Many Dropouts? Never Mind! - Employment Prospects of Dropouts from Training Programs [1]

Marie Waller
(Albert-Ludwigs-University Freiburg, CDSE University of Mannheim)

Abstract: The employment effects of training programs for the unemployed are frequently studied, but little is known about the number, the characteristics, and the labor market prospects of those who drop out of these programs. The aim of this paper is to contribute to filling this gap. Using German administrative data it turns out that one out of five participants of further training programs drops out of the program. Descriptive analysis suggests that the head start dropouts have with regard to employment vanishes over time. To estimate the medium- and long-term effects of dropout a bivariate dynamic random effects probit model taking into account state dependence and selection on unobservables is used. The model is estimated with Markov Chain Monte Carlo (MCMC) methods. Results suggest that dropping out of the program has on average no or very small effects on the long-run employment prospects of dropouts.

Keywords: active labor market policies, evaluation, administrative data
JEL: J 68, I 28, C 33

Correspondence: Department of Applied Econometrics, Institute for Economic Research, Albert-Ludwigs-University Freiburg, 79085 Freiburg, Germany, marie.waller@vwl.uni-freiburg.de.

[1]This study is part of the project "Employment effects of further training programs 2000-2002 – An evaluation based on register data provided by the Institute of Employment Research, IAB" (IAB project number 6-531.1A). The project is joint with the Swiss Institute for International Economics and Applied Economic Research at the University of St.Gallen (SIAW) and the Institute of Employment Research (IAB). Support by the IAB is gratefully acknowledged. I am grateful to the Freiburg project team, especially to Aderonke Osikominu, for her large contribution regarding the data work in the project. I thank Bernd Fitzenberger for helpful comments. All errors are my sole responsibility.

1 Introduction

Training programs represent an important part of active labor market policies in many countries and researchers have shown strong interest in analyzing the labor market effects of these programs.[2] But little is known about the number, the characteristics, and the labor market prospects of those who drop out of these programs. This is surprising as it turns out that dropouts represent a considerable group of participants: in Germany one out of five participants drops out of the program.[3] Dropouts will have a head start on the labor market, because they may already be employed while the other participants are still attending the program. But how about the medium-term and long-term effects of dropout: does it harm to drop out in the long run?

From a policy perspective knowledge about the occurrence and the labor market prospects of dropouts may be important, as institutional settings like benefits during program participation and sanctions may influence the number of those who drop out. Furthermore, studying the labor market prospects of dropouts may provide further insights in understanding the composition of average treatment effects estimated in the literature on training programs. There exists a literature for the US on dropouts of labor market programs in experimental situations (see for example Heckman, Smith and Taber (1998)). Furthermore, the threat effect of being assigned to a labor market program but not participating has been studied (see for example Rosholm and Svarer (2008)).

For the first time this paper sheds light on dropouts from training programs in western countries in a non-experimental setting.[4] Studying the effect of dropout requires to overcome two main obstacles. First, data allowing to identify which participants drop out of the program is needed. I propose a strategy to identify dropouts of fur-

[2]In Germany from 2000 to 2002 about 1.5 million entries are registered (Bundesagentur für Arbeit 2001, 2002, 2003). The employment effects of these programs have been estimated for example by Biewen et al. (2007), Hujer et al. (2006), Kluve et al. (2007), Lechner and Wunsch (2006a, 2006b, 2007), Osikominu (2008), Rinne et al. (2007), Schneider and Uhlendorff (2006), Stephan and Pahnke (2008), Wunsch and Lechner (2008).

[3]Own calculation based on the definition of dropout and the sample of participants presented in section 2.

[4]The only paper on dropouts of labor market programs in a non-experimental setting is Lee and Lee (2003). Using Korean data, the authors make an attempt to deal with dropouts in program evaluation by pairwisely comparing those who complete the program, drop out or do not participate using matching.

ther training programs using German administrative data which can be applied after having corrected measurement error in the registered end of participation. Second, to estimate the effect of dropping out versus completing the program it seems necessary to take into account observable and unobservable differences between dropouts and non-dropouts as well as state dependence and duration dependence. I estimate the medium-term to long-term effect of dropout using a bivariate dynamic random effects probit model. The model is identified by the timing-of-events and through functional form assumptions. It consists of a dropout equation and an employment equation. Both equations include an unobserved individual effect and these two random effects are allowed to be correlated. The two equations are estimated simultaneously using Markov Chain Monte Carlo (MCMC) methods, a technique from Bayesian statistics. I program a Gibbs sampling algorithm to simulate draws from the posterior distribution of the parameters. This approach provides information on all parameters of the model, including information on the unobserved individual specific effects. To get an estimate for the size of the dropout effect, I calculate average partial effects on the treated which account for the selection based on unobservables. This is possible because of the availability of the predictors of the unobserved individual specific effects from the MCMC estimation.

Usually, evaluation studies on the employment effects of training programs consider the start of a program as the treatment (possibly with the restriction that it has been attended for some weeks) and do not deal with the actual length of participation or the question if the program has been completed.[5] Exceptions are Kluve et al. (2007) who estimate the employment effect of variations in the length of German training programs, and Flores-Lagunes et. al (2007) who estimate earnings effects of the length of US training programs. Both papers use a matching strategy adapted to continuous treatment decisions. Fitzenberger et al. (2009) include the duration of participation in their model allowing for the end of participation to be endogenous. By contrast, the focus of this paper is on the difference between dropping out and completing the measure. Consider a sample of individuals who all experience a transition from employment to unemployment and who all start a training program. While they are in the program they decide in each period to continue or to drop out. Those who decide to drop out differ - from this period onwards - from the others by having experienced a dropout while the others will eventually have completed a program. So in the notion of the evaluation literature dropout would be the treatment. There are various reasons for dropout: an important one is that the individual is

[5]Biewen et al. (2007) for example consider program participation in medium-term further training programs if it has lasted for at least four weeks and consider shorter spells as no treatment.

lucky to receive a job offer and decides to drop out and start employment. Other examples for why some people drop out and others do not are different ex-ante information on the programs and dropout if expectations are not met, personal dislike of the teacher or classmates, temporarily higher opportunity costs (for example due to a work opportunity on the black market), changes in preferences, lack of endurance in relation to training or differences in individual discounting of the future.

There may be a specific effect on employment of dropping out versus completing a program which may be different from the effect of attending programs of different lengths. In addition to attending the program for less time, dropping out might involve missing parts of the curriculum, not obtaining a certificate, and a signal to potential employers. If, for example, the curriculum of a course covers all essential tasks of a profession one after the other, it might be less valuable to attend half of this course than attending a complete course which is of shorter planned length and more condensed. Obtaining a certificate might in particular be valuable for courses leading to officially recognized professional degrees. Also, a future potential employer might judge a dropout as a negative signal of endurance. On the other hand it is possible that attending a program for some time is enough to get the benefit out of it. This would for example be the case if program effects are due to an activation of the unemployed or an improved orientation of the individuals in which kind of job they might succeed. Furthermore, participants might even use the possibility to drop out for staying in the program only until the right moment (with regard to their skills or the economic situation) arrives to start searching for a job or until they receive a job offer which is a very good match. Thus, participants who follow this strategy might benefit from it as opposed to waiting until the planned end of the program and then starting to look for jobs.[6] To sum up, dropout may involve a negative, positive or zero effect on employment prospects.

The remainder of this paper is structured as follows: section two introduces the data, defines the evaluation sample and discusses how dropouts can be identified. Section three includes a descriptive analysis of the occurrence of dropouts and their employment prospects. Section four discusses the econometric model used to estimate the medium- and long-term effect of dropout, describes the estimation strategy and presents the results. Section five concludes.

[6]See Becker (2005) for a theoretical model which formalizes such a strategy.

2 Identification of Dropouts of Further Training Programs in the IEBS

2.1 The Integrated Employment Biographies Sample

The Integrated Employment Biographies Sample (IEBS) consists of a 2.2% random sample of individuals drawn from the universe of data records collected in four different administrative processes: the IAB Employment History (*Beschäftigten-Historik*), the IAB Benefit Recipient History (*Leistungsempfänger-Historik*), the Data on Job Search Originating from the Applicants Pool Database (*Bewerberangebot*), and the Participants-in-measures Data (*Massnahme-Teilnehmer-Gesamtdatenbank*).[7] The data contain detailed daily information on employment subject to social security contributions, receipt of transfer payments during unemployment, job search, and participation in different programs of active labor market policy (ALMP). To be specific, this study uses a draw of the administrative data which is called *IEB, Version 4.02*.[8]

The first of the four administrative data sources included in the IEBS, the IAB Employment History, consists of social insurance register data for employees subject to contributions to the public social security system. It covers the time period from 1990 to 2004. The main feature of these data is detailed daily information on the employment status of each recorded individual. For each employment spell, in addition to start and end dates, data from the Employment History contains information on personal as well as job characteristics such as wage, industry or occupation. In this study this information is used to account for the labor market history of individuals as well as to measure employment outcomes. The IAB Benefit Recipient History, the second data source, includes daily spells of unemployment benefit, un-

[7] For detailed information on the IEBS see Zimmermann et al. (2007). Information in English can be found on the website of the Research Data Center (FDZ) of the Federal Employment Office (BA) (http://fdz.iab.de/en). The website also describes the conditions under which researchers may use the IEBS and the process to get the permission.

[8] The specific version used here is described in IEB Benutzerhandbuch Version V4.02, 16.01.2006 and attendant documents, not published. This version includes some variables which are not in the standard version. The names of the additional variables I considered for this study are the following (some of them turned out to be irrelevant for the estimations): *Familienstand, FbW Abmeldedatum, Geburtsjahr juengstes Kind, Geplante Massnahmendauer, Gesundheitliche Einschraenkungen, Kapazitaet Teilnehmer FbW, Massnahmeerfolg, Massnahme - Lernort, Massnahmetraeger, Massnahmeziel - Prüfungsart, Rehabilitationsmassnahme, Zugangsgrund.*

employment assistance and subsistence allowance payments the individuals received between January 1990 and June 2005. In addition to the sort of the payment and the start and end dates of periods of transfer receipt the spells contain further information like sanctions, periods of disqualification from benefit receipt and personal characteristics. These data are mainly used to get additional information on the labor market history of these individuals.

