Bayesian Estimates of the Effects of Training Incidence and Length on Labor Market Transition Rates[1]

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Abstract: This paper uses a dynamic bivariate random effects probit model to estimate the effects of both the incidence and the duration of further training on labor market transition rates building on a timing–of–events approach. The model consists of a state–dependent employment equation and a participation equation. The participation equation models the start of participation in long-term training as well as the possibly endogenous end of participation. We control for selection on unobservables by allowing the random effects of both equations to be correlated. The equations are simultaneously estimated using Markov Chain Monte Carlo (MCMC) methods. Separate models are estimated for West and East Germany and for men and women. First results suggest positive treatment effects for both men and women in East and West Germany after participants have left the program.

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Contents

1 Introduction

In recent years the employment effects of long–term training as part of German active labor market policies have been studied using different evaluation methods. Most of these studies use propensity score matching to estimate the average treatment effect on the treated, see for example Biewen et al. (2008), Lechner and Wunsch (2006), Lechner and Wunsch (2007), Schneider and Uhlendorff (2006) and Stephan (2009). These studies do not account for unobserved heterogeneity, but condition on a rich set of observed variables including detailed information on the employment history of the individuals. All of them are based on German administrative data, but they differ with respect to methodological aspects, the sample of individuals used, the exact classification of training programs and the definition of the outcome variable. Osikominu (2008) uses a multivariate duration model to study the employment effects of different training programs. As opposed to the papers based on matching, her model does account for selection on unobservables. Regarding long–term training, her finding is that the treatment may increase the expected unemployment duration but has a strong positive effect on the expected employment duration.

This paper uses a dynamic bivariate random effects probit model to estimate the effects of both the incidence and the duration of long–term further training on labor market transition rates building on a timing–of–events approach. The participation equation models the start of participation in long–term training as well as the possibly endogenous end of participation. We control for selection on unobservables by allowing the random effects of both equations to be correlated. The equations are simultaneously estimated using Markov Chain Monte Carlo (MCMC) methods, a technique from Bayesian Statistics. Separate models are estimated for West and East Germany and for men and women. Interpretation of the means of the parameters is not straightforward because of the dynamic nature of the model. Therefore, average treatment effects on the treated are estimated using a simulation strategy. First results suggest positive average treatment effects for all groups.

In the context of estimating treatment effects, our Bayesian estimation of a panel discrete choice model for labor market transitions has a number of advantages compared to the estimation of continuous time mixed proportionate hazard models building on the timing–of–events approach of Abbring and van den Berg (2003), see Osikominu (2008) for an application using the same data as in this paper. First, panel discrete choice model for labor market transitions effectively use multiple spells and allow to analyze the same calendar time period for all individuals in the data, irrespetive of how many transitions an individuals has gone through. In contrast, practical application of duration models in continuous time are typically limited to a small number of spells, i.e. for each individual a fixed maximum number of transitions is considered and the events afterwards are ignored, even if they are close in calendar time. Second, the timing–of–events assumption for identification of the treatment effects translates into a time lag by at least one discret time unit for the effect of treatment on employment outcomes. The identification in Abbring and van den Berg (2003) relies on differences in hazard rates at a point of time which is very close to the start of the program. Adding a separate equation for the duration of treament until its planned end would increase considerably the complexity of the duration model in continuous time. Modelling discrete choice models allows to add this dimension in a straight forward way. A major disadvantage of our approach is that the researcher has to choose a fairly low frequency of time series observations – here we use quarterly data.

This paper involves some innovative methodological aspects in the context of estimating state dependent discrete choice models for panel data with unobserved heterogeneity. The use of Bayesian methods makes the model estimation of a state dependant two equation random effects probit model feasible (see Buchinsky et al. 2005 for a similar application). In addition, our MCMC estimates provide a posteriori information on the random effects which we use to assess the nature of selectivity of the treated and the nontreated individuals. Furthermore, we use our MCMC estimates to estimate the average treatment effect for the treated on labor market transition rates based on simulating the estimated model. We use the MCMC iterations to provide a posteriori esimates of the uncertainty in our estimates of the average treatment effects on the treated.

The remainder of this paper is structured as follows: section two introduces the program and the data. Section three discusses our evaluation method and the MCMC estimation of the model. Section four presents the results and section five concludes.

