Analyzing the Effects of On-the-Job vs. Off-the-Job Training on Unemployment Duration in West Germany[†]

by

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ABSTRACT

This study is concerned with the impact of on-the-job and off-the-job training on individual unemployment duration in West Germany. The base data used is the German Socio-Economic Panel (GSOEP) for the period from 1984 to 1993. To resolve the intriguing sample selection problem, i.e. to find an adequate control group for the group of participants, matching methods are applied which use the individual propensity score for participation in vocational training as the main matching variable. The propensity score is obtained by estimating a random effects probit model. On the basis of the matched sample a discrete time hazard rate model is utilized to assess the impact of vocational on-the-job and off-the-job training on unemployment duration. The results indicate, that on-the-job training has no significant effects on the duration of subsequent unemployment spells, whereas off-the-job training has significant negative effects on duration in the short run but not in the long run.

Keywords: discrete hazard models, unemployment duration, on-the-job training, off-the-job training, selection bias

JEL classifications: C41, J20, J64

I. Introduction

In recent years labor market policy debates in Germany regarding the value of training programs have become increasingly controversial. On one hand the persistently high level of unemployment rates stresses the necessity of training programs in helping unemployed former participants to find jobs faster and employed participants to retain their jobs longer. The main hypotheses are that participation in training reduces human capital decay, improves job search skills during unemployment and strengthens work habits during employment. On the other hand, it is often called into question whether the positive effects of training programs outweigh their costs. Moreover, advocates of a pessimistic perspective even argue that participation in training programs during episodes of high unemployment may be seen as a negative screening factor for some employers and may therefore have a negative impact on the individual's employment chances.

In order to justify or reject training as a helpful part of active labor market policy, empirical studies investigate the effectiveness of training programs on different individual outcomes. Typically such outcomes are employment or unemployment rates, earnings, wages and the duration of employment or unemployment spells. The fact that the effect of training on earnings is primarily a result of its effect on employment rates raises the question whether employment rates change because participants keep their jobs longer or because they are able to find jobs faster once unemployed. This study concentrates especially on the question whether former participants manage to find jobs faster when becoming unemployed. Hence, the outcome of interest is the individual duration of unemployment. In order to take into account that the effect of training may vary with the type of vocational training provided, the analysis distinguishes between on-the-job training and off-the-job training, i.e. between training provided or not provided during working hours.

To evaluate the causal effect of training programs on any kind of outcome one has to contrast the situation of the participants after training with the counterfactual situation in the absence of training. Because the latter situation is only hypothetical, i.e. not observable, it needs to be estimated, based on the outcome of other individuals who did not receive training, members of a so-called control group. When choosing or constructing this control group, different adjustment procedures are applied to ensure that participants and non-participants are identical with respect to all relevant characteristics except for not having obtained training. In experimental evaluations, an adequate control group is generated by means of randomization at the stage of actual assignment to the program. In studies where non-experimental data are used, different econometric adjusting or statistical matching procedures are applied to artificially construct or find an adequate control group. Failure to adjust for discrepancies between participants and non-participants may lead to substantially biased judgements about the effect of the training program. Econometric literature calls this bias a *sample selection bias*.

The fact that existing empirical studies on the effects of training programs for West Germany vary with respect to the outcome they measure, the types of training they evaluate, the econometric or statistical methods they apply and the data they use, makes a comparison of results quite difficult.[1] Hujer, Schneider (1990), for example, analyze the effects of training on the reemployment probabilities of unemployed in West Germany using the first four waves of the German Socio-Economic Panel (GSOEP) covering the time period from 1983 to 1986. They apply a continuous time duration model that accounts for unobserved heterogeneity. The estimated results indicate a significant positive short run training effect whereas a long run effect of training was not detected.

Becker (1991) examines the impact of vocational training programs on career ladder changes based on a sample of three cohorts of West Germans from the German Life History Study. The author applies a continuous time duration model to estimate independently the effects of training on up- and downward movements on the career ladder. The results imply, that successful training programs, i.e. if a certification was assigned, raise the promotion probabilities significantly.

Büchel, Pannenberg (1994) and Pannenberg (1995) are concerned with the relation between on-the-job training, firm-internal career ladders and income changes in West Germany using data from the GSOEP from 1984 to 1991. Büchel, Pannenberg (1994) estimate the relationship between on-the-job training and movements on internal career ladders by means of a bivariate probit model. To estimate the effect of on-the-job training on earnings a fixed effects model is used. The results indicate that on-the-job training has positive effects on promotion probability as well as on earnings. Pannenberg (1995) finds significant negative effects of off-the-job training

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1 For a wider overview of empirical studies related to the impact of training, see Björklund (1989), Dolton (1994) and Hujer, Maurer, Wellner (1996b).

on unemployment duration and significant positive effects of-the-job training effects on seniority and income.

Pischke (1996) conducts a detailed analysis of vocational training activities in and effects for West Germany based on data from the GSOEP for 1986 to 1989. The author distinguishes between on-the-job training and other training. The results show that prior participation in vocational training has mainly insignificant effects on wage growth.

In Prey (1997) payment of a maintenance allowance is the distinguishing feature regarding vocational training. The study uses the first ten waves of the GSOEP (1984-1993) and examines individual employment probabilities as the outcome variable. Using a dynamic random effects model that simultaneously takes the participation decision into account, no significant impacts of participation on employment probabilities are identified. This applies to vocational training with and without payment of a maintenance allowance for both men and women. In the long run, the results for men even show a significant negative effect.

Based on the first ten waves of the GSOEP, Staat (1997) examines the effect of public vocational training with payment of a maintenance allowance on employment and unemployment duration. Instrumental variables correct for possible selection bias. The estimation results show no significant results of participation in public vocational training.

Own previous work, using data from the first eleven waves of the GSOEP 1984-1994 and either instrumental variables (Hujer, Maurer, Wellner (1997a)) or matching methods (Hujer, Maurer, Wellner (1997b, 1998a)) in order to take into account sample selection bias, identifies a significant negative effect of vocational training in general on unemployment duration in the short run and insignificant effects in the long run. Hujer, Maurer, Wellner (1998b) evaluate the effect of vocational training with payment of a maintenance allowance and find that a significant negative effect of this type of vocational training on unemployment can only be expected for short training courses where the effect is directed towards the first post-training unemployment spell, if this spell does not immediately follow the training participation.

The present study extends the issue of heterogeneity of training measures to the distinction between on-the-job and off-the-job training. To keep results comparable, the outcome variable unemployment duration in West Germany, the econometric model, the semi-parametric discrete hazard rate model with gamma-distributed unmeasured heterogeneity, and the base data, the first eleven waves of the GSOEP, remain unchanged. To resolve the already mentioned sample selection problem, i.e. to find an adequate control group, we - like Lechner (1995, 1996a, 1996b) - employ matching methods proposed by Rosenbaum, Rubin (1985) and Rubin (1991). These matching methods use the individual propensity to participate in training, obtained by estimating a random effects probit model, as the main matching variable. In addition, information on the monthly pre-training employment status in order to take into account transitory shocks just prior to training, as well as information on regional labor market conditions in order to include potential demand side effects, are incorporated. Given the resulting matched sample, the necessity to estimate a discrete time hazard rate model for evaluating the impact of vocational training on unemployment duration is emphasized.

The paper proceeds as follows. The next chapter presents some features and developments of the West German labor market before and during the time span considered in our evaluations. Chapter 3 describes the base data and presents descriptive statistics for several characteristics of the chosen sample. Chapter 4 is devoted to the construction of an adequate control group. It first outlines the fundamental evaluation problem theoretically and then presents the strategy applied to deal with it. The chapter also discusses the estimation results for the propensity score and the application of the matching methods. Chapter 5 deals with the impact of on-the-job and off-the-job training on the transition from unemployment to employment. To this purpose, the semiparametric discrete time hazard rate model is introduced which is then used to evaluate the impact of vocational training. Due to restrictions immanent to the analysis the evaluation actually refers to the period between 1986 and 1993. Chapter 6 summarizes the main findings.