The third data source included in the IEBS is the so-called Data on Job Search Originating from the Applicants Pool Database, which contains rich information on individuals searching for jobs covering the period from January 1997 to June 2005. The spells include detailed information concerning job search, regional information, and personal characteristics. This information is used to control for individual characteristics of the participants in the estimations. The Participants-in-measures Data, the fourth data source, contains diverse information on participation in public sector sponsored labor market programs, for example training programs, job-creation measures or integration subsidies. It covers the period from January 2000 to July 2005. Similar to the other sources, also these data come in the form of spells indicating the start and end dates at the daily level. Information for example on the type of the program and the planned end date are added. This data source is necessary to identify participation and to gain information on the program attended.

2.2 Sample and Further Training Programs

The focus of this study is on participation in public sector sponsored further training programs starting in between July 2000 and December 2001. Further training programs are defined in this paper as those measures that train professional skills and have a typical duration of several months up to two years. This includes all programs called *FbW - Foerderung der beruflichen Weiterbildung* in the IEBS and under the legislation except those called orientation measure, because with regard to length and content they have more in common with short-term training, a different part of German active labor market policies, than with further training programs. Because further training programs differ in how they are organized and with regard to the certificate the participant may obtain, I distinguish three groups of further training programs: general further training, practical training, and retraining. General further training teaches specific professional skills, mostly in class room. A typical example would be IT-based accounting. Participants may obtain a certificate by the school or by a professional organization. The programs subsumed under practical training take place in a training firm or include an internship in a firm, and their duration is typically a bit shorter. Retraining is, with a typical length of two years, the longest program and participants are trained in a profession which differs from the one they originally learned. In the end they may obtain a new professional degree within the German apprenticeship system.

To study the core group of participants in further training, the sample is based on programs started within the first year of an unemployment period as the first intensive active labor market program. Only individuals who experienced an inflow from continuous employment into unemployment within the year before program start are considered. Entering unemployment is defined as quitting regular (not marginal), non-subsidized employment of at least three months and subsequently being in contact with the labor agency (not necessarily immediately), either through benefit receipt, program participation, or a job search spell.[9] In order to exclude individuals eligible for specific labor market programs for young people and individuals eligible for early retirement schemes, only persons aged between 25 and 53 years at the beginning of their unemployment spell are considered. Men and women living in East and in West Germany are included.

2.3 Identification of Dropouts in the Data

Dropping out of a program is defined as having started a program but not completing the program, but instead quitting it before the planned end is reached. The IEBS includes a variable for the start of the program, the end of participation and the initially planned end of the program. If the data indicate that a program has been started the question is if the program has been attended (almost) as long as initially planned (planned end date) or considerably shorter. The planned length of the program is defined here as the date of the planned end minus the date of the start of the program. It is necessary to set cut-off points for the distinction of dropout and completion as well as the distinction of realized attendance and non-attendance. In this paper, program attendance is categorized as dropout as opposed to completion if the program has been attended less than 80% of the planned length.[10]

[9]Note that this implies that the same individual could appear in the sample more than once, if he or she had more than one valid unemployment spell and attended both times a further training program. This does not happen in the sample used for this study.

[10]Several further training program spells are linked to one participation if the gaps in between are less than 15 days, thus a change from one further training program into another is not counted as a dropout. A gap of three months is allowed, if there is information in the data that the person

If attendance in the data is less than four days (and in the rare cases in which the variable *success of the program (Massnahmeerfolg)* indicates *not attended*) this is not counted as program participation for two reasons: first, dropout is understood here as having attended at least a few days and then dropping out and not as having rejected to attend a program right from the start. Second, extremely short program spells in the data may indicate in some cases that the program has not been attended at all but the registration was withdrawn too late and this was not corrected in the data. So one might count some cases as dropouts that never attended if too short spells are counted as participation. Therefore program spells which are shorter than four days do not lead to the inclusion of the individual into the sample of analysis (which is based on participants as described in section 2.2). As mentioned before, to distinguish between dropout and complete attendance, participation of 80% of the planned length is chosen. Choosing a higher limit, one would risk misclassifying participants as dropouts if the whole course ends a bit earlier than planned at the beginning. This may happen especially for two-year programs, particularly if they end with an external exam the date of which is not fixed when the program starts. The data reflects this - at around 90% percent of planned duration the number of finishing attendances rises. Apart from identification issues, one could argue that attending a very high percentage of the planned duration is more like full attendance than like a dropout.

For the identification of dropouts the reliability of the end date of participation as well as the planned end date are of utmost importance. But there is some measurement error in the end dates of participation in further training programs in the IEBS, see Waller (2008). This means it happens that a person quits a program but the end of participation in the data is nevertheless equal to the planned end date. To correctly identify dropouts it is necessary to correct these wrong end dates, otherwise far too few participants would be identified as dropouts. In this study the correction procedure proposed in Waller (2008) is used. It relies mainly on the information on subsistence allowance (a transfer payment made to the participants of further training programs for the time of their participation) of the IAB Benefit Recipient History, which is considered very reliable. In addition, the correction procedure in some cases uses certain contradictions with employment spells of the IAB Employment History as well as some further pieces of information from the data.

The planned end date of further training programs seems to be reliable in indicating until when program participation was first planned. For 7.7% of the relevant pro-

was ill in between two program spells, but this turned out to be empirically irrelevant.

grams, the planned end date is earlier than the end date of participation. This is not necessarily measurement error - it is possible that a participant attends longer than originally planned. If the difference only amounts to a few days this is very likely to be correct, because the end of the courses can change a bit after program start. For 3.2% of the programs this difference is more than 7 days. In these cases, it may be that the participant attended for a considerably longer time period than planned - in particular if the program is not a group course but an individual program - but there might also be a problem. Thus, for the total of 3.4% of the programs for which there is an indication that the reported planned end dates should not be used as the only source for the classification, the two variables *success of the program* and *duration of the course in months* are additionally used to decide if the participation spell is classified as a dropout or not. These variables have a lot of missings and are error-prone, but - used with caution and only in addition to the planned end date - they can help to decide for the major part of the 116 programs requiring further information for classification. In the end, only for 30 (0.88%) of the programs in focus it seems impossible to classify them and these cannot be used for the analysis.

The identification strategy used in this paper has been subjected to various sensitivity checks. There is no indication of systematic problems.[11] As an alternative way to identify dropouts one might think of using the variable *success of the program* which may not only indicate non-attendance but also successful completion or dropout. Taken the information literally, one could use this variable to classify participants into dropouts and non-dropouts. But there are at least three problems in doing so: Firstly, the variable is missing or not available for 14% of relevant program spells. Secondly, it is not clear how dropout is defined in the variable and under which circumstances a dropout is registered. Thirdly, the variable suffers from severe measurement error: 49% of those classified as dropouts in this paper are coded as having completed with success. For these reasons, I prefer the strategy outlined above.

[11] In particular it may be ruled out that participants classified as dropouts in fact attended a program which was shifted to an earlier time. This hypothesis has been checked first by using the information on allowance payments to check if participants have in fact started their program the day of the indicated start date: deviations are not more frequent for those classified as dropouts than for non-dropouts. A second check was to compare those who participated shortly after becoming unemployed (for whom it is impossible that the program was shifted to an earlier start date and the start date reported in the data was not changed) with later participants, in particular with regard to the planned length of their programs and the timing of drop-out.

3 Descriptive Analysis

3.1 Occurrence of Dropout

When applying the above definition of dropout to the data, it turns out that 21% of the programs end with a dropout. The share of those who drop out differs with respect to the program type. Table 1 shows that the share of dropouts is lowest for general professional training and a bit higher for the very long retraining programs. The program type practical training suffers from the highest dropout rate: about 30% of the participants drop out of these programs, even though practical training programs are relatively short. The diagrams in figure 4 in Appendix A show when dropouts quit the program. With regard to general professional training the number of dropouts grows with the elapsed duration measured as a share of the planned duration. Considering retraining many participants drop out during the first 40% of the planned program duration and relatively few afterwards. Regarding practical training the dropout rate is especially high in the third, fourth and sixth decile of the planned duration. For the participants there are no direct financial benefits or costs of attending a program. While attending a program, participants in further training usually receive the same amount of a benefit called subsistence allowance as the amount of unemployment benefit they would receive if they did not attend. The labor agency covers the direct costs for the course and in some cases transportation costs or child care costs. If participants drop out without a good reason, they might be punished by not receiving benefits for up to six weeks, but according to the data and to what case workers told me, sanctions are usually not imposed because a participant dropped out of a further training program. To check the motivation of participants, cheaper programs, like short-term training, are used.

Table 1: Share of Dropouts and Program Categories

Type of program	# of participants	Share dropout	Median planned length
General Prof. Train.	1761	18.57%	8.5 months
Retraining	761	22.47%	24 months
Practical Training	544	29.78%	6 months

After dropout, the individuals either start employment immediately or they stay in non-employment for some time. The first is called *job-aligned dropout* in the following and the latter *non-job-aligned dropout*. Job-aligned dropout occurs either because participants receive a job offer and drop out due to this job offer, or because participants drop out for other reasons but start a job (which may have been available to them before but which they did not consider). On the contrary, in the case of non-job-aligned dropout participants drop out and do not start employment (subject to social security). They prefer non-employment without attending a training program to attending a training program. The law encourages participants who receive a job offer to drop out. The general rule of the German ALMP is to give priority to placement over active labor market measures. An exception is possible if the measure is necessary for a durable placement (SGB III, § 4, § 5). But it is not clear under which circumstances it is preferable to encourage participants to continue. To see the relative importance of both types of dropout, I use the information if the participant starts employment within one month after dropout to decide whether it is a job-aligned dropout or not. According to this proxy, 45% of the dropouts experience a job-aligned dropout. Alternatively, one could use the variable *success of the program* which has potentially correct information for 38% of the dropouts. Out of these, 48% are recorded to drop out due to a job offer (this information does not seem to be missing at random). Both measures indicate that a bit less than half of the dropouts experience a job-aligned dropout.