2 Institutional Background and Data

2.1 Training in Germany

Training schemes have traditionally dominated active labor market policy in Germany. The legislation distinguishes three main types of training, further training (*Berufliche Weiterbildung*), retraining (*Berufliche Weiterbildung mit Abschluss in* *einem anerkannten Ausbildungsberuf*), and short–term training (*Trainingsmaßnahmen und Maßnahmen der Eignungsfeststellung*). Figure 1 shows the evolution of participation in the three different training programs in East and West Germany during the period of our analysis. Until 2000, enrolment into further training was around 260 thousand in West Germany and 170 thousand in East Germany. A policy reorientation favoring programs supposed to activate the unemployed in the short run led to a decline in further training and retraining and a sharp increase of short–term training. In 2004, participation in further training was about 100 thousand in West Germany and about 50 thousand in East Germany. The corresponding figures for short–term training were 800 thousand and 400 thousand, respectively, up from around 200 thousand in 1999.

— Figure 1 about here —

The main goal of active labor market policy in Germany is to permanently reintegrate unemployed individuals into employment. In this study we focus on further training programs. They are used to adjust the skills of the unemployed to changing requirements of the labor market and possibly to changed individual conditions of employability (due to health problems for example). Further training courses typically last several months to one year and are usually conducted as full–time program. Teaching takes place in class rooms or on the job in training firms. The course curriculum may also include internships. Typical examples of further training schemes are courses on IT based accounting or on customer oriented behavior and sales training. Similar to the much longer retraining schemes, that lead to a complete new degree within the German apprenticeship system, further training programs aim at improving the human capital and productivity of the participant. Short–term training, in contrast, primarily aims at improving job search and lasts typically about four weeks.

In order to become eligible for training, job seekers have to register personally at the local employment agency. This involves a counseling interview with a caseworker. In principle, they have in addition to fulfill a minimum work requirement and be entitled to unemployment compensation. However, there are exceptions to this rule. The most important criterion is that the training scheme has to be considered necessary by the caseworker for the unemployed to find a new job. Participation in training can occur at any time during unemployment.

Before 2003, training measures were assigned by the caseworker. This was often done in agreement with the job seeker, considering his or her willingness to receive training and to work in a specific field. The final decision was subject to the discretion of the caseworker. Assignment into programs was to a large extent driven by the supply of courses that were booked in advance for a year by the employment agencies from training providers. Referrals to training often occurred at very short notice in order to achieve a high capacity utilization (Schneider et al., 2006).

In 2003, the assignment procedure changed to a system where the job seeker receives a training voucher from the caseworker valid between one and three months. The voucher specifies the maximal length, the content and the objective of the training program to choose. The job seeker then chooses by himself a suitable course from a pool of accredited offers. The 2003 reform meant to make the allocation process more targeted and selective. However, potential participants were uncertain about the actual starting date because it turned out that training providers tended to collect vouchers until a critical number of participants was reached or they shortly canceled scheduled courses if there were too few participants (Kühnlein and Klein, 2003, Schneider et al., 2006). Moreover, in the first months of 2003, programs that were assigned under the old system still started. 93% of the programs in our analysis sample start before the reform. An additional 2% starts in the first quarter of 2003, thus about 5% of the programs fall in a time where vouchers have been used.

During training most participants receive a subsistence allowance of the same amount as the unemployment compensation they would receive otherwise. Participants not eligible to subsistence allowance may receive similar payments from the European Social Fund. In addition, travel and child–care costs may be covered by the employment agency.

Once a particular program or training voucher has been assigned, participation is mandatory. Non–compliance may be sanctioned with a temporary suspension of unemployment compensation. The planned duration of the further training programs considered in this paper is on average eight months. However, not all participants who start a program complete it. In fact, according to Waller (2008) one out of five participants who have started a program and attended it for at least one week drop out before having reached 80% of the planned duration. About half of the dropouts start employment soon after quitting a program. In many cases this behavior is encouraged by the employment agency because in general priority is given to placement over participation in active labor market programs. Exceptions from this rule are possible if completing the program is judged necessary for a durable placement. Those dropping out for other reasons are not sanctioned in most cases. As opposed to dropout, it also happens in some cases that participation in training is prolonged. Due to dropout and possible prolongment of participation the actual end date of a training program is to a certain extend endogenous.