II. The Labor Market in West Germany: Some Stylized Facts

Figure 1 shows the development of the unemployment rate and the average elapsed unemployment duration of these individuals for the period actually evaluated in this study. It is apparent that the average elapsed unemployment duration and the unemployment rate do not vary with each other in the way one might have expected: despite a substantial decline in the unemployment rate between 1988 and 1991, the average elapsed unemployment duration is quite stable. After 1991, when the unemployment rate increased by almost two percentage points until 1993, the average elapsed unemployment duration even decreased by almost two months. Thus, it cannot be expected that evaluations of the impact of vocational training on either unemployment probabilities or unemployment duration come to the same conclusion.

< figure 1 about here >

Figure 2 illustrates the dynamics behind the unemployment figures that will also affect unemployment duration. With approximately 2 million unemployed individuals, the figures for entries into and exits from unemployment are substantially higher. During 1986 and 1991 between 3.5 and 4 million entries into unemployment have been recorded each year. Of course, periods with decreasing unemployment figures are also periods where the exits from unemployment are higher than the entries into unemployment and vice versa.

< figure 2 about here >

These dynamics are another reason for this study's focus on unemployment duration rather than employment or unemployment rates as an outcome variable.

III. The Base Data

The sample used for the analysis is drawn from the German Socio-Economic Panel (GSOEP), a representative sample of the resident population in Germany.[2] Starting in 1984 in West Germany, about 12,000 individuals of age 16 and older in nearly 6,000 households were interviewed on a yearly basis about subjects such as employment status, personal characteristics, education, various types of income etc. From 1990 onwards, an additional sub-sample of 4,500 individuals in just under 2,000 East German households was added. Since this study is limited to West Germany, the latter sub-sample is disregarded in the following analysis.

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[2] For a detailed description of the GSOEP see Hanefeld (1987), Projektgruppe Sozio-ökonomisches Panel (1995) or Wagner, Burkhauser, Behringer (1993).

Information on individual unemployment duration stems from the retrospective monthly "calendar" that gathers detailed information on the individual's labor force status in each month of the previous calendar year. In this questionnaire the individual has to distinguish between up to eight different labor force states for each month. The states include full-time employment, part-time employment, registered unemployment, education, etc. Information on participation in vocational training comes from two special surveys carried out in 1989 and 1993, where individuals were asked about their last three vocational training courses that were either completed in the previous three years or were still ongoing. The distinction between the two types of vocational training that are considered in this study is formed using information as to whether the training took place during working hours: on-the-job training is defined as vocational training that took place completely or at least partly during working hours, all other vocational training is off-the-job training.

Due to the limited retrospectivity of the special survey on vocational training, information on vocational training activities during 1984 or 1985 is almost completely missing. In addition, as no further special survey on vocational training has been conducted since 1993, no comparable information on vocational training activities in later years is available. Hence, the evaluation in this study is limited to the period from 1986 to 1993. The panel waves for 1984, 1985 and 1994 serve as an information source for certain covariates and for information on unemployment duration in 1993.

The selected sample consists of individuals who had at least one unemployment spell during the time span 1986-1993 and who participated in both special survey on vocational training activities. Due to methodological reasons, left-censored spells have been excluded from our analysis (Hujer, Schneider (1996), Vermunt (1997)). Unemployment spells are considered to be completed if they end through a transition into employment where employment consists of both full-time and part-time employment. All other spells are considered to be right-censored. This selection results in a sample of 1,180 individuals who contribute 1,835 unemployment spells. 720 of these spells are right-censored. The average unemployment duration of all spells is 8.91 months, whereas the average duration of completed spells is 6.09 months.

The crucial problem when using non-experimental in contrast to experimental data is that participants in vocational training are not a random sample from the population of interest. The descriptive comparison between non-participants and participants in table 1 reveals that this holds also true for our sample. There are major differences in characteristics such as nationality, education or employment status. On average participants are younger, are less likely to be a foreigner and have a higher formal education level. Consequently, a simple comparison between mean unemployment duration for participants and non-participants as an indicator for the causal effect of vocational training in general has to be considered carefully since it is subject to potential selection effects. Table 1 also illustrates how sensitive the comparison of mean unemployment duration between participants and non-participants is with respect to the treatment of right-censored spells. Considering completed spells only yields a far lower difference than in the case where right-censored spells are also included.

< table 1 about here >

IV. Constructing a Control Group using Matching Methods

IV.1 Evaluation Problem and Identifying Restrictions

The causal effect of participation in vocational training that is usually considered in the evaluation literature is the mean effect of treatment on the treated which is defined as the average individual outcome gain of participants in vocational training compared to the situation in which they would not have participated in vocational training. Apparently, in order to assess this causal effect, one has to contrast the individuals' situation after training with the corresponding situation of the *same* individuals in the hypothetical case of not having participated in training, the *counterfactual* situation. This points to the central problem of all program evaluations: They have to compare two situations which can never both occur at the same time. While one can observe the first situation, the latter is always hypothetical, i.e. unobservable. Hence, it has to be estimated based on the information of *other* individuals who did not participate in the training program, members of a so-called control group.

Here the formalization of the evaluation problem is based on the Roy-Rubin model (Roy (1951), Rubin (1974)). In this model, there are two *potential* outcomes (Y_i^t, Y_i^c) for an individual i, where Y_i^t corresponds to the situation in the case of participation and Y_i^c to the case without participation. The causal effect of participation in vocational training for each individual is then defined as the difference between his or her potential outcomes (Y_i^t - Y_i^c).[3] The evaluation problem arises because one can only observe either Y_i^t or Y_i^c, but never both, and hence the difference cannot be formed for anyone.

Using this notation the mean effect of treatment on the treated is defined as

$$\alpha = E\left(Y^t - Y^c \middle| D = 1\right) = E\left(Y^t \middle| D = 1\right) - E\left(Y^c \middle| D = 1\right), \tag{1}$$

where D is a dummy variable determining whether each individual was exposed to vocational training ($D = 1$) or not ($D = 0$). The problem of not observing the counterfactual is now documented easily by the fact, that one only has information to estimate

$$\alpha^e = E\left(Y^t \middle| D = 1\right) - E\left(Y^c \middle| D = 0\right). \tag{2}$$

It is obvious that α^e is a potentially biased estimator of the training impact of interest (α), since $E\left(Y^c \middle| D = 1\right)$, i.e. the unobservable average outcome of participants in the absence of training, does not necessarily equal $E\left(Y^c \middle| D = 0\right)$, i.e. the observed average outcome of non-participants. This inequality evidently arises if participants and non-participants differ systematically in their individual characteristics as they do in the data set used in this study (see Section III).

Carefully designed experiments are often viewed to be the only valid procedure to overcome this evaluation problem and to obtain reliable estimates of the impact of vocational training.[4] In an experiment, individuals who have originally been accepted for the training program are, in a second stage, randomly assigned to either the group of actual participants in the training program, or to a group of actual non-participants. Because of the random assignment process, the two groups do not differ systematically with respect to all observable and unobservable

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3 General equilibrium effects are ignored, so that the potential outcomes for a given individual are not affected by the training status of other individuals.

4 See Ashenfelder, Card (1985), LaLonde (1986) or Burtless, Orr (1986).

characteristics, except for the fact of program participation. Thus, a difference in the outcome after training is only induced by the training program itself, i.e. the impact of training is isolated and a selection bias does not exist. In formal terms the role of randomization is precisely that the potential outcomes (Y^t and Y^c) are independent of the assignment to the training program (D). It follows that

$$E\left(Y^c \middle| D = 1\right) = E\left(Y^c \middle| D = 0\right). \tag{3}$$

Thus, the group of non-participants can be used as an adequate control group to estimate the training impact α.[5]

As the GSOEP is a non-experimental data set this study has to cope with the evaluation problem in a different way. It does so by following an approach introduced by Rubin (1977), which is very much inspired by the conduction of an experiment. To construct an adequate control group in a non-experimental setting, this approach is based on the identifying assumption that, conditional on all relevant covariates (Z), the potential outcome without training (Y^c) is independent (denoted by $\perp\!\!\!\perp$) of the assignment to training (D):

$$Y^c \perp\!\!\!\perp D \mid Z = z. \tag{4a}$$

If this assumption holds, then

$$E\left(Y^c \middle| Z = z, D = 1\right) = E\left(Y^c \middle| Z = z, D = 0\right). \tag{5a}$$