To find out which characteristics of the program and of the participants are related to dropout, a cross-sectional probit model is estimated. For the specification search variables picturing the following characteristics are considered: personal characteristics (like gender, age, nationality, occupational qualification, degree of schooling, current health problems, past health problems, disabilities, past incapacities, children), information on the last employment (occupation in last job, last job part-time, last job as a blue-collar worker, reason for the end of the last employment, last wage), regional information (labor market situation in the region, West or East Germany), information on the individual labor market history (elapsed length of unemployment period, quarter of beginning of unemployment, information on lack of motivation related to labor agency activities in the past, information on participation in programs with social assistance in the past, sanctions in the past (also interacted with number of days with transfer payments), number of days in different labor market status (unemployment benefit, unemployment assistance, program participation, out of labor market, employment) in the last three years before the start of unemployment) and information on the program (planned length of the program, capacity of the program, information on institution offering the program, the sort of the certificate the program leads to). All the above-mentioned variables have been considered, but the vast majority of them turned out not to be relevant.

Table 4 in Appendix A shows the average partial effects and standard errors of a specification which includes the variables that seem to have some relevance. No schooling degree or a low schooling degree is related to a higher probability of dropout for participants of general professional training and retraining. The effects are large - for general professional training the average partial effect of having no schooling degree is 16.3%, for retraining it is 20.2%. For participants of practical training, who on average have lower education than participants of the other programs, there are no significant effects of schooling. Having experienced a sanction in the past is related to a higher probability of dropout (but this effect is not significant) as well as signs for a lack of motivation with respect to labor agency activities (significant for general professional training and retraining). With regard to practical training women and people living in East Germany are less likely to drop out, which for the latter group is also true for retraining. There is slight evidence that younger people as well as those who live alone are more likely to drop out. For retraining the effect of living alone is large (13%) and highly significant. Having a child under the age of ten is related to a strongly increased dropout probability for men taking retraining. A longer planned duration of the program increases the probability of dropout (not significant for retraining) as well as having participated in a training program in the past (not significant for general professional training). An increased probability of dropout is also observed for those who have experienced unemployment in the last three years before the current unemployment period (significant only for general professional training).

3.2 Employment Rates and Employment Stability

In this section the employment prospects of dropouts as compared to participants who do not drop out of the program are studied descriptively.[12] The analysis is based on a panel data set in months which follows the participants from the month they start the program (t=1) until 39 months later (t=40). There is some censoring due to the end of the observation period, but every individual may be followed at least for 37 months.[13] The analysis of differences in employment chances between

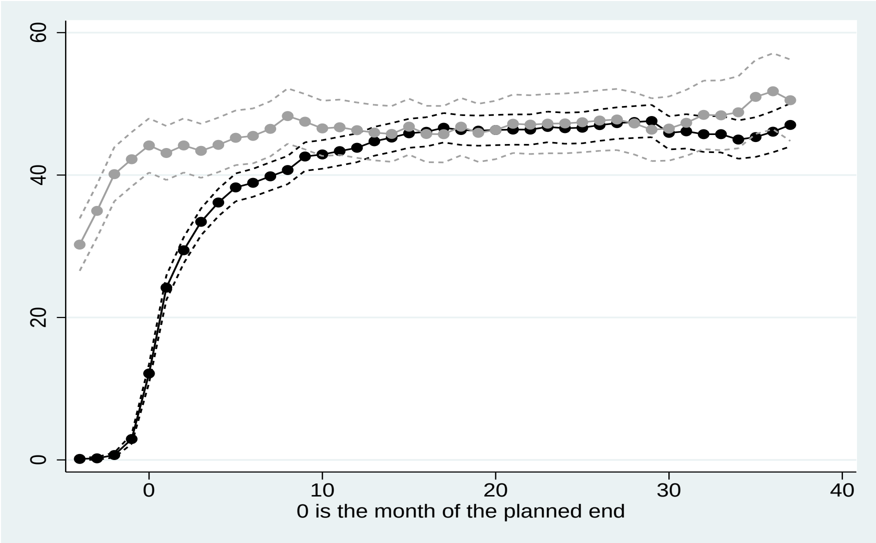
[12] When considering to analyze wage differences between dropouts and non-dropouts, I found that this is not a meaningful exercise, because differences in the annual wage are very largely driven by the number of days in employment. This is due to the fact that the majority of person-months in the sample of those who received further training within the last years indicate non-employment.

[13] A person is counted as employed in the respective month if he or she is employed for at least half of the month. The month an employment period begins is in addition counted as a month in employment if the employment period is in sum more than half of a month's length (that is even if this is split into two calendar months) and the second is then only counted if the employment period is in sum more than one month.

dropouts and non-dropouts should start at the time participants leave the program, because before that point in time all individuals experience a transition from employment to unemployment, start a further training program and they are all in non-employment while attending the program. This will be implemented when estimating the econometric model in the next section. But nevertheless the time axis of the figures (and later the time dummies in the econometric model) is aligned to the planned end of the program. In principle there are three options for the alignment: The first option is to align the time axis to the start of the programs. Dropouts leave the program earlier than non-dropouts, and as many of them take up a job, dropouts have a head start as compared to non-dropouts. While the program is still running, the employment rate of non-dropouts is zero but the employment rate of dropouts is positive, so the employment effect of dropout will be positive until the end of the program. Dropouts reduce the lock-in effect of a training program and the positive employment effects resulting from this should not be neglected when comparing employment rates of dropouts and non-dropouts. Aligning the comparison of employment rates to the start of the programs has the advantage to make the head start of dropouts visible, but if dropouts attend shorter or longer programs, the effect of this may not be distinguished from the effect of the head start. Second, if one aligned the time axis to the realized end of participation, there would be a jump in time due to dropout, because dropouts "shorten" the program. Thus, aligning the analysis to the realized end, the head start of dropouts would not be visible. The third option is an alignment to the planned end of the programs. Since this makes the head start of dropouts visible and avoids a mixture of the effect of dropout and the effect of the planned length of the program, this alignment is applied in the following.

Figure 1 compares the average employment status of dropouts and the average employment status of non-dropouts in each month aligned to the planned end of the programs. Consider for example month 10 after the planned end. The figure shows that 43% of those who completed the program are employed 10 months after they reached the planned end of their program and 47% of the dropouts are employed after they have reached the month of the planned end of their program (of course they are not in the program anymore at that time). Figure 1 shows the head start of dropouts: for example four months before the planned end of their programs, 30% of them are employed while (per definition) none of the non-dropouts is employed. The employment rate of non-dropouts begins to rise slightly two months before the planned end (remember that non-dropout is defined as attending at least 80% of the planned duration) and rises sharply in the month of the planned end and the

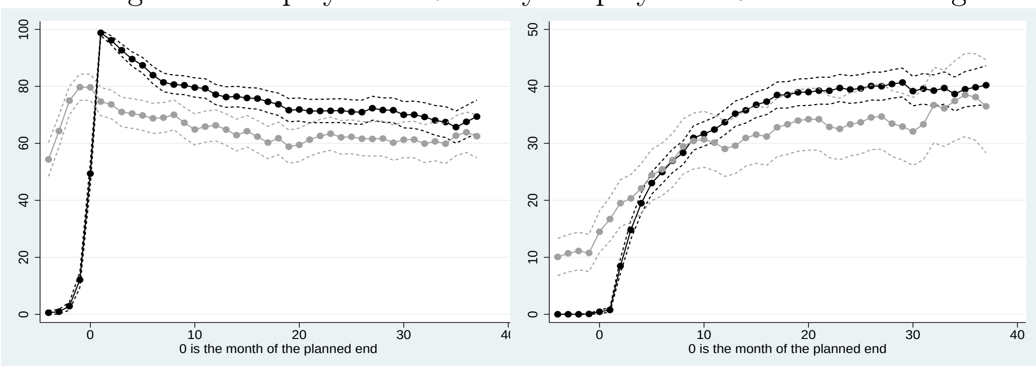
Figure 1: Employment Rates of Dropouts and Non-dropouts



Note: Dropouts in grey, non-dropouts in black. The dashed lines are 95% confidence intervals.

following months. 14 months after the planned end the head start of dropouts has vanished and employment rates of dropouts and non-dropouts are equal. In the end of the observation period dropouts do a little bit better, but it is not clear if this is significant.

Figure 2: Employment Rates by Employment Status after Program



Employment rates for those employed in the month after the program

Employment rates for those not employed in the month after the program

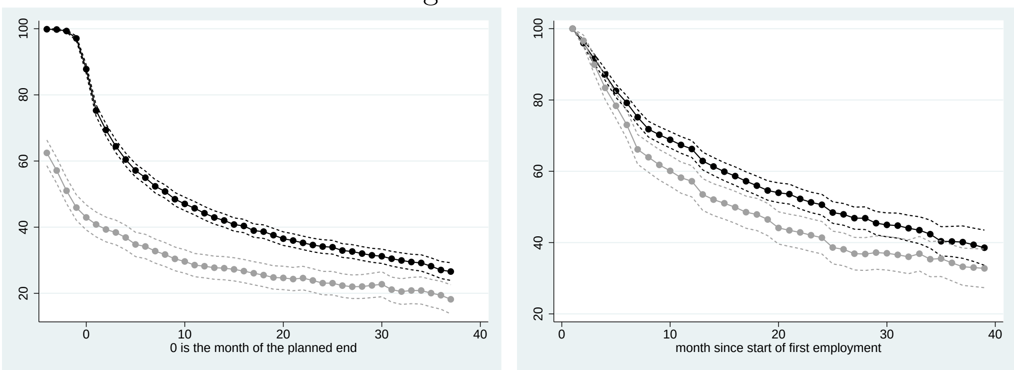
Note: Dropouts in grey, non-dropouts in black. The dashed lines are 95% confidence intervals.

Figure 2 shows the same rates as figure 1 but separately for participants who are employed in the first month after the realized end of participation (figure on the left) and those who are not employed in the first month after the realized end of participation (figure on the right).[14] The figure on the left hand side suggests that in

[14]The realized end of participation differs between individuals relative to the planned end, there-

the long run job-aligned dropouts do a bit worse than those participants who start a job right after completing the program. According to the figure on the right hand side the employment rate of non-job-aligned dropouts is in the long run a little lower compared to the rate of those who complete but do not directly start employment after leaving the program. Note that figure 2 is not inconsistent with figure 1, because the share of those who are employed in the month after the programs is higher for dropouts than for non-dropouts.

Figure 3: Survival Rates



Survival rate in unemployment

Survival rate in first employment

Note: Dropouts in grey, non-dropouts in black. The dashed lines are 95% confidence intervals.