2.2 Construction of a Panel Data Set for the Analysis

For the empirical analysis we construct a panel data set from a rich administrative database, the Integrated Employment Biographies Sample (IEBS). The IEBS is a 2.2% random sample from a merged data file containing individual 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*).[2] 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 active labor market programs.

We consider an inflow sample into unemployment consisting of individuals who became unemployed between the first of July 1999 and the end of December 2000, after having been continuously employed for at least 125 days. Entering unemployment is defined as the transition from non–subsidized employment to non–employment plus subsequently (not necessarily immediately) some contact with the employment agency, either through benefit receipt, program participation or a job search spell. In order to exclude individuals eligible for specific labor market programs targeted to youths and individuals eligible for early retirement schemes, we only consider persons aged between 25 and 53 years at the beginning of their unemployment spell.

We follow the persons in the sample from their first inflow into unemployment between 07/1999 and 12/2001 until the end of 2004. The analysis time is calendar quarters. For 77% of the individuals in the sample we observe the full sequence of 17 quarters from their inflow on. The sequences of the remaining individuals have either been censored in the quarter in which they enter a long–term active labor market program other than training as the first long–term program in an non–employment period or due to a late inflow, we do not observe 17 quarters. We ignore participation in short–term training and do not censor employment sequences in this case.

We distinguish the two outcome states non–subsidized employment and non–employment as residual state. We aggregate the employment information measured at a daily level into quarters as follows. First, short gaps of up to 45 days length

[2]For further information on the data see the appendix.

between sequences of longer employment or non–employment spells are smoothed out. Second, we align the start of non–employment and employment spells to the quarters in the following way. If a transition to non–employment occurs the employment dummy is set to zero in the corresponding calendar quarter. It continues to equal zero in the following quarter if the elapsed duration of non–employment at the end of the quarter exceeds 90 days. From the third quarter of non–employment on, the employment dummy is set to zero if the share of days in non–employment exceeds one half. Third, we take care of not dropping short employment periods that extend over two calendar quarters by correcting the employment status in this case.

Participation in further training is coded as follows in our panel data set. We construct a dummy variable that equals one in the quarter in which the job seeker starts a training program and attends it for at least 27 days. In order to model the duration of the training program we apply the same rules as for the employment dummy above to the qualification dummy. Because not only the start of a program but also the program status in each following quarter is used for the estimation, it is important to use reliable information on the realized program duration. We correct the reported end dates of training programs using the correction procedures proposed in Waller (2007). Participation can already occur in the first quarter we observe for an individual.

The panel data set for the analysis is complemented by adding personal, occupational and regional information. Some of the covariates are updated at the beginning of each quarter. The estimations are carried out separately for men and women and West and East Germany. Table 2 gives an overview of the four samples and their basic characteristics. On average we observe 15 to 17 quarters per person, with the number of non–employment quarters ranging from nine to eleven. This corresponds to between 1.5 and two unemployment and about one employment spell on average per person. One in ten to one in five persons participate in training throughout the observation period.

— Table 2 about here —

3 Evaluation Framework

3.1 Model

We are interested in the effect of participating in training on a quarterly employment dummy. We model the employment and the training decision as a two equation system with possibly dependent individual specific effects. This means that we allow for selection into and out of training based on unobservables. As both dependent variables are binary we specify a random effects probit model for each.

Estimation of discrete choice–models for labor market transitions can be viewed as a discrete time version of the timing–of–events approach by Abbring and van den Berg (2003) which uses a continuous time duration model with unobserved heterogeneity, where time until treatment start and unemployment duration constitute two competing risks. Note however, that our approach also models the length of the training program. The goal of the timing–of–events approach by Abbring and van den Berg (2003) is to estimate the causal treatment effect on the hazard to leave unemployment. Identification of the causal effect of entering a program relies on the conditional randomness of program starts and a no–anticipation condition as well as functional form assumptions involving e.g. a mixed proportional hazard model and functional form assumption qualitatively similar to the ones used here. Similar to Abbring and van den Berg (2003), our approach relies on a selection on unobservables strategy. Our estimates allow for heterogeneity of treatment effects and they attempt to estimate both the effect of training incidence and duration.