Rewriting the crucial term in (1) as

$$E\left(Y^c \middle| D = 1\right) = E_{Z|D=1}\left[E\left(Y^c \middle| Z = z, D = 1\right) \middle| D = 1\right] \tag{6}$$

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5 Despite this advantage of the experimental approach there are, however, some general and methodological problems related to experiments which have been discussed in literature. Especially ethical arguments against the random selection process and practical difficulties to adequately conduct an experiment are most often mentioned. For a wider discussion of relative advantages of experimental and non-experimental approaches see e.g. Burtless, Orr (1986), Björklund (1989) and Heckman, Smith (1995).

and inserting equation (5a) leads to

$$E\left(Y^c \middle| D=1\right) = E_{Z|D=1}\left[E\left(Y^c \middle| Z=z, D=0\right) \middle| D=1\right]. \tag{7a}$$

An evaluation of (7a) – and thus of α – on the basis of the group of non-participants is now basically possible by conditioning on the distribution of all relevant covariates ($Z=z$) in the group of participants. The implementation of conditioning is, however, usually limited due to the high dimensionality of the vector z. In order to deal with this problem of dimensionality, Rosenbaum, Rubin (1983) suggest the use of the propensity score, i.e. the conditional probability of participating in training given the set of all relevant covariates, defined as $P(Z=z) \equiv P\left(D=1 \middle| Z=z\right)$. They show that if the potential outcome without training is independent of the assignment mechanism conditional on $Z=z$, then the conditional independence assumption extends to the propensity score:

$$Y^c \perp\!\!\!\perp D \mid P(Z=z). \tag{4b}$$

This leads to:

$$E\left(Y^c \middle| P(Z=z), D=1\right) = E\left(Y^c \middle| P(Z=z), D=0\right). \tag{5b}$$

The crucial term in (1) can now be written as:

$$E\left(Y^c \middle| D=1\right) = E_{P(Z)|D=1}\left[E\left(Y^c \middle| P(Z=z), D=0\right) \middle| D=1\right]. \tag{7b}$$

The major advantage of the identifying assumption (4b) is that it turns the estimation problem into a much easier task as one only has to condition on a univariate scale, i.e. on the propensity score.

In order to condition on the propensity score the next step involves the estimation of this propensity score. This is done in subsection IV.2. by means of a random effects probit model. Since the aim is to construct an adequate control group that does not systematically differ from the participant group with respect to the relevant characteristics, an attractive way to condition on the estimated propensity score is the application of matching methods proposed by Rosenbaum, Rubin (1985) and Rubin (1991) (subsection IV.3).

IV.2 Estimating the Propensity Score

The estimation of the propensity scores in this study has to deal with several problems. First, it has to take into account the unbalanced nature of the sample. Second, there is the problem that the starting dates of the training programs vary. Hence, if there are relevant (time-varying) covariates which are related to the beginning of the training program, they are not clearly defined for the non-participants (Lechner (1995)). Third, one has to be careful to consider only covariates which influence the decision to participate in training (D) *as well as* the potential outcome without training (Y^c) *but* which are unaffected by the training program, i.e. are exogenous. Thus, the relevant covariates should be pre-training variables.

It is assumed that observations are missing at random. Consequently, estimation uses an unbalanced random effects probit model for the decision to participate in vocational training. For a given year or wave an individual is defined as participating in vocational training if he enters a vocational training measure in the period after the current interview and up to the following interview and as non-participating otherwise. In order to ensure that the covariates ($Z = z_{it}$) are dated prior to the beginning of the training program they refer to the time of the current interview. Estimation is based on the eight waves with information on vocational training (1986 to 1993).

Table 2 contains the estimation results. The selection of potentially relevant covariates relies on theoretical hypotheses related to human capital theory and also considers variables proposed by other empirical studies of training participation (e.g. Blundell, Dearden, Meghir (1996)). Theory suggests that investment into human capital and hence participation in training decreases with age. The estimation results exhibit a concave influence of age with a maximum at approximately age 31. The hypothesis that men (MALE) have better access to training due to discrimination against women could not be confirmed. A foreign nationality (FOREIGNER) has a significant negative effect, which confirms hypotheses that minority groups have a poor access to training programs. However, a negative effect of being DISABLED was not detected. The hypothesis that variables related to family context might influence the training probability, due to a greater marginal value of non-market time, could only be verified for martial status (PARTHH) but not for children (KS, KM, KL). The results concerning the variables that capture the formal educational level confirm the assumption that human capital accumulated earlier positively influences the investment into new human capital. Individuals who have completed an apprenticeship (LEHRE) or who have a university degree (DIPLOM) participate significantly more often in vocational training.

< table 2 about here >

Evidently, participation in vocational training is also related to the actual labor market status since this can reflect a special need to participate in training as well as different access possibilities to training programs. Being employed (EMPLOYED) increases the training participation probability. This increase is even stronger if the individual is employed in the public sector (PUBLIC SECTOR). Moreover, the probability of participation in training rises with firm size, i.e. large firms seem to provide more training than small firms (FIRMSIZE). The results relating to variables describing the specific job position show that individuals with jobs which require a high qualification participate in training more often (JOBQUALIF). The status "blue collar worker" (BLUCOLLAR) has a negative effect compared to "white collar worker" (WHICOLLAR) and the reference group. The fact that the individual is working in the occupation he was originally educated for (JOBEDUC) may provide a (deceptive) feeling of safety, as it lowers the probability of participation. An alternative explanation of this coefficient may be the fact that the function of vocational training is to compensate for a missing original education.[6]

Concerning the influence of employment history, individuals who were employed in the last two years (EMP2YRS) have an increased training participation probability. As emphasized by Heckman et al. (1997), variables that predict job-seeking might be very important determinants of training participation. Hence a variable is included that is related to future plans regarding employment. Individuals who are currently not employed and are seeking for an employment in the near future (FUTEMPIMM) are most likely to participate in a training measure.

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6 This interpretation was suggested by Friedhelm Pfeiffer, Zentrum für Europäische Wirtschaftsforschung, Mannheim.

Finally, the specification contains a "technical" variable in order to take into account the specific (retrospective) nature of the questionnaire concerning vocational training (SPECQUEST). This variable exhibits a negative "memory"-effect, i.e. an increasing distance between the current wave and the following special questionnaire makes the observation of a training participation less likely.

IV.3 Application of Matching Methods

The aim of matching methods is to select for each participant non-participants, that resemble him or her as well as possible in terms of pre-training characteristics and thus to achieve a conditional independence between the potential outcome without training (Y^c) and the decision to participate in training (D). If this is done correctly, it will result in a matched sample consisting of participants and non-participants who on average - similar as in a randomized experiment - do not differ systematically in all relevant characteristics, thus eliminating the need to take into account the selection process into training when estimating its impact on unemployment duration.

The central conditioning or matching variable is the estimated propensity score. As stressed by Heckman et al. (1996), a successful application of matching methods is only possible within the range of common support of the distribution of the propensity scores of the groups of participants and non-participants. Obviously this requires a large a-priori overlap between the densities of the propensity score for the participants and non-participants. A comparison of the distributions of the propensity score for every year reveals that a large overlap indeed exists, despite the fact that the mass of the distribution of the non-participants is to the left of that of the participants.[7]

The estimation of the propensity score only incorporates yearly characteristics. Potentially important differences like a particularly bad labor market situation for participants just prior to the training program, as emphasized by Lechner (1995, 1996a, 1996b) for East Germany or by studies for the US (Ashenfelder, Card (1985); Card, Sullivan (1988)), might not be adequately captured. Therefore the set of matching variables is extended to include variables obtained from the retrospective calendar and which describe the monthly pre-training employment history. The

[7] See figure A.1 in the appendix for an example.

employment status in the last month before training is included as well as the average employment status in the last 4 and 12 months before training. Moreover, Heckman et al. (1996) point out that accounting for differences in regional labor market conditions might also be essential to constructing an adequate control group. Hence, the set of matching variables also contains an indicator that captures the regional labor market tightness (ANSPINDEX). To further enhance matching quality, the matching procedure also directly incorporates the subset of significant variables used for the propensity score estimation. These variables are: AGE, FOREIGNER, LEHRE, DIPLOM, EMPLOYED, JOBQUALIF, FIRMSIZE, FUTEMPIMM and EMP2YRS. Finally, due to an initial condition problem (Ham, LaLonde (1990, 1996)) that would later arise when comparing *post*-training unemployment spells of participants with the non-participants that are already in progress when training ends, the matching procedure is restricted to non-participants whose first *post*-training unemployment spell is a fresh spell (i.e. the starting point of the unemployment spell is dated after the end of the training).

