337)	(0.317)	(0.485)	(0.485)	(0.271)	(0.255)	(0.705)	(0.704)	(0.263)	(0.277)	(0.624)	(0.623)
Labour Market Status t-4[3]	0.899	0.925	-0.026	1.299	0.869	0.883	-0.014	0.336	0.905	0.920	-0.015	0.282	0.914	0.914	0.000	0.000
(Employment=1)	(0.300)	(0.262)	(0.255)	(0.254)	(0.337)	(0.321)	(0.563)	(0.562)	(0.293)	(0.272)	(0.597)	(0.595)	(0.280)	(0.280)	(1.000)	(1.000)
Labour Market Status t-5[3]	0.883	0.906	-0.023	0.843	0.875	0.895	-0.02	0.701	0.879	0.910	-0.031	0.958	0.907	0.916	-0.009	0.219
(Employment=1)	(0.321)	(0.292)	(0.359)	(0.359)	(0.331)	(0.306)	(0.403)	(0.402)	(0.325)	(0.286)	(0.329)	(0.328)	(0.290)	(0.277)	(0.640)	(0.639)
Labour Market Status t-6[3]	0.870	0.873	-0.003	0.015	0.880	0.898	-0.018	0.533	0.884	0.899	-0.015	0.235	0.905	0.914	-0.009	0.215
(Employment=1)	(0.336)	(0.332)	(0.904)	(0.904)	(0.324)	(0.302)	(0.466)	(0.465)	(0.319)	(0.300)	(0.629)	(0.628)	(0.293)	(0.280)	(0.644)	(0.643)
Long Term Unemployed	0.305	0.334	-0.029	0.604	0.257	0.286	-0.029	0.738	0.281	0.317	-0.036	0.587	0.241	0.261	-0.020	0.476
	(0.460)	(0.471)	(0.438)	(0.437)	(0.436)	(0.451)	(0.391)	(0.390)	(0.449)	(0.465)	(0.445)	(0.443)	(0.428)	(0.439)	(0.491)	(0.490)

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] “t-n” denotes the number of quarters until the start of the considered unemployment spell — [4] standard deviation in brackets — [5] p-value in brackets — [6] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Table A1.2 (continued)