Consider first the equation for the employment decision. In order to model the employment dynamics we introduce employment lags up to the order of 15 (i.e. $E_{i(t-1)},\ E_{i(t-2)},\ \ldots,\ E_{i(t-15)}$, where i indexes individuals and t quarters) as explaining variables of current employment status. A lagged variable is set to zero if the inflow is too recent for the corresponding lag to be available. Furthermore, we include a vector of observed characteristics, $x_{it,E}$, in the employment equation. In particular, we use information on schooling and occupational qualification, age, occupation and salary in the previous employment, health, children, labor market characteristics of the residential municipality, season, year and the elapsed unemployment duration in days. Additional dummies are included that indicate the elapsed number of quarters of an individual in the panel.

We assume that a participation in training in a given quarter affects the employment probability in subsequent quarters. Thus, the employment equation includes dummies of lagged training ($Q_{i(t-1)},\ Q_{i(t-2)},\ \ldots,\ Q_{i(t-16)}$) which indicate the training history of the individual, i.e. whether the individual was participating in a training program in preceding quarters. We interact the training history dummies with the lagged employment status in order to distinguish between the effect of training on entering employment and on staying in employment.

Identification of the treatment effects comes partly through a timing–of–events assumption in discrete time such that $Q_{i(t-1)}$ is the most recent lag assumed to influence employment transitions. Put differently, we rule out that anticipation of participation in the future affects current or future employment. This assumption seems plausible in the present context as enrolment into training largely depends on short–term indicators (cf. section 2.1).

Latent employment E^*_{it} and observed employment status E_{it} are then given by the following equations:

$$\begin{aligned} E^*_{it} = {} & x_{it,E}\beta_E + \textstyle\sum_{l=1}^{15} \gamma_{l,E} E_{i(t-l)} + \delta_{1,E} Q_{i(t-1)} + \\ & \textstyle\sum_{k=2}^{16} \delta_{k,E} Q_{i(t-k)} \cdot E_{i(t-1)} + \theta_{k,E} Q_{i(t-k)} \cdot (1 - E_{i(t-1)}) + \alpha_{i,E} + \epsilon_{it,E} \\ E_{it} = {} & \mathbf{1}[E^*_{it} > 0] \end{aligned} \tag{1}$$

where $\mathbf{1}[\bullet]$ is the indicator function, $\alpha_{i,E}$ the individual specific effect and $\epsilon_{it,E}$ the idiosyncratic error term.

Consider next the participation equation modeling the transition into and out of training. It is estimated simultaneously with the employment equation if the individual is not employed in the respective quarter and has not yet left a training program. We do not consider reentry into training after the completion of a first training program because this only occurs very rarely in our data. The training equation includes a vector of observed regressors, $x_{it,Q}$. This vector comprises a dummy indicating whether the individual is currently in training and the planned duration is greater or equal to one more quarter, and if this is true in addition the duration in months until the planned end date. For those cases with planned end date missing the equation contains a dummy equal to one if the individual is currently in training and the planned end date is missing, and if this is true additionally the elapsed duration in training as substitute for the information on the remaining planned duration. These variables are equal to zero if the individual is not enrolled in training. Furthermore, the vector of independent variables includes variables summarizing the employment history since the inflow quarter. There are dummy variables indicating whether the current quarter is the inflow quarter, whether a second or further transition from employment to non–employment has occurred and a polynomial of the elapsed unemployment duration in days. Finally, information on age, schooling, vocational qualification, last job, health, children and entitlement to unemployment compensation, season and year is incorporated.

In particular, the equations for latent training Q^*_{it} and observed training status Q_{it} have the following form:

$$
\begin{aligned}
Q^*_{it} =& \; x_{it,Q}\beta_Q + \alpha_{i,Q} + \epsilon_{it,Q} \\
Q_{it} =& \; \mathbf{1}[Q^*_{it} > 0]
\end{aligned}
\tag{2}
$$

where $\alpha_{i,Q}$ the individual specific effect and $\epsilon_{it,Q}$ the idiosyncratic error term.

The two individual specific effects, $\alpha_{(i,E)}$ and $\alpha_{(i,Q)}$, follow a *joint* normal distribution, $(\alpha_{i,E}, \alpha_{i,Q})' \sim \mathcal{N}(\mathbf{0}, \Sigma)$. The error terms $\epsilon_{it,E}$ and $\epsilon_{it,Q}$ are independently standard normal distributed. Thus, the model includes two individual specific effects which are allowed to be correlated. Let $z_{it,E} = (E_{i(t-1)}, \ldots, E_{i(t-15)}, Q_{i(t-1)}, \ldots, Q_{i(t-16)}, x_{it,E})$, $z_{it,Q} = x_{it,Q}$, $\eta'_E = (\beta_E, \gamma_E, \delta_E, \theta_E)'$, $\eta_Q = \beta_Q$ and T_i the number of quarters individual i is in the panel. Then the likelihood contribution of individual i is as follows:

$$
L_i = \int \prod_{t=1}^{T_i} f(E_{it}|z_{it,E}, \alpha_{i,E}; \eta_E) \cdot f(Q_{it}|z_{it,Q}, \alpha_{i,E}; \eta_Q)^{C_{it}} dG(\alpha_{i,E}, \alpha_{i,Q}) \tag{3}
$$

where $f(y_{it}) = \Phi(z_{it,y}\eta_y + \alpha_{i,y})^{y_{it}} \cdot (1 - \Phi(z_{it,y}\eta_y + \alpha_{i,y}))^{(1-y_{it})}$, $y \in \{E, Q\}$, $\Phi(\bullet)$ denotes the standard normal cumulative distribution function, C_{it} is a dummy equal to one if the individual is non–employed and has not yet completed a training program. As the individual specific effects are not directly observed one would have to integrate them out, as suggested in equation 3, in order to estimate the model. This could be done by simulating multivariate normal integrals. In this paper, however, we follow a different approach, which we describe in the following section.

3.2 MCMC Estimation of Random Effects Probit Models

We estimate the model presented in the previous section using Markov Chain Monte Carlo (MCMC) simulation methods, a technique from Bayesian statistics.[3] The idea 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

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

(Train, 2003). To obtain the sample from the posterior distribution we 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. A recent example of an economic application of a very much related (though more complex) model is Buchinsky, Fougère, Kramarz and Tchernis (2005). Details of the algorithm are given in Appendix C. We programmed the Gibbs sampler in Stata. Conjugate but very diffuse priors are used. The results reported below are based on running the algorithm for 20,000 iterations. We monitor convergence by comparing the means at different stages of the chains. We discarded the first 5,000 (the burn–in phase). Thus the results are based on 15,000 draws.

3.3 Estimation of the Average Treatment Effects on the Treated

To gain information on the average treatment effect on the treated (ATT) for each group, we simulate draws of the posterior distribution of these treatment effects. This is done in the following way for every 10th draw of the posterior distribution (after the burn–in phase):

1. For each participant simulate the employment outcome for each period starting with the first period after program participation. To do this go through the dynamic process and predict the employment status for each period based on the respective draw from the vector of coefficients $\eta_E' = (\beta_E, \gamma_E, \delta_E, \theta_E)'$, the individual characteristics $z_{it,E} = (E_{i(t-1)}, \ldots, E_{i(t-15)},\ Q_{i(t-1)}, \ldots, Q_{i(t-16)}, x_{it,E})$ (where variables involving lagged employment status are updated while going through the process), the respective draw of the $\alpha_{i,E}$ and an error term $\epsilon_{it,E}$ which is drawn from a standard normal distribution.

2. For each participant simulate the counterfactual employment outcome (i.e. the outcome if he had not participated in a program) for each period starting with the quarter of program start. Again go through the dynamic process and predict the employment status for each period based on the same η_E, $\alpha_{i,E}$ and $\epsilon_{it,E}$ as before but adapt the $z_{it,E}$ to a situation with no participation and

again update the $z_{it,E}$ while going through the process.

3. To get the ATT aligned to the end of the program, for each period starting with the first period after the end of program participation average the difference of the two predictions over all participants. This gives a draw of the posterior distribution of the ATT for each period.

4. To get the ATT aligned to the start of the program, for each period starting with the start of program participation average the difference of the two predictions over all participants.

The resulting 1,500 draws can be used to describe the posterior distribution of the ATT for example by giving the mean and the standard deviation.

4 Estimation Results

The detailed estimation results are listed in table 1 in Appendix A. The share of the variance on the individual level varies between 29% and 35% for the employment equation and between 32% and 38% for the qualification equation. The covariance between the random effects of both equations is negative for all groups. The Pearson correlation coefficient is -.177 for males in West Germany, -.040 for females in West Germany, -.202 for males in East Germany, and -.194 for females in East Germany. Thus the results suggest that those who have a higher unobserved propensity to participate in a program have a tendency to have a lower unobserved propensity to be employed. Note that the random effect of the participation equation relates to both entering a program and staying in the program.