Basically, it seems straightforward to match each participant only with the closest non-participant ("one-to-one-sampling"). However, neglecting the other non-participants leads to a small sample size and thus lower degrees of freedom when later estimating the impact of training on unemployment duration. Therefore, in order to obtain a larger sample size, this study applies a matching procedure that groups each participant with more than one non-participant ("oversampling").[8]

Table 3 demonstrates the quality of the matching procedure. A comparison between randomly selected non-participants and participants reveals significant differences especially in the propensity score and education, as well as some socio-demographic and job related variables. In contrast, the distribution of characteristics of the matched non-participants resembles the group of participants very closely, and no significant differences were detected in the means.

< table 3 about here >

With respect to differences in the monthly pre-training employment status, figure 3 shows that participants have a higher unemployment rate just prior to the training program in comparison with random non-participants (panel (a)). Looking at the difference in unemployment rates

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[8] See Hujer, Maurer, Wellner (1997b) for a detailed description of the matching procedure.

between the non-participants selected through the matching procedure and the participants reveals that the matching algorithm is able to reduce this upward shift (panel (b)): Here the 95%-confidence interval always includes zero so that for all twelve months prior to participation in vocational training no significant differences between both groups exist.

< figure 3 about here >

V. Training and Unemployment Duration

V.1 Duration Analysis based on a Matched Sample

So far this study has considered the evaluation problem that arises as a consequence of selection into training. Application of the matching procedure results in a matched sample that consists of 113 participants and 218 selected non-participants who on average – as in a randomized experiment – do not systematically differ in any relevant characteristics. 160 *post*-training unemployment spells are observed for the participants and 295 for the non-participants. An obvious way to obtain the impact of training on unemployment duration is to compare the average *post*-training unemployment duration of participants and non-participants.

Yet, as Ham, LaLonde (1990, 1996) demonstrate, even in an experimental framework which eliminates the need to control for selection into training, the appropriate evaluation method is heavily dependent on the particular outcome of interest. If the outcome of interest is the employment or unemployment rate, it suffices to simply compare participants' and non-participants' average post-training employment or unemployment rates. However, with unemployment duration as the outcome variable of interest there are three reasons, why a simple comparison of participants' and non-participants' average duration would be insufficient and would lead to potentially biased estimates of the training effect:

- The first problem with simply comparing the participants' and non-participants' average duration is the existence of right censored spells. A comparison of average unemployment duration neglects the information that right censored spells are still ongoing and not completely observed until their end.

- A second problem is that participants' and non-participants' unemployment spells do not necessarily originate at the same time and, thus, time-varying characteristics and demand conditions may differ.

- Finally, the following problem still remains even if the unemployment spells of participants and non-participants begin at the same time, e.g. the first period after training: Whilst, with the exception of having participated in vocational training, participants and non-participants do not systematically differ on average with respect to their characteristics in this period, in subsequent periods, the average characteristics of those participants and non-participants who are still unemployed do not necessarily equal (as in the initial groups). If for example, participation in vocational training has the effect that relatively more participants with bad labor market characteristics are able to exit unemployment than are non-participants with bad labor market characteristics, the group of unemployed participants in the second period will tend to have better labor market characteristics than the corresponding group of unemployed non-participants.

These issues emphasize that even with a matched sample an econometric model is still required for the evaluation. An appropriate approach which considers right censoring, and controls for relevant observable and unobservable characteristics besides training participation is the hazard rate model.

V.2 A Discrete Time Hazard Rate Model

Hazard rate models are concerned with observation i’s instantaneous rate of leaving a certain state of interest (here: unemployment) per unit time period at t, i.e. the hazard or transition rate: $\lambda_i(t) = \lim_{dt \to 0^+} P(t \le T_i < t + dt | T_i \ge t) \cdot (dt)^{-1}$. Duration T_i is a continuous non-negative random variable with realization t. The probability of survival up to t is given by the corresponding survivor function $S_i(t) = \exp - \int_0^t \lambda_i(u) du$.

The derivation of the particular hazard rate model utilized in this study is based on the well-known and widely used Proportional Hazards model for continuous time as proposed by Cox (1972):[9]

$$\lambda_i\big(t \big| x_i(t)\big) = \lambda_0(t)\exp\big(x_i'(t)\beta\big). \tag{8}$$

The hazard rate is a function of a set of explanatory variables $x_i(t)$ and a so-called baseline hazard rate λ_0 which is the hazard rate for $\exp(0)$. β is the vector of coefficients to be estimated. In contrast to parametric models (e.g. a Weibull hazard rate model) the form of λ_0 is not restricted to a particular parametric specification. Instead the baseline hazard rate is estimated non-parametrically.

Equation (8) only considers individual heterogeneity in the form of covariates $x_i(t)$, i.e. in the form of observable heterogeneity. Any unobservable heterogeneity is not taken into account. As Elbers, Ridder (1982) point out, failure to control for unobserved heterogeneity may lead to spurious duration dependence. In order to also control for any unobserved heterogeneity the Cox model is extended to the Mixed Proportional Hazards model:

$$\lambda_i\big(t \big| x_i(t), \omega_i\big) = \lambda_0(t)\exp\big(x_i'(t)\beta + \omega_i\big), \tag{9}$$

where ω_i is a random variable with expectation zero that is not correlated with the covariates by assumption. Heckman, Singer (1984) propose non-parametric methods to assess the distribution of ω_i. They show that parameter estimates are sensitive to different parametric assumptions regarding the distribution of ω_i. However, as Trussell, Richard (1985) point out, much of the parameter instability found by Heckman, Singer (1984) might be the result of the parametric specification of the baseline hazard in their model. Therefore, when estimating the baseline non-parametrically, the functional form of the heterogeneity distribution may as well be unimportant.

Up to now, it has been assumed that time is observed continuously. Yet, as the duration in the GSOEP data is only available on a monthly basis, it is not adequate to apply a model based on

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9 For a general overview of discrete-time hazard models and their empirical applications see Hujer, Maurer, Wellner (1996a).

the notion of continuous time. When using continuous time models with grouped duration data, parameter estimates may be useless due to the existence of ties, i.e. equal durations for different observations (Kalbfleisch, Prentice (1980), Cox, Oakes (1984)). Assuming that duration data is grouped into $J+1$ intervals with the j-th interval defined as $\left[t_j, t_{j+1}\right)$, $j = 0,1,...J$, and that changes in the covariates only occur at the lower bound of each interval, the conditional discrete time survivor function for surviving up to time t_j is defined as:

$$S_i\left(t_j \middle| \omega_i\right) = \exp\left(-\sum_{m=0}^{j-1} \int_{t_m}^{t_{m+1}} \lambda_0(u) \exp\left(x_i'\left(t_m\right)\beta + \omega_i\right) du\right)$$

$$= \exp\left(-\exp(\omega_i) \sum_{m=0}^{j-1} \exp\left[\left(x_i'(t_m)\beta\right) + \gamma_m\right]\right), \qquad (10)$$

where $\gamma_m = \ln\left(\int_{t_m}^{t_{m+1}} \lambda_0(u) du\right)$. To obtain the unconditional survivor function it is assumed that $\tau_i = \exp(\omega_i)$ follows a gamma distribution with mean one and variance σ^2. Integration with respect to this mixing distribution leads to:

$$S_i\left(t_j\right) = \left(1 + \sigma^2 \sum_{m=0}^{j-1} \exp\left[\left(x_i'(t_m)\beta\right) + \gamma_m\right]\right)^{-\sigma^{-2}}. \qquad (11)$$

To derive the resulting likelihood function define a dummy variable δ_i, which indicates whether the i-th observation is right-censored ($\delta_i = 0$) or not ($\delta_i = 1$), and let N indicate the number of observations:

$$L\left(\gamma, \beta, \sigma^2\right) = \prod_{i=1}^{N} \left[S_i\left(t_j\right) \cdot S_i\left(t_{j+1}\right)^{-1} - 1\right]^{\delta_i} \cdot S_i\left(t_{j+1}\right). \qquad (12)$$

Inserting (11), rearranging terms and taking logarithms results in the following log-likelihood:

$$l\left(\gamma,\beta,\sigma^2\right)=\sum_{i=1}^{N}\ln\left\{\delta_i\cdot\left[1+\sigma^2\cdot\sum_{m=0}^{j-1}\exp\left\{x_i'\left(t_m\right)\beta+\gamma_m\right\}\right]^{-\sigma^{-2}}\right.$$
$$\left.+\left(1-2\delta_i\right)\cdot\left[1+\sigma^2\cdot\sum_{m=0}^{j}\exp\left\{x_i'\left(t_m\right)\beta+\gamma_m\right\}\right]^{-\sigma^{-2}}\right\} \qquad (13).$$

Similar models have already been applied by Meyer (1990) and Narendranathan, Stewart (1993) to assess the impact of unemployment benefits on unemployment duration.