The diagram on the left hand side of figure 3 shows the rate of those who have not left the unemployment period in focus in the respective quarter. Non-dropouts survive longer in unemployment. The difference decreases over time but does not vanish completely. This difference to figure 1 indicates that dropouts leave unemployment faster but their employment is less stable. The figure on the right hand side shows the rate of those individuals who are still in their first employment period in the respective month (based on those individuals who start employment during the observation period). Month one is the first month the individual is employed in, irrespective of when he or she left the program. Two years after starting employment 41% of the dropouts and 51% of the non-dropouts are still employed. Thus, employment of non-dropouts is a bit more stable.

In sum, the descriptive analysis gives the impression that dropouts enter employment earlier but non-dropouts catch up after some time, and that employment of non-dropouts is slightly more stable. But from the descriptive analysis we can of course not infer if there exists a negative or positive effect of dropout, because the treatment dropout is not randomized, there will be selection based on observable variables and unobservables. Even the direction of selectivity is not clear ex ante. On the one hand

fore there is no month with an employment rate of 100%.

it may be that those participants who drop out are on average those with better employment chances or a higher motivation for employment (for example having a high utility of earning a salary in the short run). Possible reasons for an increased dropout rate among them may be that they are more likely to receive a job offer, more likely to drop out due to a job offer or more likely to conclude that they do not need the program and prefer to intensify job search instead of attending the program. On the other hand it may be that those participants with characteristics which deteriorate employment prospects (like low schooling, low general ability or a low motivation for work) tend to drop out, because they find it also hard to complete the program. The nature of selectivity may also be more complex and, thus, positive and negative characteristics with respect to employment chances may partly cancel out even on the individual level: the results of the probit estimation in section 3.2 suggest for example a negative correlation between schooling and dropout and a positive correlation between having to support a family (proxied by men who have a child under the age of ten) and dropout for participants of retraining programs.

4 Joint Estimation of Dropout and Employment: Does Dropout Harm in the Long Run?

4.1 The Model

The descriptive analysis in the previous section suggests that dropouts enter employment earlier but non-dropouts catch up after some time. But purely descriptive analysis does not provide insights if this is an effect of dropping out. Therefore, in this section I use a bivariate dynamic random effects probit model to jointly estimate the dropout probability and the employment probability taking into account unobserved heterogeneity. To see how this may account for various differences of dropouts and non-dropouts which are potentially included in a simple comparison of employment rates like in section 3.2, start by considering this purely descriptive difference of average employment rates. Now, first think of estimating a simple pooled probit of an employment dummy on observable variables for the periods in which participants have finished program participation. The variable of interest would be a dummy if the individual has dropped out of the program in the past. Compared to purely descriptive analysis this will account for differences between dropouts and non-dropouts due to observables like schooling, age, last occupation, different labor market histories or the planned length of the program. It may also take into account time, season, and labor market conditions in the region. The estimation will also deal with state dependence. While in the descriptive analysis the initial luck of a job-aligned dropout will still influence the employment status a few months later if state dependence exists, the dynamic model will account for this. When estimating the effect of dropout in the past, the luck the dropout had in the past to receive a job offer will not influence the estimates in later periods. Second consider estimating a dynamic random effects probit model of an employment dummy. This will in addition include a time-constant unobserved heterogeneity term and thus account for time-constant differences of individuals' propensity to be employed. Thus, estimating a separate dynamic random effects probit model of an employment dummy will already take out much of the differences between dropouts and non-dropouts. But dropout may still be endogenous in the way that it is correlated with the error of the employment equation due to some dependence of unobserved dropout propensity and unobserved employment propensity. This problem is accounted for by introducing a dropout equation and estimating it simultaneously with the employment equation. In the following, firstly the model is presented and then the model assumptions are discussed.

The dropout equation is a random effects probit model of a dropout dummy:

$$Drop^*_{it} = \beta_D x_{it,D} + \alpha_{i,D} + \epsilon_{it,D} \tag{1}$$

where $Drop = \mathbf{1}[Drop^* > 0]$.

The equation is estimated for the first time in the month participants start the program and estimation goes on until either participants drop out or they have reached 80% of the planned duration so that they cannot drop out anymore according to the definition of dropout. The dropout equation may also be interpreted as a hazard model with right censoring when the program is finished. The vector of independent variables β_D includes the following information: remaining time until the planned end, a dummy if the person is still in the beginning of the program, and observable information on schooling, age, gender, family, if the last job was a blue collar job, past sanctions or signs of lack of motivation with regard to activities of the labor agency, health problems, East or West, earlier contact with the labor agency and past program participation. Other information like for example wages or occupation of the last job, year, season or detailed regional information turned out to be irrelevant.

Now consider the employment equation, which is a random effects probit model of an employment dummy:

$$E^*_{it} = \delta_E DropInPast_{it,E} + \beta_E x_{it,E} + \alpha_{i,E} + \epsilon_{it,E} \tag{2}$$

where $E = \mathbf{1}[E^* > 0]$.

$\alpha_{(i,E)}$ and $\alpha_{(i,D)}$ follow a **joint** normal distribution. $\epsilon_{(it,E)}$ and $\epsilon_{(it,D)}$ are independently standard normal distributed. Thus, the model includes two individual effects which are allowed to be correlated and represent the link between the two equations.

The employment equation is estimated once the individuals are again available for employment (which is in the month after they have left the program) until month 40 counted from program start onwards. On average the employment status is estimated for 32.2 periods for general professional training, for 23.9 periods for retraining and for 34.2 periods for practical training. The equation accounts for state dependence and duration dependence by including all employment lags (they are set to zero also for periods in which the individual has not reached a period in which the lag may take a one), elapsed unemployment or employment duration in months since the end of participation (also squared), planned length of the program, and information on the employment history before program participation. By using separate variables for the elapsed duration in unemployment, if applicable, and the elapsed duration in employment, if applicable, the model allows for different non-linear patterns of duration dependence in employment or unemployment, respectively. Observables like for example schooling, professional qualification, gender, health problems, region, wage in last employment, year and season are added. Dummies capture the alignment to the planned end of the program; they indicate if the current period lies before the planned end or in which month after the planned end, respectively, whereby later months are summarized. The effect of interest is the medium and long run effect of dropout. This is captured by a dummy variable called *dropout in past* indicating that the individual has dropped out in the past and has now reached at least month four after the planned end of the program.

The model also includes a dummy for dropout in the last period and for dropout which has occurred in the past given that the person has not reached month four after the planned end. The model does not provide causal estimates for the short-term effects of dropout. If participants drop out because they were lucky to receive a job offer, $\epsilon_{it,D}$ of the last period in which the dropout equation is estimated and

$\epsilon_{it,E}$ of the first period the employment equation is estimated are correlated. The short-term effect of dropout is, in a way, the other side of the coin of the lock-in effect usually found when evaluating employment effects of training programs. It has to be either positive or zero. From the descriptive analysis in section 3.2 we know that many dropouts are employed soon after dropout while non-dropouts are by definition not employed while they are locked in the program. Thus, there is certainly a positive short-term effect of dropout, but it is not possible to infer to which extent this is a causal effect of dropout, i.e. what would be the size of the short-term effect of dropout if dropout was a randomized treatment. The medium-term and long-term effect of dropout may be estimated, because the model allows for state dependence and duration dependence and, thus, the initial luck which may have influenced the decision to drop out may be accounted for in later periods.

The model estimated in this paper shares important features with the timing-of-events approach proposed by Abbring and van den Berg (2003) in the context of continuous duration models. The model of Abbring and van den Berg (2003) and the model in the present paper both consist of two equations: one relating to the treatment and one to the outcome of interest. Both models allow for duration dependence and for unobserved heterogeneity terms in both equations which are allowed to be dependent. Abbring and van den Berg (2003) show that in their model and under the assumptions they make (mainly conditional randomness of treatment starts, a no-anticipation assumption and functional form assumptions) the treatment effect may be separated from the selection effect. The unobserved heterogeneity term of the outcome equation is identified from the competing risk part of the model and the treatment effect is then identified from differences in hazard rates (Abbring and van den Berg (2003)). The present model also uses the timing-of-events and relies in addition on functional form assumptions. Apart from a different model specification and from using discrete data, the present model differs in two main aspects from the model by Abbring and van den Berg (2003). First, the employment equation only kicks in if the individual has left the program: this is because there is no third state (like employment in the model of Abbring and van den Berg (2003)) involved at the beginning. Starting employment before having reached the planned end of the program necessarily involves the treatment dropout. Second, the period close to the one the treatment occurs must not be used for identification, because soon after dropout individuals may be employed because they were lucky to receive a job offer due to which they choose the treatment dropout. Thus, the outcome soon after the treatment is linked to the treatment due to other factors in addition to a possible causal effect of treatment. In the discrete model this endogeneity problem may be solved for later periods by accounting for state dependence and duration dependence and by relying on the functional form of the model.

To estimate a causal effect of past dropout, some exogenous variation in the decision to drop out as well as the functional form assumptions of the model (including the assumption that the random effects are uncorrelated with observed variables) are needed. The timing of the model is the following: in the first period all individuals start a program. In each of the following periods participants decide to continue to attend or to drop out. In the sense of the literature on treatment effects, dropout would be the treatment. From the month after the individual has left the program onwards, the employment status is estimated taking into account the time-constant unobserved propensity to employment, the estimation of which takes into account the time-constant unobserved propensity to drop out through the correlation of the two random effects, both being estimated simultaneously. For identification it is necessary that there is exogenous variation that influences the dropout decision. By exogenous I mean factors that do not directly influence long-term employment prospects conditional on observed and time-constant unobserved characteristics. Exogenous factors may for example be randomness in expectations between participants due to different information and dropout if expectations are not met, personal dislike of the teacher or classmates, temporarily higher opportunity costs (for example due to a work opportunity on the black market), changes in preferences, lack of endurance in relation to training or differences in individual discounting of the future. Factors leading to dropout which are not captured by observed or unobserved variables of the model and which have a direct **long-term** effect on employment (not only through state dependence) would violate the model assumptions. This means that dropout due to the luck of receiving a job offer does not violate the model assumptions, because lagged employment is endogenized in the dynamic model. If, however, the dropout occurred only because by pure luck a job with a long-term contract is offered this would violate the model assumptions because the sort of contract may not be controlled for. Similarly dropout to non-employment due to factors that do influence the long-time employment prospects and which neither can be controlled for nor are time-constant (one example would be a pregnancy) would bias the estimated effect of past dropout. These two examples show that biases may go into both directions, and if biases exist they might to some extent cancel out. As there is no instrument for dropout available, I think estimating the bivariate dynamic model is all that can be done to identify the effect of dropout. Anticipation of dropout is not a problem in this model because dropout to take up employment involves per definition dropout and employment, and dropout to leisure involves per definition dropout and non-employment - there is no third state involved. Dropout reflecting a strategy of participants to choose the optimal time to leave the program (considering to drop out in case the right job is offered or the economic situation in the region is favorable) would be an effect of dropout and does not violate the model assumptions.