Variable	Start of Unemployment Spell								Duration of Measure											
	Between 1993 and 1996				From 1997				Shorter than 4 quarters				4 to 7 quarters				Longer than 7 quarters			
	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean			Distribution[6]	Mean	Distribution[6]	Mean	Distribution[6]
	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]	P[4]	NP[4]	Difference[5]	Test Result[5]
Gender	0.448	0.452	-0.004	0.009	0.500	0.464	0.036	0.429	0.404	0.400	0.004	0.009	0.406	0.391	0.015	0.156	0.337	0.337	0	0.000
(male = 1)	(0.497)	(0.497)	(0.926)	(0.925)	(0.500)	(0.498)	(0.514)	(0.512)	(0.490)	(0.489)	(0.924)	(0.924)	(0.491)	(0.487)	(0.694)	(0.693)	(0.472)	(0.472)	(1.000)	(1.000)
Start of Unemployment-Spell	23.139	23.070	0.069	0.513	39.399	39.351	0.048	0.655	23.996	23.409	0.587	0.513	20.767	21.084	-0.317	0.541	16.375	16.558	-0.183	0.377
	(4.837)	(4.789)	(0.877)	(0.955)	(4.216)	(4.172)	(0.917)	(0.785)	(13.290)	(12.845)	(0.631)	(0.955)	(11.253)	(11.724)	(0.722)	(0.932)	(8.126)	(8.602)	(0.795)	(0.999)
Completed Apprentice-	0.826	0.865	-0.039	1.349	0.798	0.810	-0.012	0.075	0.822	0.826	-0.004	0.015	0.758	0.767	-0.009	0.074	0.881	0.888	-0.007	0.069
ship/Technician	(0.379)	(0.341)	(0.246)	(0.245)	(0.401)	(0.392)	(0.784)	(0.784)	(0.383)	(0.379)	(0.903)	(0.903)	(0.428)	(0.422)	(0.786)	(0.785)	(0.324)	(0.315)	(0.794)	(0.793)
University/College Degree	0.100	0.087	0.013	0.231	0.101	0.101	0.000	0.000	0.126	0.126	0.000	0.000	0.152	0.155	-0.003	0.011	0.060	0.056	0.004	0.032
	(0.300)	(0.282)	(0.632)	(0.631)	(0.302)	(0.301)	(1.000)	(1.000)	(0.332)	(0.332)	(1.000)	(1.000)	(0.359)	(0.362)	(0.915)	(0.915)	(0.236)	(0.230)	(0.858)	(0.858)
Age	36.939	37.104	-0.165	0.513	41.494	41.357	0.137	0.327	37.948	37.617	0.331	0.513	36.994	37.116	-0.122	0.464	34.526	34.723	-0.197	0.419
	(4.593)	(4.363)	(0.693)	(0.955)	(4.763)	(4.637)	(0.790)	(1.000)	(5.732)	(5.491)	(0.529)	(0.955)	(5..389)	(5.392)	(0.769)	(0.983)	(4.690)	(4.645)	(0.616)	(0.995)
Residence Chemnitz	0.348	0.374	-0.026	0.339	0.351	0.375	-0.024	0.206	0.365	0.365	0.000	0.000	0.343	0.346	-0.003	0.007	0.382	0.389	-0.007	0.030
	(0.476)	(0.483)	(0.561)	(0.560)	(0.477)	(0.484)	(0.651)	(0.650)	(0.481)	(0.481)	(1.000)	(1.000)	(0.475)	(0.475)	(0.935)	(0.935)	(0.486)	(0.487)	(0.864)	(0.863)
Residence Dresden	0.413	0.422	-0.009	0.036	0.411	0.411	0.000	0.000	0.391	0.391	0.000	0.000	0.424	0.427	-0.003	0.060	0.389	0.393	-0.004	0.007
	(0.492)	(0.493)	(0.850)	(0.850)	(0.492)	(0.492)	(1.000)	(1.000)	(0.488)	(0.488)	(1.000)	(1.000)	(0.494)	(0.495)	(0.938)	(0.938)	(0.487)	(0.488)	(0.932)	(0.932)
Frequency of Changes into	0.046	0.044	0.002	0.979	0.070	0.087	-0.017	0.600	0.038	0.034	0.004	0699	0.031	0.034	-0.003	0.618	0.025	0.021	0.004	0.461
Unemployment[1]	(0.107)	(0.137)	(0.831)	(0.293)	(0.125)	(0.149)	(0.255)	(0.864)	(0.108)	(0.111)	(0.703)	(0.712)	(0.084)	(0.105)	(0.642)	(0.839)	(0.077)	(0.079)	(0.610)	(0.984)
Frequency of Changes into	0.893	0.901	-0.008	0.746	0.875	0.860	0.015	0.546	0.893	0.897	-0.004	0.513	0.913	0.916	-0.003	0.773	0.906	0.913	-0.007	0.503
Employment[1]	(0.203)	(0.212)	(0.673)	(0.634)	(0.208)	(0.223)	(0.518)	(0.927)	(0.224)	(0.227)	(0.836)	(0.955)	(0.198)	(0.201)	(0.824)	(0.589)	(0.217)	(0.220)	(0.733)	(0.962)
Frequency of Changes into	0.061	0.055	0.006	0.466	0.055	0.053	0.002	0.818	0.069	0.068	0.001	0.280	0.056	0.049	0.007	0.695	0.069	0.066	0.003	0.251