V.3 Estimation Results

Because the empirical specification of the hazard rate model has been extensively discussed in earlier work (e.g. Hujer, Maurer, Wellner (1997b, 1998a)) it will not be discussed again here. For a similar reason, the complete estimation results have been referred to table A.2 in the appendix. The estimation results, apart from the causal effects, do not differ very much from Hujer, Maurer, Wellner (1997b), so the focus here is on the discussion of the parameter estimates for vocational training participation.

The empirical specification includes a simple participation indicator that equals one if the individual has participated in vocational training and zero otherwise. As the main interest of this study is to analyze the effect of on-the-job and off-the-job training, an additional dummy variable has been included that equals one if the individual participated in on-the-job training. As the causal effect may vary over time, a difference in the short-term and long-term effect is also allowed for. The short run is defined as the first twelve months after the end of the particular training measure, the long run as thirteen months and beyond. Finally, another important aspect, the duration of the training course, is also considered by distinguishing between short and long training courses, where lon course are training courses of a duration of three months or longer.

< table 4 about here >

The estimated causal effects on the probability of transition from unemployment into employment resulting from this specification are given in table 4 which is an excerpt of table A.2

in the appendix. The interpretation of these effects is not straightforward. The estimated coefficient for participation in vocational training (VOCTRAINING) refers to the reference category of participation in a short off-the-job training course which took place within twelve months prior to spell begin. Compound effects on the transition probability for all other kinds of vocational training participation that result from the estimated coefficients in table 4 are given in table 5.

< table 5 about here >

The compound effects show that participation in on-the-job training has no significant impact on the probability of transition from unemployment into employment. This applies to the effect of short and long training measures as well as to the long-term and short-term effect of on-the-job training. A possible explanation might be that on-the-job training is more likely to provide firm-specific human capital which is of no or of little use in a different firm and thus does not help in getting a new employment. In contrast, off-the-job training has significant effects on the transition probability in the short run. If the individual participated in a long course, i.e. in a training course that took three months or longer, the effect is slightly larger than for the case of participation in a shorter course. However, in the long run the significant effect of participation in off-the-job training vanishes. The fact that the long-term effect is insignificant, whereas the short-term effect is significant, has also been found for vocational training in general by Hujer, Maurer, Wellner (1997a, 1997b, 1998a).

To further illustrate the estimated causal effects figure 4 shows simulated survivor functions for participants and non-participants based on the estimation results and figure 5 shows the difference in survival probabilities along with the bounds of the 95%-confidence interval. The assumptions for the participant are a participation in a longer training course in either on-the-job or off-the-job training within 12 months prior to spell begin. The non-participant did not participate in any form of vocational training at all but otherwise equals the participant in all socio-economic charcateristics. Panel (a) of figure 4 compares the survivor function of a participant in on-the-job training with the survivor function of a non-participant in vocational training. After the sixth month the survival probability for the participant has already halved, whereas the survival probability of the non-participant only falls to about 50% after thirteen months of elapsed unemployment duration. The probability of becoming long-term unemployed, i.e. to experience an unemployment duration of more than 12 months is 53% for the non-participant and 36% for the participant in on-the-job training. Between the seventh and fourteenth month of elapsed unemployment duration the difference between both survivor functions is greatest and amounts to about 17 percentage points. However, the difference between both survivor functions is not significant as already shown above and as panel (a) of figure 5 illustrates: the 95%-confidence interval includes zero for all 36 simulated months.

< figure 4 about here >

< figure 5 about here >

Panel (b) of figure 4 contains the simulated survivor functions for a participant in off-the-job training and a non-participant. The latter is of course equal to the survivor function of the non-participant in panel (a). It is obvious that the causal effect of participation in off-the-job training is more pronounced. Here it takes only four to five months of elapsed unemployment duration for the participant to have a survival probability of about 50%. His risk of becoming long-term unemployed amounts to 31% which is 5 percentage points less than the risk for a participant in on-the-job training. Between months eight and ten the difference in survival probabilities has its maximum of about 23 percentage points. As panel (b) of figure 5 shows the difference in survival probabilities is significant for all months except for the first where the confidence interval includes zero.

VI. Conclusion

This paper presents estimates of the causal effect of participation in vocational training on individual unemployment duration in West Germany for the period 1986 to 1993. Because of the non-experimental nature of the data set, the German Socio-Economic Panel, an important factor in obtaining reliable estimates of causal effects is to control for sample selection bias. This study uses matching methods to construct an adequate control group. The resulting sample can be used in a way that is very similar to experimental data. Yet, it is still necessary to apply an econometric model due – amongst other reasons – to censoring of the outcome variable.

With regard to the causal effect, vocational training is divided into two groups according to whether the training took place during working hours or not. Additional aspects that are taken into account are the duration of the particular training course and the elapsed time between participation and the date of the inception of the unemployment spell. It is assumed that selection into a training measure does not depend on these training characteristics. The assumption is necessary because a separate estimation of the participation equation for the various forms of vocational training does not seem feasible due to the small number of observations.

The results show that on-the-job training has no significant effect on the duration of a subsequent unemployment spell. In this respect it does not matter whether the long-term or the short-term effect is considered or whether the training course was a longer or a shorter course. In contrast, a participation in off-the-job training has a significant negative impact on unemployment duration in the short run. The absolute effect is slightly larger for longer courses. In the long run, however, the effect of off-the-job training is also insignificant.

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Table 1:
Selected Socio-Economic Characteristics for Participants vs. Non-Participants [a)]

Variable	Non-Participants	Participants
Individual-specific characteristics (1988)		
Number of individuals	715	219
Mean age (years) *	35.90	31.22
Male (%)	54.41	51.60
Foreigner (%) *	41.12	11.87
Abitur (%) *	9.79	20.55
Lehre (%) *	46.29	71.69
Diplom (%) *	2.80	9.59
Employed (%) *	61.28	70.78
Spell-specific characteristics (1986-1993)		
Number of spells	1404	431
Mean duration of uncensored spells (months) *	6.49	4.97
Mean duration all spells (months) *	9.77	6.11

a) Participants are those who received vocational training at least once during the period 1986-1993. Non-participants are those who never received vocational training during the period 1986-1993.

* Denotes 95%-significance of difference in sample means.