4.2 MCMC Estimation

To estimate the bivariate model presented in the previous section complex estimation techniques are needed. In principle the estimation could be done by maximum likelihood, but as the individual specific effects $\alpha_{it,D}$ and $\alpha_{it,E}$ are not observed one would have to integrate them out and simulate the multivariate normal integrals. I made an attempt to estimate the model using GLLAMM (a Stata routine for multilevel models), but this turned out to be far too time-consuming. Even the estimation of a much simplified one factor model ran too long to be practically applicable. But with Markov Chain Monte Carlo (MCMC) simulation methods, a technique from Bayesian statistics, an attractive alternative to maximum likelihood is available.[15] The idea of MCMC methods is to obtain a large sample from the posterior distribution of the parameters. From a classical perspective, the mean of the posterior distribution converges to the maximum of the likelihood function and the variance of the posterior distribution converges to the asymptotic variance of an ML estimation. Thus, the standard deviation of the draws may be interpreted as standard errors from the classical perspective (Train, 2003). To obtain the sample from the posterior distribution I use a Gibbs sampler, which works by forming blocks of the model parameters and then drawing in turn from the conditional distributions of the blocks of parameters. The resulting sequence is a Markov Chain and after convergence the draws are samples from the desired posterior distribution. The key idea for the estimation of probit models is to estimate the latent variables as one step of the simulation (Albert and Chib, 1993). A similar strategy is used for the random effects (Zeger and Karim, 1991). Odejar (2002) proposes a Gibbs sampler for a model sharing important features with the one estimated in this paper. Recent examples for economic applications of very much related models are Buchinsky et al. (2005) and Fitzenberger et al. (2009). Details of the algorithm are given in Appendix B. I programmed the Gibbs sampler in Stata. For the calculation-intensive steps of the algorithm I used Mata, the matrix programming language of Stata. Conjugate but very diffuse priors are used. The results reported below are based on running

[15] Chib (2001) reviews important concepts of MCMC simulation methods.

the algorithm for 20,000 iterations. Convergence is monitored by comparing the means at different stages of the chains. The first 5,000 iterations are discarded (burn-in phase). Thus, the results are based on 15,000 draws. Covariates have been selected considering the size of the effects, significance (based on posterior means and standard deviations) and economic importance. Several interactions have been tested but turned out to be statistically irrelevant.

It is an important advantage of the MCMC estimation that it provides information on all parameters of the model including information on the unobserved individual specific effects $\alpha_{i,D}$ and $\alpha_{i,E}$. This information is needed to calculate average partial effects on the treated. To calculate these effects it is a natural solution to get an estimate of the average treatment effect on the treated which takes into account the selection on unobservables. To get these effects I developed the following strategy: for every tenth iteration of the MCMC estimation I calculate the partial effect for all person-periods in which the variable *dropout in past* takes a one. This strategy uses the β_E and δ_E vector of the respective iteration and the predictor of the $\alpha_{i,E}$ of the respective iteration together with the $x_{it,E}$ of the person-period. Averaging this effect over the person-periods gives a draw of the posterior distribution of the average partial effect of dropout in the past. The resulting 1,500 draws may then be used to describe the posterior distribution of the average partial effect of dropout for those who have dropped out in the past. This distribution may be described by giving the mean and the standard deviation, so information on statistical significance is readily available and there is no need to calculate standard errors (for instance using the delta method) as for classical estimators.

4.3 Results

Table 5 in Appendix A shows the results of the MCMC estimation. The posterior distributions of the parameters are summarized by means and standard deviations. First consider the variance parameters. An important part of the variance of both equations is on the individual level: in between 34% and 44% for the employment equation and in between 37% and 39% for the dropout equation. The correlation between the two random effects is relatively strong (36.9%) and significant for general professional training. A positive correlation suggests that those who have a higher propensity to be employed have also a higher propensity to drop out. For retraining, the correlation is also positive (27.9%), but insignificant. For practical training the estimation suggests a negative (-16.8%) and insignificant correlation. A negative correlation indicates that those unobserved characteristics that make a dropout more likely also decrease the employment probability. In theory both positive and negative correlations seem plausible. For the latter one could for instance think of general motivation of career improvement captured in the individual effect. It is plausible that someone who has a high motivation to study and work hard may be less likely to drop out of an offered training program and in general more likely to be employed. For a negative correlation one could also think of someone who has problems to comply with social norms and rules, such a person would have an increased risk to drop out of the program and also be less likely to succeed in finding employment or keeping a job in the long run. With respect to a positive correlation one could think of a high utility of earning money in the short run captured in the individual effect. Someone who is keen on earning a salary in the short run, for instance because of high discounting of the future or because he is the only earner in a family, is on the one hand likely to drop out of the program if he has chances to find some job. On the other hand, he will put a lot of effort in finding a job and not becoming unemployed again. A positive correlation between the random effects is also likely if participants with high ability find that the level of the programs is too low for them and thus tend to drop out.

The parameter of interest is the effect of the variable *dropout in past*. This dummy takes a one if the person experienced a dropout in the past and the current time period lies at least four months after the planned end of the program. The means of the posterior distribution (see table 5 in Appendix A and also the bottom line in table 2) suggest a negative effect of *dropout in past* for general professional training and for retraining. For practical training the effect is positive, but all three effects are insignificant on the 5% level. To estimate the size of the effect, I calculate average partial effects on the treated using the strategy described at the end of the previous section. As described above this strategy takes into account the selection based on unobservables by including the predictors of the α_E. The first line in table 2 depicts the results. They suggest that in the medium and long run dropout decreases employment chances of those who actually have dropped out only by 1.8 percentage points for general professional training and 3.1 percentage points for retraining. The effect of dropout is +2.2 percentage points for practical training. These effects are small compared to the effects of program participation (see for example Fitzenberger et al. (2009)). All three effects are insignificant, even on a 10% level. Thus the hypothesis that dropping out has no long run effect on dropouts can not be rejected.[16]

[16]Estimations of a simple pooled probit and a separate ML estimation of the employment equa-

Table 2: Estimation Results

	General Prof.		Retraining		Practical	
	Average partial long-term effect of dropout:					
	Mean	SD	Mean	SD	Mean	SD
dropout in past	-0.018	0.011	-0.031	0.026	0.022	0.014
	Parameters from MCMC estimation:					
	Mean	SD	Mean	SD	Mean	SD
dropout in past	-0.250	0.134	-0.342	0.275	0.374	0.220

The small and insignificant effects of dropout in the past might hide effect heterogeneity in several dimensions. It might be that dropout has a positive long-term effect for those who drop out with a job perspective and a negative effect for non-job-aligned dropouts, and these effects might have canceled out in the estimation. Also, dropout in the past may have a different effect on finding employment as on staying in employment. The descriptive analysis suggests a lower job stability for dropouts. Also, the interaction of these two dimensions might be relevant.[17] Table 6 in Appendix A shows the results when separating the effect of *dropout in past* between job-aligned and non-job-aligned dropout. Job-aligned dropouts are those who are employed in the first month after dropout, which is also the first period estimated in the employment equation. Dropping out job-aligned versus non-job-aligned may be interpreted as two different treatments. The distinction is endogenous in the model. Furthermore, the dropout effect is separated with respect to those who are employed in the last period and those who are not employed in the last period (effect on finding a job or keeping a job). Table 3 gives the average partial effect on the treated (calculated as above). Note that the estimated partial effect of job-aligned dropout is the effect of a dropout in the past and employment in the first month after leaving the program versus completing and being employed in the first month, and the analogous for non-job-aligned dropout.

With regard to general professional training all effects are again very small and negative. The negative effect of a job-aligned dropout on job stability is significant

tion also suggest only insignificant effects of the dummy *dropout in past*.

[17]Additional estimations (not shown in the paper) have shown that effect heterogeneity over time is not relevant. The effect of dropout in the past for example half a year after the planned end is not systematically different for the effect of dropout one year after the planned end of the program.

Table 3: Estimation Results (Flexible Specification)

	General Prof.		Retraining		Practical Tr.	
	Mean	SD	Mean	SD	Mean	SD
Average partial effect of dropout in the past:						
job-aligned and e[t-1]=0	-.030	.021	.021	.043	.013	.014
job-aligned and e[t-1]=1	-.019	.008	-.002	.015	.032	.027
non-job-aligned and e[t-1]=0	-.015	.013	-.029	.026	.012	.006
non-job-aligned and e[t-1]=1	-.009	.013	-.022	.024	.091	.053

but very small (-1.9%). The effect of a job-aligned dropout on finding a new job is a bit larger (-3%) but insignificant. Thus, there is some slight evidence that dropping out because of a job offer might be a little bit harmful in the long run for dropouts from general professional training. For retraining the effects are a bit less negative than in the less flexible estimation and they are again all insignificant. Concerning practical training the effects of a non-job-aligned dropout on finding employment is slightly significant but very small (1.2%). There is one effect which is relatively large (though almost insignificant, p-value: 0.09%): the effect of a non-job-aligned dropout on employment stability. This says that those who are employed but have not been employed in the first period after leaving the program do better in keeping employment as opposed to the counterfactual situation in which they would have completed the program. But only 5% of the participants in practical training experience such a combination, so the estimated size of the effect is based only on a few people. To sum up, the results suggest that the effects for dropout are zero or very small. Studies evaluating the employment effects of participation in further training programs (see for example Fitzenberger et al. (2009)) conclude that further training programs have positive long-term effects. According to Fitzenberger et al. (2009) the size of these effects amounts to an increase in employment of 10 to 20 percentage points depending on the group of participants. If in this context the effect of dropout for those who actually drop out is very small, this might for example indicate that for those participants who drop out it is enough to attend part of the program (for example because the programs work through activation of the participants) or that those choose to drop out who have a low benefit from training programs.