Non-Employment[1]	(0.166)	(0.164)	(0.712)	(0.982)	(0.155)	(0.166)	(0.913)	(0.515)	(0.192)	(0.198)	(0.981)	(1.000)	(0.178)	(0.175)	(0.615)	(0.719)	(0.196)	(0.198)	(0.860)	(1.000)
Mean Duration of	0.935	0.665	0.270	0.979	1.657	1.429	0.228	0.655	0.742	0.513	0.229	0.699	0.664	0.558	0.106	0.618	0.530	0.375	0.155	0.586
Unemployment[2]	(2.020)	(2.256)	(0.196)	(0.293)	(2.705)	(2.532)	(0.432)	(0.785)	(1.995)	(1.790)	(0.198)	(0.712)	(1.791)	(1.921)	(0.460)	(0.839)	(1.726)	(1.520)	(0.257)	(0.882)
Mean Duration of	16.429	16.938	-0.509	0.886	22.908	23.664	-0.756	0.655	15.575	15.841	-0.266	0.653	14.156	14.297	-0.141	0.348	11.793	11.925	-0.132	0.670
Employment[2]	(7.782)	(7.283)	(0.470)	(0.413)	(13.567)	(13.682)	(0.612)	(0.785)	(11.618)	(11.341)	(0.805)	(0.788)	(9.407)	(9.285)	(0.845)	(1.000)	(7.299)	(7.086)	(0.827)	(0.760)
Mean Duration of Non-	1.187	1.052	0.135	0.466	1.464	1.446	0.018	0.818	1.158	1.130	0.028	0.280	0.942	0.897	0.045	0.657	0.807	0.911	-0.104	0.209
Employment[2]	(3.317)	(3.205)	(0.659)	(0.982)	(3.890)	(4.816)	(0.971)	(0.515)	(3.247)	(3.870)	(0.934)	(1.000)	(2.954)	(3.750)	(0.864)	(0.781)	(2.365)	(2.963)	(0.645)	(1.000)
Labour Market Status t-1[3]	0.904	0.922	-0.018	0.438	0.905	0.893	0.012	0.131	0.909	0.900	0.009	0.101	0.931	0.937	-0.006	0.097	0.926	0.933	-0.007	0.108
(Employment=1)	(0.294)	(0.268)	(0.509)	(0.508)	(0.293)	(0.309)	(0.718)	(0.718)	(0.288)	0.300	(0.752)	(0.751)	(0.252)	(0.242)	(0.756)	(0.755)	(0.261)	(0.249)	(0.743)	(0.743)
Labour Market Status t-2[3]	0.878	0.909	-0.031	1.119	0.881	0.893	-0.012	0.119	0.883	0.891	-0.008	0.087	0.922	0.937	-0.015	0.572	0.912	0.933	-0.021	0.887
(Employment=1)	(0.326)	(0.288)	(0.291)	(0.290)	(0.324)	(0.309)	(0.731)	(0.730)	(0.321)	(0.311)	(0.769)	(0.768)	(0.267)	(0.242)	(0.450)	(0.449)	(0.283)	(0.249)	(0.347)	(0.346)
Labour Market Status t-3[3]	0.883	0.909	-0.026	0.837	0.845	0.881	-0.036	0.907	0.852	0.878	-0.026	0.671	0.919	0.931	-0.012	0.346	0.909	0.919	-0.01	0.201
(Employment=1)	(0.322)	(0.288)	(0.361)	(0.360)	(0.361)	(0.324)	(0.342)	(0.341)	(0.355)	(0.326)	(0.414)	(0.413)	(0.272)	(0.252)	(0.557)	(0.556)	(0.288)	(0.273)	(0.655)	(0.654)
Labour Market Status t-4[3]	0.878	0.9	-0.022	0.551	0.833	0.869	-0.036	0.846	0.848	0.874	-0.026	0.653	0.910	0.925	-0.015	0.495	0.895	0.916	-0.021	0.736
(Employment=1)	(0.327)	(0.300)	(0.459)	(0.458)	(0.372)	(0.337)	(0.359)	(0.358)	(0.359)	(0.331)	(0.42)	(0.419)	(0.285)	(0.262)	(0.482)	(0.482)	(0.307)	(0.277)	(0.392)	(0.391)
Labour Market Status t-5[3]	0.861	0.883	-0.022	0.486	0.827	0.833	-0.006	0.021	0.852	0.857	-0.005	0.017	0.890	0.919	-0.029	1.728	0.888	0.916	-0.028	1.267
(Employment=1)	(0.346)	(0.321)	(0.487)	(0.486)	(0.378)	(0.372)	(0.885)	(0.884)	(0.355)	(0.350)	(0.895)	(0.895)	(0.313)	(0.272)	(0.189)	(0.189)	(0.316)	(0.277)	(0.261)	(0.260)
Labour Market Status t-6[3]	0.857	0.878	-0.021	0.472	0.833	0.839	-0.006	0.022	0.865	0.874	-0.009	0.077	0.881	0.899	-0.018	0.547	0.884	0.895	-0.011	0.161
(Employment=1)	(0.350)	(0.327)	(0.493)	(0.492)	(0.372)	(0.367)	(0.883)	(0.883)	(0.341)	(0.332)	(0.782)	(0.782)	(0.324)	(0.302)	(0.460)	(0.460)	(0.320)	(0.307)	(0.689)	(0.689)
Long Term Unemployed	0.322	0.357	-0.035	0.621	0.327	0.423	-0.096	3.251	0.257	0.283	-0.026	0.397	0.325	0.343	-0.018	0.241	0.246	0.256	-0.01	0.084
	(0.467)	(0.479)	(0.432)	(0.431)	(0.469)	(0.494)	(0.072)	(0.071)	(0.437)	(0.450)	(0.529)	(0.528)	(0.468)	(0.475)	(0.624)	(0.623)	(0.430)	(0.436)	(0.772)	(0.772)