Table 2:
Maximum Likelihood Estimates for Participation in Vocational Training
Unbalanced Random Effects Probit Model for 1986-1993

Variable	**Coefficient**	**t-value**
Intercept	–3.9085	–7.1871
Age/10	0.7536	2.6109
$Age^2/100$	–0.1219	–3.1155
Male	0.0891	1.1630
Foreigner	–0.5200	–4.9833
PartHH	–0.1688	–1.9922
Disabled	–0.1971	–1.1153
KS	–0.0446	–0.6939
KM	0.0266	0.2994
KL	0.0095	0.1219
Abitur	0.1676	1.4412
Lehre	0.3389	3.8343
Diplom	0.3575	2.1662
Employed	0.8481	3.7026
WhiCollar	0.2360	1.8856
BlueCollar	–0.2704	–2.0256
JobTenur	–0.0078	–0.8761
JobQualif	0.5896	5.7010
JobEduc	–0.2336	–2.5547
Firmsize	0.0823	2.2252
Public Sector	0.1986	1.9102
FutEmpImm	0.9538	4.9961
Emp2yrs	0.3252	2.2582
SpecQuest	–0.3853	–10.2369
σ_μ	0.7341	6.2275
N	3131	
Log-Likelihood	–1421.8714	

Table 3:
Comparison between Participants, Selected and Random Non-Participants for Mean of Selected Characteristics Referring to the Interview Prior to Training Entry

Variable	Random Non-Participants	Non-Participants Selected by Matching Algorithm	Participants
Number of observations	113	218	113
Propensity Score	–2.48*	–1.73	–1.69
Age (years)	34.69	30.00	32.34
Male (%)	60.18	55.50	49.56
Foreigner (%)	40.71*	16.06	15.04
Disabled (%)	7.96	3.67	3.54
Abitur (%)	5.31*	12.84	16.81
Lehre (%)	44.25*	64.67	69.91
Diplom (%)	1.77	4.59	7.08
Employed (%)	70.80	78.44	77.88
WhiCollar (%)	10.62*	37.16	43.36
BlueCollar (%)	46.90*	20.64	15.93
JobTenure (years)	4.93	3.48	4.37
AnspIndex	11.81	12.75	12.71

* denotes 95%-significance of difference in sample means

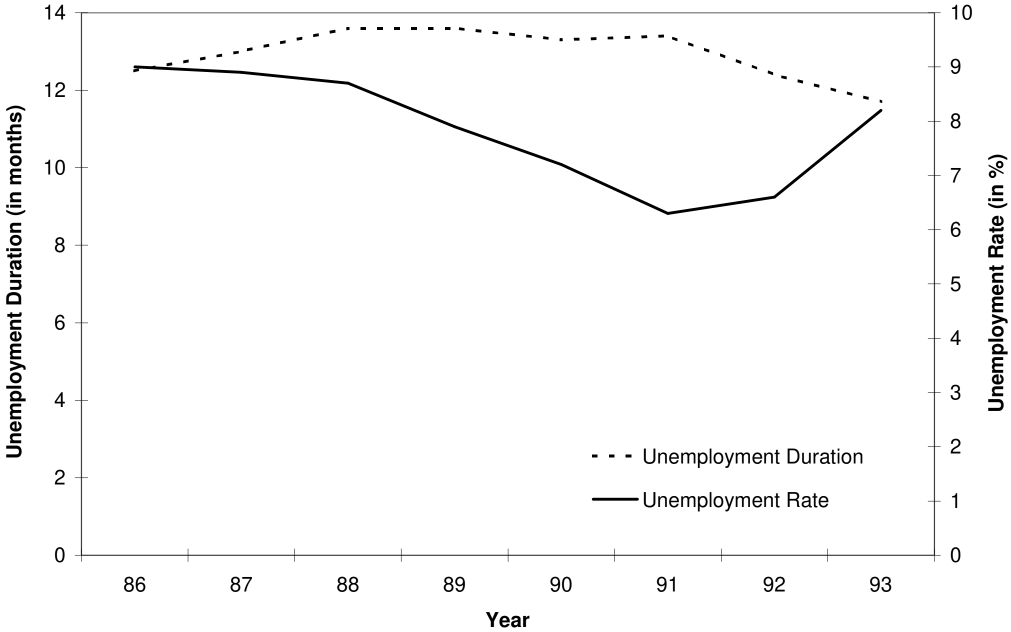
Table 4:
Maximum Likelihood Estimates for Causal Effect of Participation in Vocational Training on the Transition Unemployment ⇒ Employment

Variable	Coefficient	t-value
VocTraining	0.7539	2.2100
On-The-Job-Training	–0.1997	–0.6424
Long-Term	–0.3296	–1.0919
Long Course	0.0638	0.1749

Table 5:
Compound Effects of Participation in Vocational Training
on the Transition Unemployment ⇒ Employment

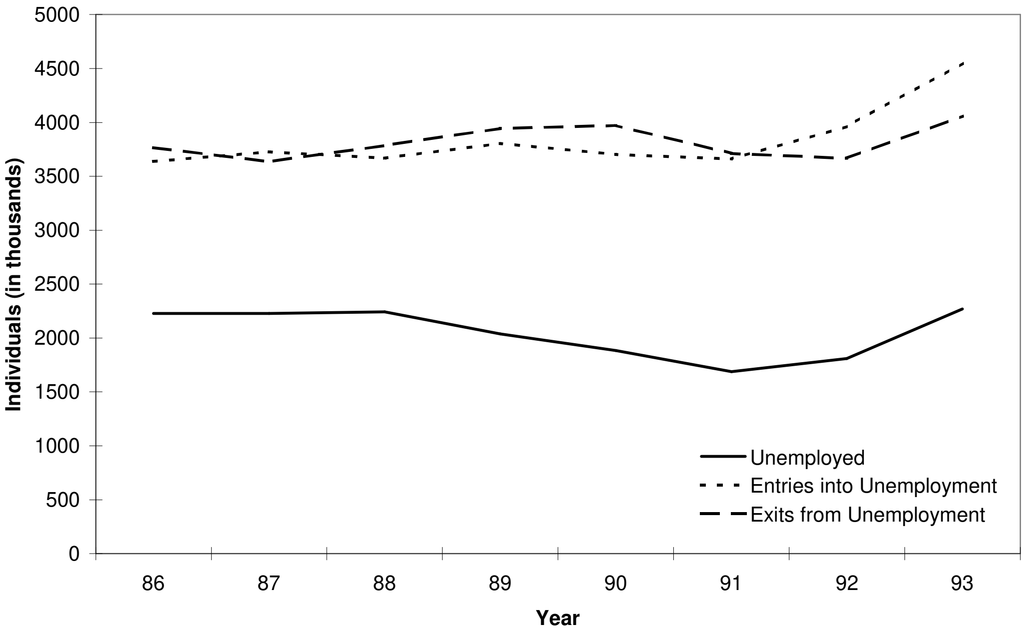
coefficient (t-value)	On-the-Job Training		Off-the-Job Training	
	Short Course	Long Course	Short Course	Long Course
Short-term Effect	0.5542 (1.5859)	0.6180 (1.2643)	0.7539 (2.2100)	0.8177 (2.2135)
Long-term Effect	0.2246 (0.8593)	0.2884 (0.6536)	0.4242 (1.4955)	0.4881 (1.4706)

Figure 1:
Unemployment Rate and Average Elapsed Unemployment Duration in West Germany 1984–1994



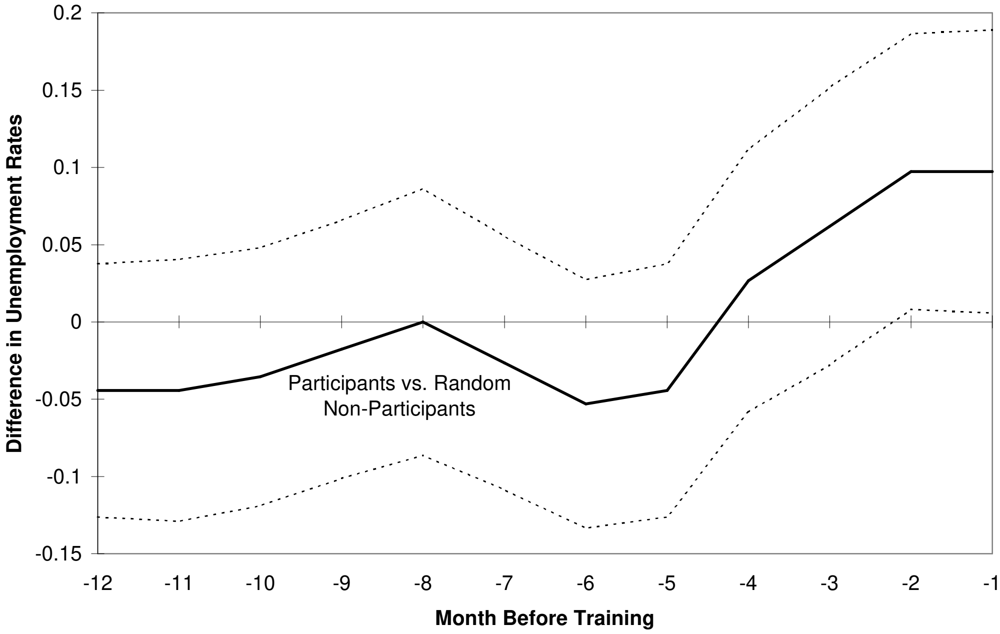
Source: BUNDESANSTALT FÜR ARBEIT: Amtliche Nachrichten der Bundesanstalt für Arbeit, various issues.