5 Conclusion

This study has shown that dropout is a relevant phenomenon in further training programs for the unemployed and that it occurs job-aligned as well as without a job perspective. One out of five participants drops out of the program. The first objective of this paper was to identify dropouts in the IEBS and to gain knowledge about the occurrence of dropouts - how often and when do people drop out and which characteristics are related to an increased probability of dropout. It is possible to distinguish participants that attend at least 80% of the program from those who drop out if taking into account some particularities and sensitivities of the data. Practical training is the program type with the highest dropout rate. Less than half of the dropouts take up employment within one month. Results of a probit model estimating the probability to drop out indicate that for instance low schooling, being young and living alone is related to an increased dropout probability. Participants for whom signs of lack of motivation with regard to activities of the labor agency can be identified from the data also face an increased probability to drop out. To study the employment prospects of dropouts I first use purely descriptive analysis. Comparing employment rates of dropouts and non-dropouts shows that the head start of dropouts decreases over time and 14 months after participants have reached the date of the planned end of the program the employment rates of dropouts and non-dropouts intersect. Survival rates indicate that the first employment of dropouts is a bit less durable than the first employment of those who completed the measure.

Dropout and employment status are jointly estimated using a bivariate dynamic random effects probit model. The individual effects of the two equations are allowed to be correlated. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. I programmed a Gibbs sampling algorithm to simulate draws from the posterior distribution of the parameters. This approach provides information on all parameters of the model, including the unobserved individual specific effects. To get an estimate for the size of the dropout effect, I calculated average partial effects on the treated which account for the selection based on unobservables. Results suggest that long run effects of dropout are very small and insignificant. A more flexible estimation with respect to job-aligned and non-job-aligned dropout and with respect to transition to employment and transition to non-employment, respectively, shows only small effects. Thus, this study concludes in finding that on average the decision to drop out neither harms nor enhances the future employment prospects.

References

Abbring, J. and G.J. van den Berg (2003). "The Nonparametric Identification of Treatment Effects in Duration Models." *Econometrica* 71, 1491-1517.

Albert, J. and S. Chib (1993). "Bayesian Analysis of Binary and Polychotomous Response Data." *Journal of the American Statistical Association*, 88, 669-679.

Becker, S. (2005). "Introducing Time-to-Educate in a Job Search Model." IZA Discussion Paper No. 1801.

Biewen, M., B. Fitzenberger, A. Osikominu and M. Waller (2007). "Which program for whom? Evidence on the comparative effectiveness of public sponsored training programs in Germany." IZA Discussion Paper No. 2885.

Buchinsky, M., D. Fougère, F. Kramarz and R. Tchernis (2005). "Interfirm Mobility, Wages, and the Returns to Seniority and Experience in the U.S." IZA Discussion Paper No. 1521.

Bundesagentur für Arbeit (2000, 2001, 2002). *Arbeitsmarkt 2001, 2002, 2003*, Nürnberg (various issues).

Chib, S. (2001). "Markov Chain Monte Carlo Methods: Computation and Inference." In J. Heckman and E. Leamer (eds.): *Handbook of Econometrics*, Volume 5, Amsterdam: Elsevier Science, 3569-3649.

Fitzenberger, B., A. Osikominu and M. Waller (2009). "The Heterogeneous Effects of Training Incidence and Duration on Labor Market Transitions." mimeo, Albert-Ludwigs-University Freiburg.

Flores-Lagunes, A., A. Gonzalez and T. Neumann (2007). "Estimating the Effects of Length of Exposure to a Training Program: The Case of Job Corps." IZA Discussion Paper No. 2846.

Heckman, J., J. Smith and C. Taber (1998). "Accounting for Dropouts in Evaluations of Social Programs." *The Review of Economics and Statistics*, 80, 1, 1-14.

Hujer, R., S. Thomsen and C. Zeiss (2006). "The Effects of Vocational Training Programmes on the Duration of Unemployment in Eastern Germany." *Allgemeines Statistisches Archiv* 90, 299-321.

Kluve, J., H. Schneider, A. Uhlendorff and Z. Zhao (2007). "Evaluating Continuous Training Programs Using the Generalized Propensity Score." IZA Discussion Paper No. 3255.

Lechner, M. and C. Wunsch (2006a). "Active Labour Market Policy in East Germany: Waiting for the Economy to Take Off." IZA Discussion Paper No. 2363.

Lechner, M. and C. Wunsch (2006b). "Are Training Programs More Effective When Unemployment Is High?" IZA Discussion Paper No. 2355.

Lechner, M. and C. Wunsch (2007). "The Curse and Blessing of Training the Unemployed in a Changing Economy: The Case of East Germany after Unification." *German Economic Review*, 8, 468-509.

Lee, M. and S. Lee (2003). "Analysing Effects of Job-Trainings Suffering Dropouts with an Optimal Multiple Matching." mimeo, Singapore Management University.

Odejar, A. (2002). "Bayesian Analysis of Sample Selection and Endogenous Switching Regression Models with Random Coefficients Via MCMC Methods." SFB 386 Discussion Paper No. 291.

Osikominu, A. (2008). "Is Short Training Short-Lived and Long Training Long-Lasting? A Multi-State Duration Analysis of the Dynamic Effects of Training Schemes for the Unemployed." Discussion Papier, Albert-Ludwigs-University Freiburg.

Rinne, U., M. Schneider and A. Uhlendorff (2007). "Too Bad to Benefit? Effect Heterogeneity of Public Training Programs." IZA Discussion Paper No. 3240.

Rosholm, M. and M. Svarer (2008). "The Threat Effect of Active Labour Market Programmes." *Scandinavian Journal of Economics*, 110, 385-401.

Schneider, H. and A. Uhlendorff (2006). "Die Wirkung der Hartz-Reform im Bereich der beruflichen Weiterbildung." *Journal for Labor Market Research* 39, 477-490.

Stephan, G. and A. Pahnke (2008). "The Relative Effectiveness of Selected Active Labour Market Programmes and the Common Support Problem." IZA Discussion Paper No. 3767.

Train, K. (2003). “Discrete Choice Methods with Simulation.” Cambridge University Press.

Waller, M. (2008). “On the Importance of Correcting Reported End Dates of Labor Market Programs.” *Schmollers Jahrbuch (Journal of Applied Social Science Studies)* 128, 213-236.

Wunsch, C. and M. Lechner (2008). “What Did All the Money Do? On the General Ineffectiveness of Recent West German Labour Market Programmes.” *Kyklos*, 61, 134-174.

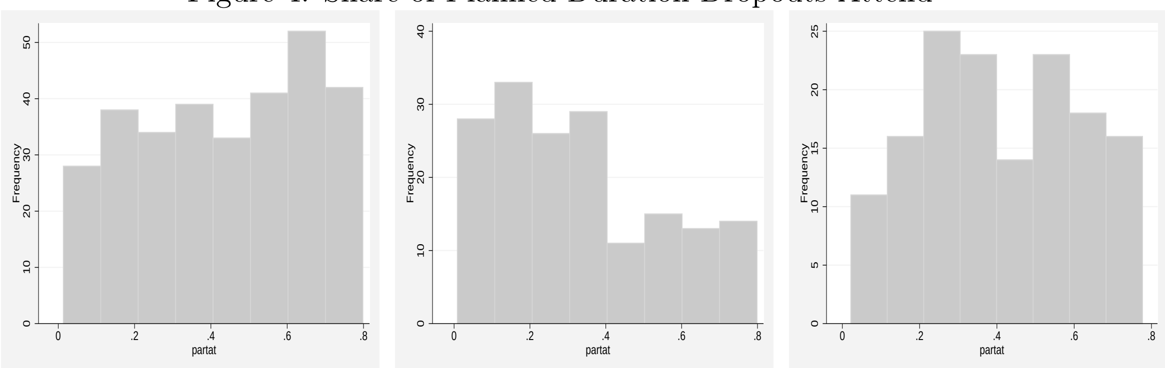
Zeger, S. and M Karim (1991). “Generalized Linear Models with Random Effects: a Gibbs Sampling Approach.” *Journal of the American Statistical Association*, 86, 79-86.

Zimmermann, R., S. Kaimer and D. Oberschachtsiek (2007). “Dokumentation des "Scientific Use Files der Integrierten Erwerbsbiographien" (IEBS-SUF V1) Version 1.” FDZ Datenreport 1/2007, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Appendix A

Descriptive Results

Figure 4: Share of Planned Duration Dropouts Attend



General Professional Training | Retraining | Practical Training

Table 4: Cross-sectional Probit of Dropout Dummy by Program Type

	Gen. Prof. Train.	Retraining	Practical Train.
no schooling degree	0.163 (0.060)	0.202 (0.092)	0.080 (0.075)
lower second. schooling	0.024 (0.023)	0.078 (0.033)	-0.049 (0.046)
sanction in past	0.100 (0.083)	0.064 (0.200)	0.073 (0.119)
lack of motivation in past	0.077 (0.034)	0.117 (0.048)	0.037 (0.059)
healthproblem	0.008 (0.032)	0.012 (0.052)	0.027 (0.056)
female	0.026 (0.023)	0.059 (0.036)	-0.122 (0.048)
living in East Germany	-0.012 (0.021)	-0.068 (0.038)	-0.146 (0.045)
25 to 29 years old	0.045 (0.031)	0.063 (0.038)	0.032 (0.065)
30 to 35 years old	0.050 (0.027)	-0.036 (0.036)	0.056 (0.056)
training program in past	0.022 (0.035)	0.153 (0.077)	0.136 (0.077)
unemployed before	0.048 (0.024)	0.028 (0.037)	0.053 (0.050)
last job blue-collar	0.006 (0.022)	-0.080 (0.035)	0.039 (0.046)
industry with seasonal work	-0.029 (0.043)	-0.030 (0.060)	0.110 (0.092)
living alone	0.028 (0.023)	0.130 (0.041)	0.050 (0.045)
child under 10 * female	0.023 (0.038)	0.061 (0.069)	0.044 (0.087)
child under 10 * male	-0.008 (0.035)	0.251 (0.069)	-0.100 (0.059)
planned length in months	0.004 (0.002)	0.001 (0.002)	0.021 (0.007)
constant	-1.407 (0.146)	-1.337 (0.269)	-0.967 (0.273)

Average partial effects with standard errors in brackets.