Table 1 also depicts the means and standard deviations of the independent variables of both equations. The first (and in some cases second) lag of the qualification dummy has a negative effect on employment, the coefficients of the dummies for higher lags are strongly positive, both for the interaction with employment and non-employment in the quarter before. Thus the results suggest a positive effect of long-term training on the medium run and the long run both on starting employment as well as on staying in employment. Because of the dynamics of the model, it is difficult to get an impression of the size of the treatment effect; that is why we estimate the ATT based on these results.

— Table 3 about here —

— Table 4 about here —

Table 3 and 4 summarize the results for the estimation of the ATTs as described in section 3.3. The results shown in table 3 are aligned to the end of the program. For West German males the ATT is negative for the first quarter after participants have left the program. In the next quarter is turns positive. The results suggest an increasing ATT which is relatively stable a bit more than 8% from one and a half years after the end of the program until the end of the observation period. The ATT for females in West Germany is positive from the first quarter after the end of the program on and reaches a size of 11.0% to 12.8% after quarter 2. The results are similar for East German women, but the size of the effect is about 1 to 3 percentage points lower. For East German men it takes longest for the ATT to turn positive, but at the end of the observation period the ATT is even a bit higher for East German men than for West German men. Table 4 depicts the results aligned to the start of the program. Here we see a negative treatment effect (lock-in effect) which lasts for the first year since program start (and even for the first one and a half years for men in East Germany). Afterwards the effects turn positive, increase and finally reach roughly the same levels as the ATTS depicted in table 3.

5 Conclusion

This paper estimates the effects of long-term training on discrete time labor market transitions in Germany using a dynamic random effects probit model with an employment equation and a participation equation. The participation equation models the start of participation in long-term training as well as the possibly endogenous end of participation. We control for selection on unobservables by allowing the random effects of both equations to be correlated. The models are specified in a flexible way and account for various forms of effect hetergeneity. The equations are simultaneously estimated using Markov Chain Monte Carlo (MCMC) methods. Separate models are estimated for West and East Germany and for men and women. Interpretations of the means of the parameters is not straightforward because of the dynamic nature of the model. Therefore average treatment effects on the treated are estimated using a simulation strategy. First results suggest positive reemployment effects which evolve soon after the participants have left the program and continue until the end of our observation period two years later. Two years after the end of program participation the employment effect of the program lies in between 8% and 12%. In comparison to the literature, our results show more positive employment effects. This is consistent with the strong negative selection of treated individuals as estimated by our model.

The results of the MCMC estimation allow us not only to estimate the ATTs aligned to the end and the start of the program. We also use the MCMC simulations for providing an a posteriori estimate of estimation error. As the next steps of our analysis we are planning to estimate additional parameters of interest, like for example the effect of participating an additional quarter in the program or like the effect of participating in a program in a certain quarter after the inflow as opposed to later.

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Appendix A

Detailed Information on the Data

This study uses data from the IEBS Version 4.02. A German description of the IEBS Version 3.01 can be found in Zimmermann et al. (2007). Information in English can be found on the website of the Research Data Center of the Federal Employment Agency (http://fdz.iab.de/en.aspx). The website also describes the conditions under which researchers may obtain access to the IEBS.

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 and firm characteristics such as wage, industry or occupation.

The IAB Benefit Recipient History, the second data source, includes daily spells of unemployment benefit, unemployment 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. Furthermore, the information in the Employment and the Benefit Recipient History allows one to calculate the individual entitlement periods to unemployment benefits.[4]

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. It contains all the records starting January 2000 to June 2005 and partly also those beginning before 2000 if the person in question keeps the same client number throughout. The database includes a rich variety of information on personal characteristics (in particular education, family status and health condition), and information related to placement fields (e.g. qualification and experience in the target profession), regional information.

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, integration subsidies, business start–up allowances covering the period January 2000 to July 2005. Comparing the entries into different programs in 1999 with the figures for later years shows that information on programs starting in 1999 seems to be already complete for most active

[4]For the calculation of the claims, the present study relies on Plaßmann (2002) that contains a summary of the different regulations.

labor market programs. Furthermore, this database allows to distinguish subsidized employment in the context of active labor market policy from regular employment. Similar to the other sources, information comes in the form of spells indicating the start and end dates at the daily level, the type of the program as well as additional information on the program such as the planned end date or if the program ends with a certificate.