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] "t-n" denotes the number of quarters until the start of the considered unemployment spell — [4] standard deviation in brackets — [5] p-value in brackets — [6] for metrical scaled variables KS-test; for nominal scaled variables chi-square test

Appendix 2

Table A2.1: Parameter estimates of the proportional hazards 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		
				Men	Women	Younger than 40	40 and older	High skilled	Skilled	Chemnitz	Dresden	Leipzig	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)	0.276*** (0.103)	0.358*** (0.098)	0.264** (0.130)	0.3397*** (0.08414)	0.31480*** (0.11699)	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)	-0.011 (0.011)	-0.001 (0.010)	-0.032*** (0.011)	-0.00439 (0.00880)	-0.02856** (0.01337)	-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)	-	-	-0.765*** (0.293)	-	-	-	-	-	-
	Secondary School Degree	0.249* (0.149)	-	-	0.448** (0.180)	-	-	-	-	-	-	-	0.41752** (0.17908)	-	-	-	-	-
	Completed Apprentice-ship/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)	-	-	-0.130 (0.191)	0.031 (0.198)	0.221 (0.388)	-0.17803 (0.17780)	0.21278 (0.27002)	-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)	-	-	0.316 (0.241)	0.533** (0.229)	-0.089 (0.506)	0.15893 (0.26044)	0.59834* (0.31950)	-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)	-0.017*** (0.006)	-0.012** (0.005)	-	-	-	-	-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)	3.811** (1.639)	7.613*** (2.362)	-	-	4.67188** (2.05756)	4.341*** (1.604)	3.050* (1.825)	-	-
	Frequency of Changes into Employment[1]	-	-	-	-	-	2.277** (1.130)	-	-	-	-	-	-	-	-	-	-	-
	Mean Duration of Unemployment[2]	-0.050** (0.023)	-	-0.113** (0.049)	-	-	-	-	-0.044* (0.025)	-	-0.1213** (0.0501)	-	-	-	-	-	-	-
	Mean Duration of Employment[2]	-	-	-	0.013* (0.008)	-	-	-	-	-	-	-	-	-	-	-	-	-
	Labour Market Status t-1[3] (Employment=1)		-	-0.018*** (0.006)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Labour Market Status t-2[3] (Employment=1)	-	-		-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Labour Market Status t-3[3] (Employment=1)	-	-	-0.963** (0.49)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Labour Market Status t-4[3] (Employment=1)	-	-	-	-	0.282** (0.129)	-	-	-	0.420** (0.205)	-	-	0.26577* (0.15117)	-	-	-	-	-
	Labour Market Status t-5[3] (Employment=1)	-	-	-	-	-	-	-	-	-	-	-	-	0.35570* (0.19618)	-	-	-	-
	Labour Market Status t-6[3] (Employment=1)	-	-		-	-	-	-	0.244** (0.120)	-	-	-	-	-	-	-	-	-

[1] Number of changes into the respective employment status relative to the time until the start of the considered unemployment spell. – [2] Time spent in the respective employment status relative to the time until the start of the considered unemployment spell – [3] "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

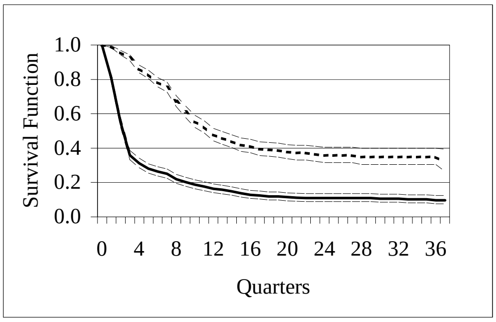
Table A2.2: Model statistics of the proportional hazards model for the sub-samples