MCMC Estimation Results

Table 5: Results of MCMC Estimation (Simple Specification)

Variable	General Mean	General SD	Retraining Mean	Retraining SD	Practical Mean	Practical SD
Employment equation:						
last month dropout	0.487	0.185	0.010	0.301	1.229	0.272
dropout in recent past	-0.695	0.171	-0.917	0.281	-0.161	0.256
dropout in past	-0.249	0.151	-0.342	0.275	0.374	0.220
month of planned end or before	0.314	0.123	-0.000	0.178	0.663	0.210
month 1 after planned end	0.119	0.095	0.034	0.151	0.502	0.170
month 2 after planned end	-0.251	0.091	-0.071	0.137	0.033	0.160
month 3 after planned end	-0.147	0.083	-0.140	0.134	-0.022	0.153
month 4 to 6 after planned end	-0.184	0.058	-0.224	0.095	-0.156	0.108
month 7 to 12 after planned end	-0.144	0.041	-0.035	0.071	-0.126	0.077
month 24 to 40 after planned end	0.072	0.046	0.133	0.145	0.073	0.086
e[t-1]	2.928	0.073	2.905	0.127	3.145	0.140
e[t-2]	-0.192	0.059	-0.239	0.108	-0.172	0.114
e[t-3]	0.009	0.058	-0.097	0.102	-0.071	0.109
e[t-4]	0.014	0.059	0.109	0.107	0.004	0.108
e[t-5]	-0.000	0.063	-0.155	0.109	0.146	0.114
e[t-6]	-0.036	0.054	0.004	0.096	0.019	0.102
$\sum_{j=7}^{12} e[t-j]$	-0.001	0.010	0.003	0.020	0.001	0.019
$\sum_{j=13}^{18} e[t-j]$	-0.060	0.010	-0.061	0.023	-0.057	0.018
$\sum_{j=19}^{24} e[t-j]$	-0.035	0.012	-0.036	0.029	0.002	0.021
$\sum_{j=38}^{25} e[t-j]$	-0.028	0.010	-0.057	0.026	-0.026	0.018
elap. mon. in current state & e[t-1]=1	0.001	0.011	-0.029	0.023	-0.001	0.019
elap. mon. in current state squ. & e[t-1]=1	0.001	0.000	0.002	0.001	0.000	0.001
elap. mon. in current state & e[t-1]=0	-0.038	0.009	-0.054	0.015	-0.010	0.016
elap. mon. in current state squ. & e[t-1]=0	0.001	0.000	0.002	0.000	-0.000	0.000
planned length in days/31	-0.010	0.006	0.016	0.007	-0.027	0.018

<continued on next page>

Results of MCMC Estimation (Simple Specification) <continued>

	General		Retraining		Practical	
Variable	Mean	SD	Mean	SD	Mean	SD
female	0.050	0.049	0.168	0.097	0.133	0.108
living in East Germany	-0.060	0.058	-0.414	0.137	-0.023	0.122
no vocational degree	0.005	0.066	-0.144	0.091	-0.224	0.115
no schooling degree	-0.093	0.118	0.277	0.232	-0.327	0.183
lower secondary (Hauptschule)	-0.064	0.057	-0.109	0.108	0.055	0.112
high school (Abitur)	-0.054	0.059	-0.202	0.128	0.002	0.147
25-29 years old	0.156	0.065	0.023	0.108	0.098	0.135
30-34 years old	0.066	0.059	-0.163	0.105	0.184	0.119
35-40 years old	-0.122	0.060	-0.179	0.187	-0.112	0.119
50-54 years old	-0.405	0.082	-0.071	0.360	-0.637	0.148
child under 10 * male	0.144	0.075	-0.059	0.150	0.204	0.153
child under 10 * female	-0.056	0.087	-0.311	0.184	-0.018	0.183
health problems	-0.105	0.085	-0.152	0.171	-0.076	0.151
unemployed before (last three years)	0.056	0.058	0.042	0.105	-0.314	0.117
days/31 unempl. assistance last 3 years	-0.023	0.007	-0.020	0.012	-0.028	0.011
training program before	-0.054	0.079	-0.272	0.204	-0.156	0.172
days/31 employed last 3 years	0.006	0.003	0.009	0.006	0.004	0.006
spring (second quarter)	0.023	0.030	0.019	0.058	0.072	0.056
fall (fourth quarter)	-0.110	0.030	-0.035	0.056	-0.208	0.055
winter (first quarter)	-0.061	0.031	-0.190	0.061	-0.049	0.060
year 2002	-0.079	0.035	-0.085	0.078	0.101	0.065
year 2003	0.028	0.045	-0.053	0.077	0.178	0.084
year 2004	0.061	0.060	-0.108	0.094	0.107	0.108
log last real wage	-1.094	0.682	-0.652	1.530	-0.511	1.129
log last real wage squared	0.058	0.036	0.033	0.082	0.028	0.061
last job in industry with seasonal work	-0.042	0.103	0.089	0.171	0.008	0.185
urban region high unempl. in East	-0.107	0.089	0.287	0.248		
urban region, good conditions in West	-0.066	0.096	-0.143	0.163	0.525	0.243
non-urban region, good conditions in West	0.129	0.061	0.267	0.110	0.037	0.107
constant	3.991	3.203	2.057	7.118	1.090	5.282

<continued on next page>

Results of MCMC Estimation (Simple Specification)
<continued>

Variable	General Mean	General SD	Retraining Mean	Retraining SD	Practical Mean	Practical SD
Dropout equation:						
days/31 until planned end	-1.962	0.453	-0.134	0.192	-3.068	0.873
near to program begin	-0.073	0.088	-0.093	0.109	-0.209	0.132
no schooling degree	0.600	0.176	0.644	0.251	0.161	0.210
lower secondary (Hauptschule)	0.178	0.090	0.301	0.114	-0.148	0.145
sanction in last 3 years	0.507	0.257	-0.016	0.567	0.304	0.346
lack of motivation w.r.t. agency's activities	0.229	0.112	0.351	0.143	0.059	0.172
health problems	0.037	0.148	-0.023	0.215	-0.220	0.214
female	0.101	0.092	0.127	0.130	-0.377	0.156
living in East Germany	-0.100	0.084	-0.286	0.166	-0.533	0.163
25-30 years old	0.143	0.109	0.193	0.126	0.203	0.202
30-34 years old	0.140	0.098	-0.199	0.139	0.201	0.169
training program before	0.102	0.126	0.502	0.218	0.415	0.209
unemployed before (last three years)	0.177	0.105	0.152	0.147	0.183	0.168
last job as blue-collar worker	0.063	0.089	-0.279	0.126	0.173	0.144
last job in industry with seasonal work	-0.118	0.194	-0.085	0.234	0.220	0.254
living alone	0.147	0.094	0.474	0.127	0.041	0.140
child under 10 * female	0.135	0.137	0.212	0.203	0.066	0.262
child under 10 * male	0.036	0.140	0.759	0.201	-0.391	0.232
constant	-2.641	0.165	-3.018	0.225	-1.629	0.239
Individual level variances:						
individual level variance employ. equ.	0.505	0.064	0.811	0.161	0.612	0.118
individual level variance dropout equ.	0.653	0.179	0.660	0.258	0.610	0.211
individual level covariance	0.215	0.100	0.209	0.156	-0.107	0.123
share on individual level, employ. equ.	0.334	0.028	0.444	0.048	0.376	0.045
share on individual level, dropout equ.	0.388	0.061	0.385	0.083	0.369	0.074
correlation between equations	0.134	0.057	0.118	0.083	-0.064	0.072
correl. between random effects	0.369	0.139	0.279	0.182	-0.168	0.185

Table 6: Results of MCMC Estimation (Flexible Specification)

Variable	General Mean	General SD	Retraining Mean	Retraining SD	Practical Mean	Practical SD
Employment equation:						
last month dropout	0.487	0.190	0.185	0.258	1.317	0.305
dropout in recent past	-0.688	0.176	-0.762	0.244	-0.039	0.290
job-aligned dropout in past & e[t-1]=0	-0.262	0.172	0.156	0.274	0.284	0.276
job-aligned dropout in past & e[t-1]=1	-0.356	0.167	-0.081	0.255	0.390	0.276
non-job-aligned dropout in past & e[t-1]=0	-0.198	0.174	-0.306	0.248	0.501	0.285
non-job-aligned dropout in past & e[t-1]=1	-0.134	0.179	-0.257	0.254	0.745	0.303
month of planned end or before	0.311	0.123	0.017	0.179	0.644	0.217
month 1 after planned end	0.112	0.093	0.061	0.158	0.465	0.170
month 2 after planned end	-0.260	0.089	-0.056	0.144	0.001	0.166
month 3 after planned end	-0.155	0.082	-0.131	0.135	-0.044	0.157
month 4 to 6 after planned end	-0.185	0.058	-0.223	0.098	-0.160	0.110
month 7 to 12 after planned end	-0.143	0.040	-0.034	0.072	-0.135	0.077
month 24 to 40 after planned end	0.073	0.045	0.135	0.145	0.070	0.086
e[t-1]	2.919	0.074	2.923	0.126	3.103	0.135
e[t-2]	-0.198	0.060	-0.237	0.108	-0.177	0.116
e[t-3]	0.008	0.059	-0.092	0.103	-0.077	0.109
e[t-4]	0.010	0.060	0.115	0.105	0.001	0.112
e[t-5]	0.001	0.062	-0.148	0.110	0.142	0.113
e[t-6]	-0.041	0.054	-0.001	0.097	0.018	0.102
$\sum_{j=7}^{12} e[t-j]$	-0.001	0.010	0.004	0.020	0.001	0.019
$\sum_{j=13}^{18} e[t-j]$	-0.061	0.010	-0.064	0.023	-0.057	0.018
$\sum_{j=19}^{24} e[t-j]$	-0.036	0.012	-0.037	0.030	0.003	0.021
$\sum_{j=38}^{25} e[t-j]$	-0.027	0.010	-0.063	0.026	-0.025	0.018
elap. mon. in current state & e[t-1]=1	0.003	0.011	-0.029	0.022	-0.000	0.019
elap. mon. in current state sq. & e[t-1]=1	0.001	0.000	0.002	0.001	0.000	0.001
elap. mon. in current state & e[t-1]=0	-0.038	0.009	-0.055	0.016	-0.010	0.016
elap. mon. in current state sq. & e[t-1]=0	0.001	0.000	0.002	0.000	-0.000	0.000