Figure 2:
Unemployment Individuals and Entries into and Exits from Unemployment in West Germany 1986–1996

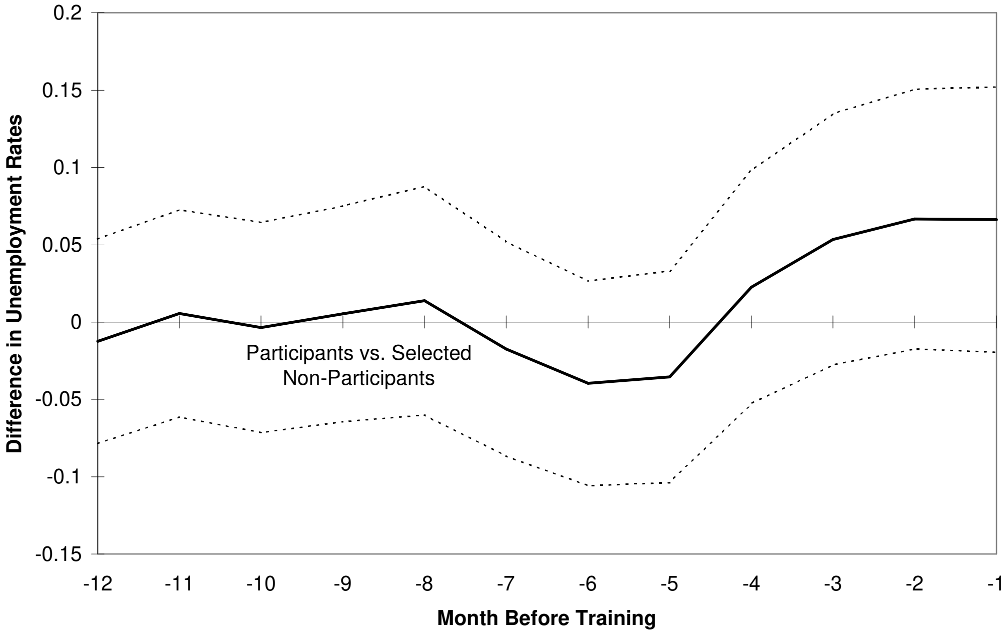


Source: BUNDESANSTALT FÜR ARBEIT: Amtliche Nachrichten der Bundesanstalt für Arbeit, various issues.

Figure 3:
Difference in Pre-Training Unemployment Rates
between Participants and Random Non-Participants (a)
and between Participants and Selected Non-Participants (b)

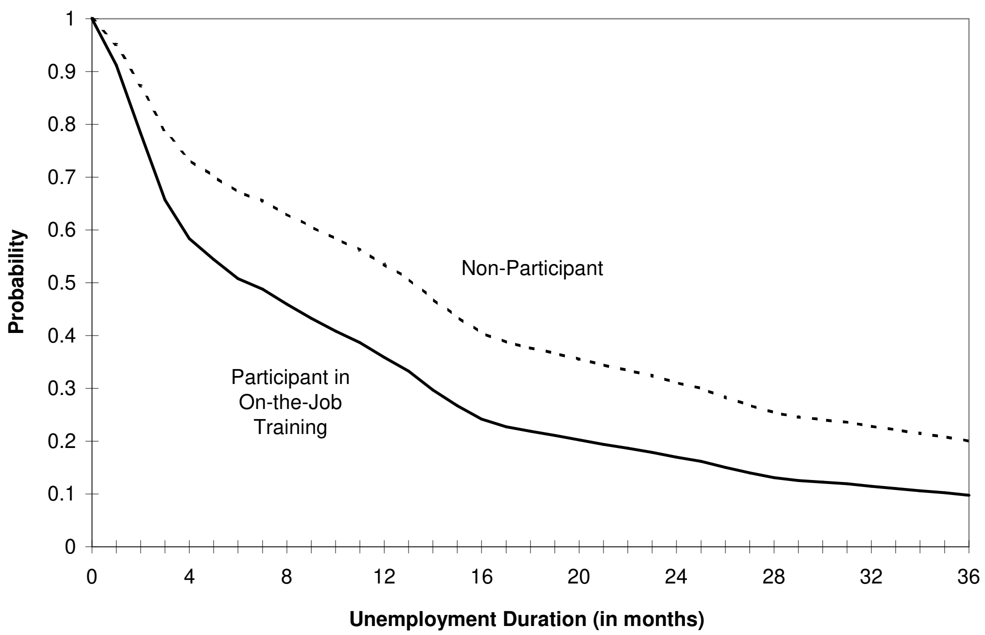


(a)

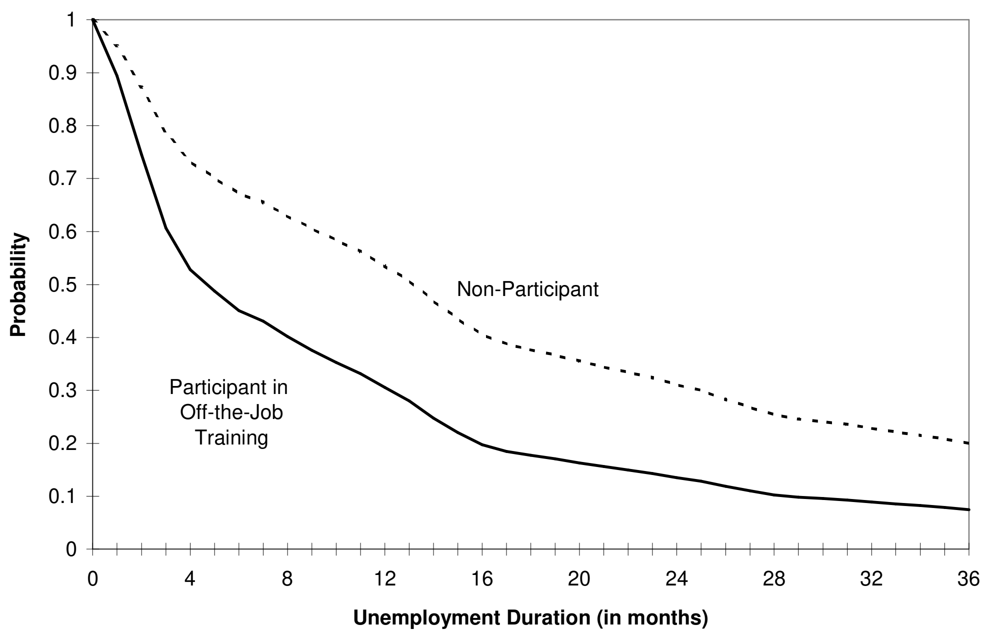


(b)

Figure 4:
Simulated Survivor Functions
for Participant in On-the-Job Training vs. Non-Participant (a)
and Participant in Off-the-Job Training vs. Non-Participant (b)

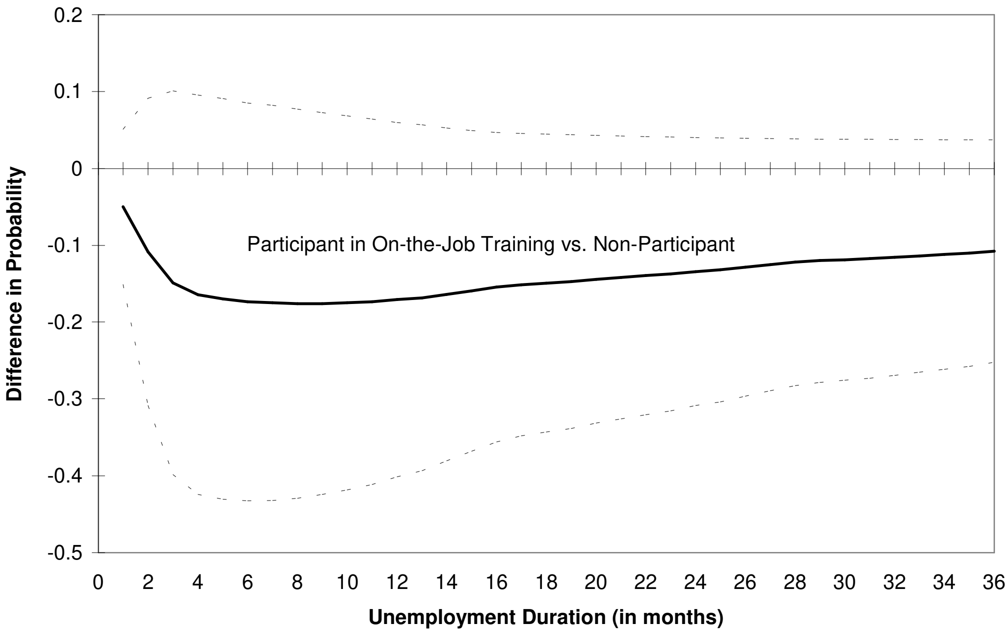


(a)