Variable	Whole Sample	Long Term Unemployed	Gender		Age		Human Capital		Residence			Start of the Unemployment Spell			Duration of the Measure		
			Men	Women	Younger than 40	40 and older	High skilled	Skilled	Chemnitz	Dresden	Leipzig	until 1992	between 1993 and 1996	from 1997	shorter than 4 quarters	4 to 7 quarters	longer than 7 quarters
Number of Matched Pairs	850	238	325	525	591	259	97	694	308	343	199	452	230	168	230	335	285
LR-Test of Global Null Hypothesis[1]	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)	34.013 (0.000)	48.525 (0.000)	22.664 (0.001)	58.984 (0.000)	21.4754 (0.0015)	22.162 (0.001)	41.793 (0.000)	40.738 (0.000)	19.835 (0.000)
Wald Proportionality Test[1]	11.707 (0.2304)	4.430 (0.619)	8.644 (0.471)	11.034 (0.0873)	9.965 (0.1906)	4.467 (0.484)	4.031 (0.258)	11.6018 (0.114)	4.689 (0.6978)	6.918 (0.4374)	5.942 (0.312)	4.3604 (0.6280)	3.7142 (0.7153)	7.024 (0.319)	11.513 (0.0738)	3.478 (0.6267)	1.347 (0.8533)

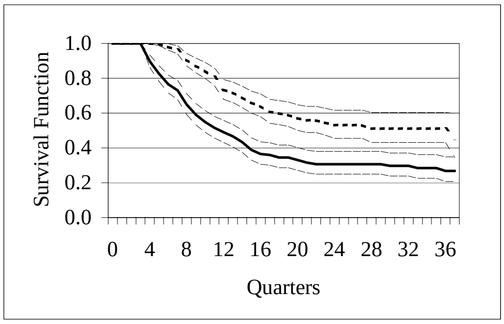
[1] p-value in brackets

Figure A2: Covariate-adjusted survival functions in participation and non-participation case for the sub-samples