<continued on next page>

Results of MCMC Estimation (Flexible Specification) <continued>

Variable	General Mean	General SD	Retraining Mean	Retraining SD	Practical Mean	Practical SD
planned length in days/31	-0.010	0.006	0.015	0.006	-0.033	0.020
female	0.052	0.049	0.168	0.096	0.158	0.112
living in East Germany	-0.054	0.059	-0.377	0.141	-0.033	0.134
no vocational degree	0.009	0.066	-0.131	0.090	-0.240	0.127
no schooling degree	-0.099	0.127	0.237	0.208	-0.337	0.204
lower secondary (Hauptschule)	-0.067	0.057	-0.125	0.104	0.049	0.114
high school (Abitur)	-0.050	0.060	-0.202	0.122	0.011	0.152
25-29 years old	0.161	0.067	0.015	0.104	0.099	0.144
30-34 years old	0.072	0.060	-0.145	0.104	0.188	0.127
35-40 years old	-0.121	0.059	-0.169	0.177	-0.130	0.125
50-54 years old	-0.406	0.080	-0.012	0.339	-0.679	0.163
child under 10 * male	0.143	0.079	-0.084	0.153	0.255	0.158
child under 10 * female	-0.063	0.087	-0.312	0.179	-0.028	0.198
health problems	-0.109	0.087	-0.150	0.165	-0.085	0.159
unemployed before (last three years)	0.065	0.062	0.033	0.105	-0.334	0.136
days/31 unempl. assistance last 3 years	-0.024	0.007	-0.020	0.012	-0.030	0.012
training program before	-0.056	0.079	-0.294	0.191	-0.172	0.183
days/31 employed last 3 years	0.006	0.003	0.009	0.005	0.005	0.006
spring (second quarter)	0.023	0.029	0.021	0.058	0.072	0.055
fall (fourth quarter)	-0.109	0.030	-0.035	0.054	-0.210	0.056
winter (first quarter)	-0.059	0.032	-0.185	0.060	-0.049	0.060
year 2002	-0.080	0.035	-0.082	0.080	0.115	0.065
year 2003	0.028	0.044	-0.057	0.077	0.187	0.085
year 2004	0.058	0.058	-0.116	0.091	0.110	0.112
log last real wage	-1.101	0.651	-0.610	1.490	-0.576	1.238
log last real wage squared	0.058	0.035	0.030	0.080	0.031	0.067
last job in industry with seasonal work	-0.048	0.107	0.091	0.161	-0.022	0.208
urban region high unempl. in East	-0.116	0.086	0.250	0.240		
urban region, good conditions in West	-0.067	0.098	-0.148	0.154	0.571	0.259
non-urban region, good conditions in West	0.136	0.062	0.250	0.098	0.046	0.112

<continued on next page>

Results of MCMC Estimation (Flexible Specification) <continued>

Variable	General Mean	General SD	Retraining Mean	Retraining SD	Practical Mean	Practical SD
constant	4.020	3.064	1.850	6.916	1.456	5.800
Dropout equation:						
days/31 until planned end	-1.986	0.450	-0.118	0.186	-3.150	0.902
near to program begin	-0.074	0.095	-0.060	0.099	-0.209	0.131
no schooling degree	0.605	0.179	0.627	0.231	0.176	0.212
lower secondary (Hauptschule)	0.184	0.091	0.283	0.109	-0.139	0.153
sanction in last 3 years	0.500	0.258	-0.023	0.536	0.319	0.344
lack of motivation w.r.t. agency's activities	0.219	0.120	0.361	0.134	0.053	0.170
health problems	0.040	0.153	-0.018	0.205	-0.234	0.224
female	0.109	0.089	0.133	0.123	-0.362	0.153
living in East Germany	-0.099	0.079	-0.279	0.144	-0.533	0.164
25-30 years old	0.155	0.112	0.189	0.121	0.202	0.196
30-34 years old	0.142	0.098	-0.174	0.126	0.204	0.167
training program before	0.099	0.129	0.482	0.202	0.424	0.214
unemployed before (last three years)	0.191	0.115	0.138	0.133	0.186	0.168
last job as blue-collar worker	0.066	0.088	-0.259	0.119	0.182	0.145
last job in industry with seasonal work	-0.123	0.195	-0.089	0.211	0.209	0.248
living alone	0.143	0.094	0.453	0.121	0.044	0.135
child under 10 * female	0.121	0.148	0.195	0.207	0.057	0.265
child under 10 * male	0.025	0.141	0.720	0.191	-0.385	0.224
constant	-2.659	0.184	-2.974	0.183	-1.651	0.236
Individual level variances:						
individual level variance employ. equ.	0.530	0.066	0.741	0.143	0.718	0.147
individual level variance dropout equ.	0.662	0.212	0.553	0.161	0.619	0.200
individual level covariance	0.217	0.104	0.108	0.110	-0.148	0.151
share on individual level, employ. equ.	0.345	0.028	0.422	0.046	0.414	0.049
share on individual level, dropout equ.	0.389	0.073	0.350	0.061	0.373	0.072
correlation between equations	0.134	0.060	0.065	0.066	-0.085	0.084
correl. between random effects	0.363	0.147	0.167	0.168	-0.208	0.201

Appendix B

Algorithm for the MCMC Estimation

The following independent priors are set: the prior distributions of the coefficients $\eta_E = \beta_E$ and δ_E are given by independent normal priors with distribution $\mathcal{N}(b_{E,0}, B_{E,0})$. $\mathcal{N}(\bullet)$ denotes the normal distribution. Setting very large values for the variance $B_{E,0}$, I use extremely diffuse priors. The same is done for the coefficients of the β_D vector, the prior distributions are given by $\mathcal{N}(b_{D,0}, B_{D,0})$. The prior distribution of the random effects is $\mathcal{N}(0, \Sigma)$. The hyperparameter Σ^{-1} follows the prior distribution $\mathcal{W}^{-1}(H_0, h_0)$, where H_0 is the inverse scale matrix and h_0 denotes the degrees of freedom. $\mathcal{W}^{-1}$ denotes the inverse Wishart distribution. To use a diffuse prior I set a small h_0. For the diagonal elements of H_0 the individual level variances of a separate ML estimation of the two equations times h_0 are set and I set the off-diagonal elements to zero. The algorithm is presented in the following. Let $z_{it,E}$ and $z_{it,D}$ denote the whole set of covariates in the employment or dropout equation, respectively.

- Set starting values for the coefficient vectors η_E and β_D, the individual specific effects ($\alpha_{i,E}$, $\alpha_{i,D}$) and the variance covariance matrix of the individual specific effects Σ.

- Step 1a: Sample E^*_{it} from $\mathcal{N}(z_{it,E}\eta_E + \alpha_{i,E}, 1)$ with support $[0, \infty]$ if $E_{it} = 1$ and with support $[-\infty, 0]$ if $E_{it} = 0$ (if the employment equation is to be estimated). $\mathcal{N}(\bullet)$ denotes the normal distribution.

- Step 1b: Sample D^*_{it} from $\mathcal{N}(z_{it,D}\beta_D + \alpha_{i,D}, 1)$ with support $[0, \infty]$ if $D_{it} = 1$ and with support $[-\infty, 0]$ if $D_{it} = 0$ (if the dropout equation is to be estimated).

- Step 2: Sample $(\alpha_{i,E}, \alpha_{i,D})'$ from its bivariate normal conditional posterior distribution $\mathcal{N}(\mu, V_{\alpha_i})$, where $\mu = V_{\alpha_i} \cdot \begin{pmatrix} T_{i,E} & 0 \\ 0 & T_{i,D} \end{pmatrix} \cdot \begin{pmatrix} (\bar{E}^*_i - \bar{z_{i,E}}\eta_E) \\ (\bar{D}^*_i - \bar{z_{i,D}}\beta_D) \end{pmatrix}$ and $V_{\alpha_i} = \left(\Sigma^{-1} + \begin{pmatrix} T_{i,E} & 0 \\ 0 & T_{i,D} \end{pmatrix} \right)^{-1}$, a bar over a variable denotes its mean across time, $T_{i,E}$ the number of observations for person i for which the employment equation is to be estimated, and $T_{i,D}$ the number of observations for person i for which the dropout equation is to be estimated.

- Step 3a: Sample the η_E vector from its multivariate normal conditional posterior distribution $\mathcal{N}(M_E, V_E)$, where $M_E = V_E(B_{E,0}^{-1}b_{E,0} + \sum_{i=1}^{N}\sum_{t=1}^{T_{i,E}} z'_{it,E}(E^*_{it,E} - \alpha_{i,E}))$ and $V_E = (B_{E,0}^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_{i,E}} z'_{it,E}z_{it,E})^{-1}$. N is the number of persons in the data using all person-periods for which the employment equation is to be estimated.

- Step 3b: Sample the β_D vector from its multivariate normal conditional posterior distribution $\mathcal{N}(M_D, V_D)$, where $M_D = V_D(B_{D,0}^{-1}b_{D,0} + \sum_{i=1}^{N}\sum_{t=1}^{T_{i,D}} x'_{D,it}(D^*_{D,it} - \alpha_{i,D}))$ and $V_D = (B_{D,0}^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_{i,D}} z'_{it,D}z_{it,D})^{-1}$ using all person-periods for which the dropout equation is to be estimated.

- Sample Σ^{-1} from its conditional posterior distribution $\mathcal{W}^{-1}\left(\begin{pmatrix} \sum\limits_{i=1}^{N}\alpha_{i,E}^2 & \sum\limits_{i=1}^{N}\alpha_{i,E}\alpha_{i,D} \\ \sum\limits_{i=1}^{N}\alpha_{i,E}\alpha_{i,D} & \sum\limits_{i=1}^{N}\alpha_{i,D}^2 \end{pmatrix} + H_0,\ N + h_0\right)$. $\mathcal{W}^{-1}$ denotes the inverse Wishart distribution.

- Go to Step 1. Always use current values.