Appendix B

Detailed Estimation Results

Table 1: Estimation results

	Male West		Female West		Male East		Female West	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Employment equation:								
q[t-1]	-0.353	0.044	-0.216	0.050	-0.494	0.051	-0.269	0.071
q[t-2] if e[t-1]=1	-0.026	0.088	0.063	0.113	0.007	0.119	-0.145	0.168
q[t-3] if e[t-1]=1	0.189	0.077	0.340	0.098	0.109	0.102	0.188	0.150
q[t-4] if e[t-1]=1	0.309	0.070	0.324	0.083	0.371	0.091	0.264	0.137
q[t-5 6] if e[t-1]=1	0.214	0.056	0.213	0.065	0.103	0.070	0.256	0.106
q[t-7 8] if e[t-1]=1	0.239	0.054	0.221	0.060	0.307	0.067	0.383	0.095
q[t-9 10] if e[t-1]=1	0.283	0.059	0.296	0.064	0.323	0.068	0.151	0.096
q[t-11 12] if e[t-1]=1	0.332	0.063	0.309	0.065	0.249	0.073	0.311	0.104
q[t-13 16] if e[t-1]=1	0.415	0.067	0.279	0.069	0.338	0.084	0.212	0.115
q[t-2] if e[t-1]=0	0.367	0.045	0.351	0.052	0.288	0.055	0.170	0.078
q[t-3] if e[t-1]=0	0.207	0.049	0.320	0.054	0.145	0.057	0.173	0.082
q[t-4] if e[t-1]=0	0.278	0.048	0.323	0.056	0.199	0.058	0.265	0.077
q[t-5 or 6] if e[t-1]=0	0.043	0.046	0.200	0.053	0.084	0.052	0.209	0.068
q[t-7 or 8] if e[t-1]=0	0.117	0.050	0.259	0.058	0.245	0.054	0.187	0.074
q[t-9 or 10] if e[t-1]=0	0.138	0.053	0.121	0.064	0.229	0.061	0.139	0.082
q[t-11 or 12] if e[t-1]=0	0.152	0.062	0.165	0.072	0.164	0.075	0.215	0.097
q[t-13 or 16] if e[t-1]=0	0.233	0.072	0.231	0.078	0.094	0.093	0.282	0.115
e[t-1]	1.464	0.030	1.728	0.029	1.592	0.039	1.681	0.050
e[t-2]	-0.063	0.013	-0.062	0.019	-0.045	0.019	-0.105	0.031
e[t-3]	0.103	0.013	0.095	0.019	0.085	0.019	0.124	0.032
e[t-4]	0.574	0.014	0.525	0.020	0.422	0.019	0.553	0.033
e[t-5]	-0.291	0.015	-0.350	0.021	-0.185	0.021	-0.348	0.037