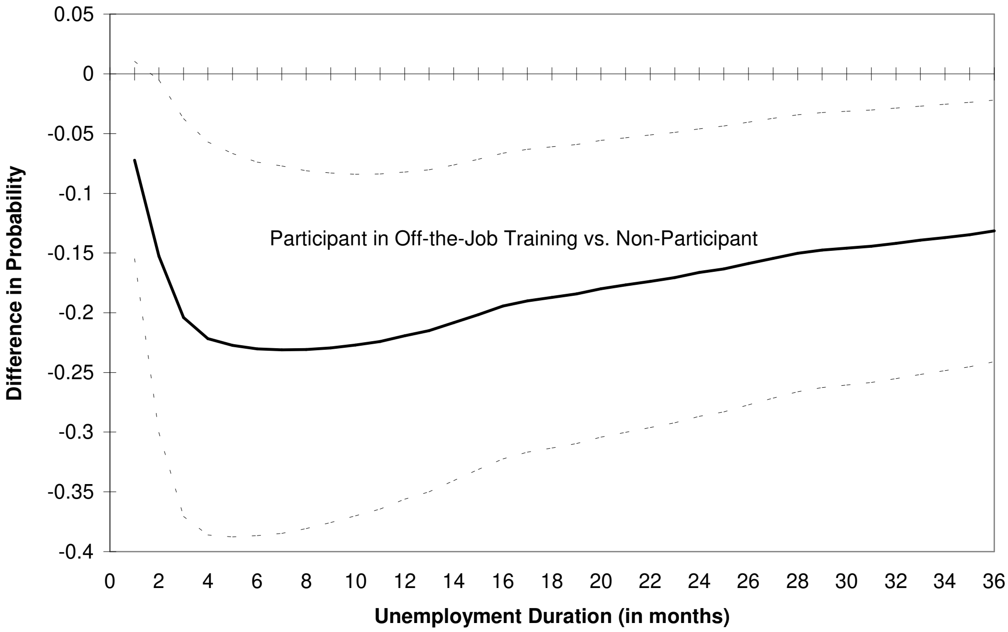


(b)

Figure 5:
Difference in Simulated Survivor Functions
for Participant in On-the-Job Training vs. Non-Participant (a)
and Participant in Off-the-Job Training vs. Non-Participant (b)



(a)



(b)

Appendix

Table A.1: Definition of Variables

Variable	Description
Training variables	
VocTraining	1 if individual participated in vocational training
On-the-Job Train.	1 if vocational training took place at least partly during working hours
Long-Term	1 if vocational training ended earlier than twelve months prior to spell begin
Long Course	1 if duration of vocational training course was three months or longer
Baseline dummy variables — reference category is first month of spell duration	
Basexx	1 if current month is month xx since spell begin
Basexx-yy	1 if current month is one of the months xx to yy since spell begin
Basexx+	1 if current month is month xx or higher since spell begin
Seasonal variables	
Spring	1 if current month is February, March or April
Summer	1 if current month is June or July
December	1 if current month is December
Variables related to the regional labor market	
AnspIndex	Number of unemployed divided by vacancies at the regional level
Age variables	
Age/10	Age divided by 10
$(Age/10)^2$	Age squared and divided by 100
Age dummy variables — reference category is 55 years or older	
Age –21yrs	1 if individual is 21 years or younger
Age 22–39yrs	1 if individual is 22 years or older, but younger than 40
Age 40-54 yrs	1 if individual is 40 years or older, but younger than 55
Other socio-demographic variables	
Male	1 if individual is male
Foreigner	1 if individual is not a German national
PartHH	1 if individual is married or living together with his/her partner
Disabled	1 if individual is disabled
KS	Number of children aged up to 6 years
KM	Number of children aged 7 to 10 years
KL	Number of children aged 11 to 15 years
Kids	1 if individual has children aged up to 15
Abitur	1 if individual has Abitur or Fachhochschulreife (comp. to high school degree)
Lehre	1 if individual has completed an apprenticeship
Diplom	1 if individual has a university degree or a degree of a Fachhochschule
SatisLife	Satisfaction with life in general (0 = totally dissatisfied; 10 = totally satisfied)

Table A.1: Definition of Variables (continued)

Variables related to current employment	
Employed	1 if individual is currently employed (full or part time)
Occupational Status — reference category are apprentices and self-employed	
WhiCollar	1 if individual is currently employed and has a white collar status
BluCollar	1 if individual is currently employed and has a blue collar status
JobTenure	Years of affiliation with current employer
JobQualif	1 if individual is currently employed and the current job requires special instructional courses, a completed apprenticeship or a university degree
JobEduc	1 if individual is working in the occupation he/she was originally educated for
Firmsize	1 if firm has less than 20 employees or individual is self-employed 2 if firm has 20 or more, but less than 200 employees 3 if firm has 200 or more, but less than 2000 employees 4 if firm has 2000 or more employees
Public Sector	1 if individual is working in the public sector
Variables related to future plans regarding employment	
FutEmpImm	1 if individual is currently not employed but wishes to be employed in the *near* future (i.e. immediately or next year)
Variables related to employment history	
Emp2yrs	1 if individual was employed sometime within the last two years
NoUneSp3	Number of unemployment spells during the last three years (measured from spell begin)
DurUneSp3	Cumulated number of unemployment months during the last three years (measured from spell begin and divided by 12)
PrvEmployed	1 if individual was previously, i.e. prior to the unemployment spell, employed
ReplacementRatio	Level of unemployment benefits in relation to the last labor market gross income
„Technical“ variables	
SpecQuest	Years to the following special questionnaire on vocational training

Table A.2:
Maximum Likelihood Estimates for Transition Unemployment ⇒ Employment
Discrete Hazard Rate Model with Unobserved Heterogeneity

Variable	Coefficient	t-value
Constant	–5.4093	–6.4049
Base02	0.1244	0.5175
Base03	0.3631	1.2676
Base04	0.0583	0.1569
Base05	0.0197	0.0495
Base06	0.5086	1.2169
Base0712	–0.0009	–0.0020
Base1320	0.0044	0.0066
Base21+	–0.2815	–0.3341
Age -21yrs	3.6135	4.4464
Age 22-39yrs	2.9646	4.1369
Age 40-54yrs	2.5199	3.6419
Male	0.4564	2.5217
Foreigner	–0.2260	–0.9788
Disabled	–0.3921	–0.9603
PartHH	0.4958	2.3145
Kids	–0.4569	–1.8317
Abitur	–0.0090	–0.0319
Lehre	0.1230	0.5648
Diplom	0.3457	0.8224
PrvEmployed	0.3403	1.6115
NoUneSp3	0.4346	3.3734
DurUneSp3	–0.5606	–2.5867
ReplacementRatio	–0.3051	–0.8519
AnspIndex	–0.0720	–3.3612
December	0.3222	1.5094
Spring	0.4484	2.7789
Summer	–0.4539	–1.8001
VocTraining	0.7539	2.2100
On-The-Job-Training	–0.1997	–0.6424
Long-Term	–0.3296	–1.0919
Long Course	0.0638	0.1749
$Ln(\sigma^2)$	–0.5442	–0.7470
Number of spells	455	
Log-Likelihood	–805.0531	

Figure A.1:
Distribution of the Propensity Score for Participant and Non-Participant Group in 1988
(Kernel Density Estimates)