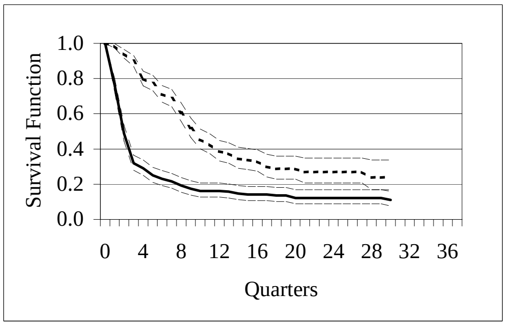
A2.1: Whole Sample



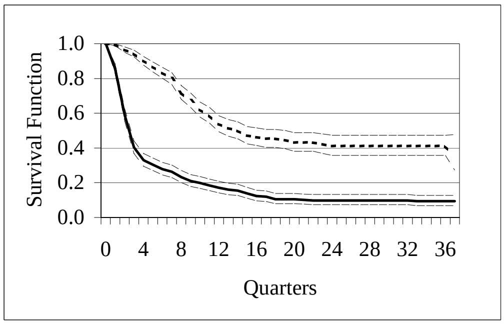
A2.2: Long Term Unemployed



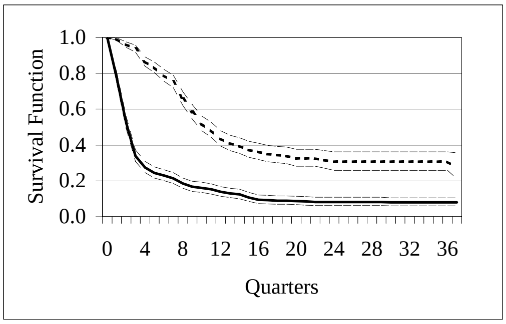
A2.3: Men



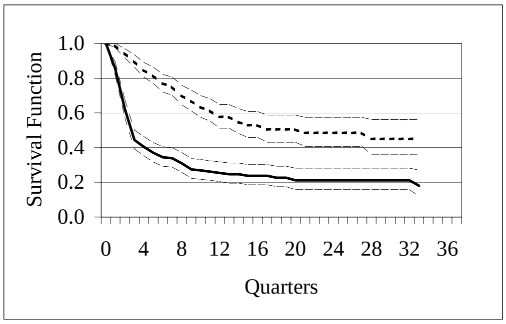
A2.4: Women



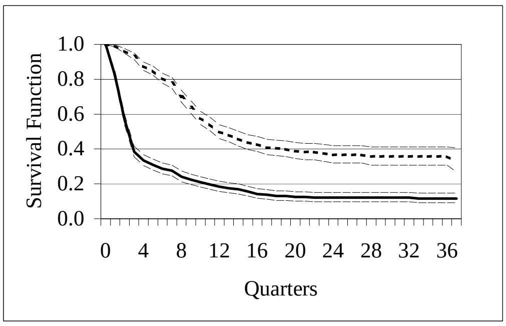
A2.5: Younger than 40



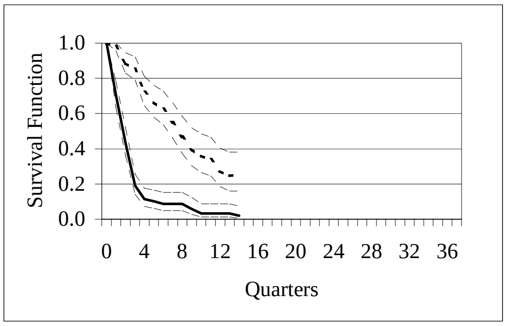
A2.6: Older than 40



A2.7: Skilled



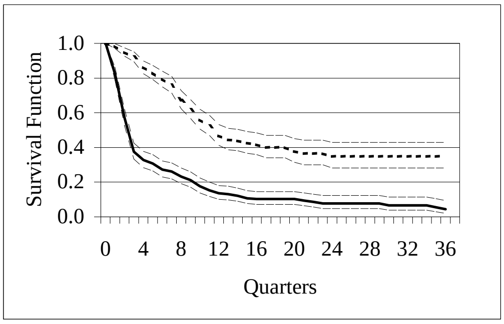
A2.8: High Skilled



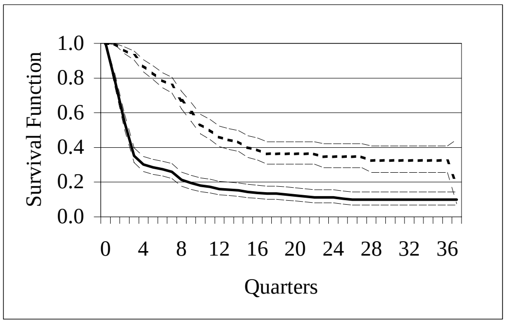
– – – Participation ——— Non-Participation

Figure A2 (continued)

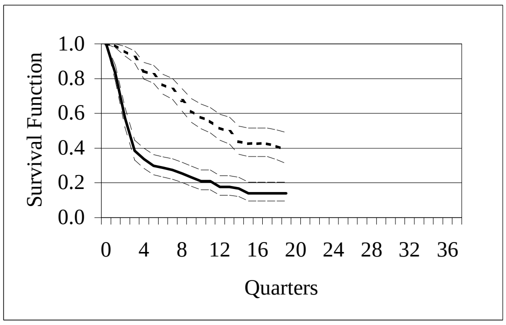
A2.9: Chemnitz



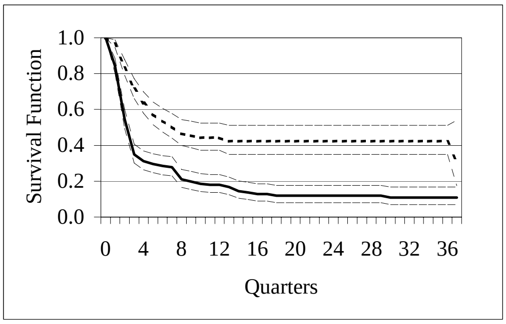
A2.10: Dresden



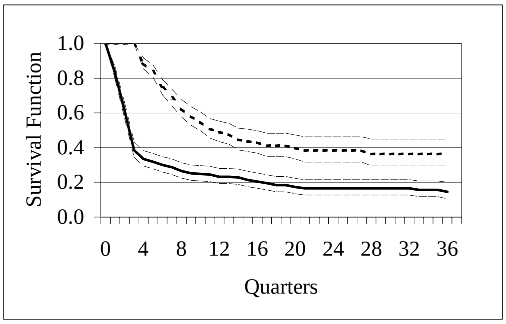
A2.11: Leipzig



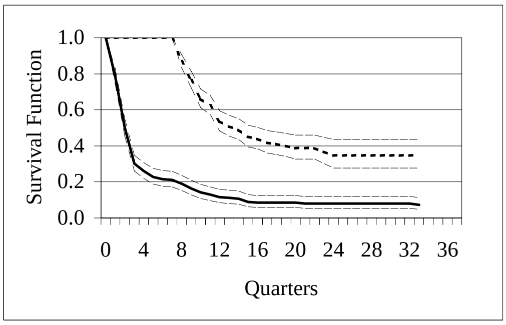
A2.12: Measure shorter than 4 Quarters



A2.13: Measure 4 to 7 Quarters



A2.14: Measure longer than 7 Quarters



– – – Participation ——— Non-Participation