e[t-6]	-0.238	0.015	-0.238	0.022	-0.185	0.022	-0.469	0.039
e[t-7]	-0.063	0.015	0.008	0.023	-0.009	0.023	0.123	0.039
e[t-8]	0.350	0.016	0.297	0.023	0.273	0.023	0.404	0.040
e[t-9 or 10]	-0.260	0.017	-0.355	0.023	-0.183	0.025	-0.420	0.041
e[t-11 or 12]	-0.004	0.019	0.062	0.026	0.087	0.028	0.073	0.045
e[t-13 or 14 or 15]	-0.170	0.023	-0.212	0.030	-0.167	0.032	-0.211	0.054
t larger 1	0.185	0.019	0.196	0.024	0.205	0.026	0.261	0.042
t larger 2	-0.046	0.020	-0.039	0.025	-0.048	0.028	-0.016	0.042
t larger 3	-0.260	0.020	-0.160	0.026	-0.219	0.029	-0.250	0.044
t larger 4	0.253	0.021	0.158	0.027	0.233	0.029	0.230	0.046
t larger 5	0.085	0.022	0.087	0.028	0.039	0.030	0.119	0.048
t larger 6	0.017	0.023	0.009	0.028	-0.009	0.032	0.033	0.048
t larger 7	-0.141	0.022	-0.132	0.029	-0.109	0.032	-0.147	0.048
t larger 8	0.221	0.023	0.105	0.029	0.056	0.033	0.175	0.049
t larger 9	0.031	0.022	0.098	0.027	0.099	0.031	0.052	0.046
t larger 11	-0.026	0.020	0.001	0.025	-0.068	0.031	0.003	0.043
t larger 13	0.137	0.021	0.114	0.027	0.054	0.031	0.119	0.046
younger than 30	0.036	0.018	-0.091	0.024	-0.040	0.028	-0.083	0.049
30-34 years old	0.066	0.014	-0.134	0.019	0.038	0.020	-0.066	0.034
45-49 years old	-0.101	0.017	0.024	0.021	-0.100	0.021	-0.058	0.034
older than 50	-0.276	0.020	-0.078	0.024	-0.267	0.026	-0.234	0.041
no vocational degree	-0.116	0.014	-0.037	0.018	-0.078	0.028	-0.208	0.048
no schooling degree	-0.052	0.020	-0.153	0.032	-0.182	0.040	-0.075	0.076
high school (Abitur)	-0.026	0.021	0.022	0.022	0.047	0.033	-0.037	0.041
last job: assisting workers	-0.013	0.015	0.024	0.028	-0.043	0.020	-0.084	0.046
last job: jobs in service	-0.027	0.024	0.072	0.025	-0.025	0.040	-0.051	0.042
last job: office or business job	0.020	0.024	0.074	0.028	-0.122	0.041	-0.030	0.047
last job: technician or related	0.007	0.024	0.046	0.031	-0.072	0.039	0.035	0.053
last job: academic or managers	-0.070	0.030	0.077	0.033	-0.158	0.044	0.031	0.056
last job: whitecollar job	0.045	0.021	-0.005	0.022	-0.004	0.034	0.039	0.036
last job: seasonal worker	0.059	0.021	0.066	0.025	0.071	0.029	0.109	0.039
last job: parttime worker	-0.004	0.024	-0.017	0.020	-0.095	0.040	0.065	0.035
region with bad conditions	-0.015	0.063	0.075	0.088	-0.507	0.047	-0.953	0.077
urban region high unempl.	-0.130	0.020	-0.054	0.027	-0.622	0.050	-0.946	0.081
health problems	-1.265	0.024	-1.113	0.033	-1.106	0.040	-1.258	0.068
at least one child	0.050	0.013	0.201	0.017	-0.069	0.017	-0.023	0.028
unempl. rate in community	-0.004	0.002	-0.002	0.003	-0.005	0.002	0.004	0.004

wage quartile last job if e[t-1]=0	0.079	0.007	0.001	0.008	0.076	0.010	0.002	0.015
wage quartile last job if e[t-1]=1	0.089	0.008	0.053	0.009	0.042	0.011	0.066	0.018
winter (first quarter)	0.037	0.015	0.028	0.018	-0.095	0.021	-0.011	0.032
spring (second quarter)	0.460	0.013	0.198	0.016	0.427	0.019	0.255	0.028
summer (third quarter)	0.339	0.012	0.108	0.014	0.369	0.017	0.169	0.025
year 99 or 2000	0.515	0.056	0.270	0.071	0.293	0.080	0.111	0.125
year 2001	0.358	0.045	0.216	0.057	0.207	0.064	0.101	0.101
year 2002	0.180	0.033	0.138	0.041	0.071	0.047	0.029	0.073
year 2003	0.159	0.021	0.079	0.026	0.112	0.030	0.011	0.046
elapsed unempl.duration	-0.001	$7e^{-5}$	-0.001	$9e^{-5}$	-0.001	$1e^{-4}$	-0.001	$2e^{-4}$
elapsed unempl. duration sq.	$3e^{-7}$	$6e^{-8}$	$5e^{-7}$	$7e^{-8}$	$5e^{-7}$	$9e^{-8}$	$3e^{-7}$	$1e^{-8}$
constant	-1.569	0.070	-1.492	0.088	-0.821	0.105	-0.718	0.163
Qualification equation:								
enough planned duration left	2.925	0.085	3.097	0.108	3.055	0.114	3.251	0.143
months until planend	0.001	$4e^{-4}$	0.002	0.001	0.001	$4e^{-4}$	0.002	0.001
not enough planned duration left	-0.116	0.097	-0.112	0.129	-0.467	0.125	-0.595	0.127
planned end missing	2.134	0.148	1.437	0.201	2.522	0.287	1.679	0.412
elaps. partic. if plan end missing	$8e^{-5}$	0.001	0.001	0.001	-0.003	0.001	-0.001	0.003
inflowquarter	0.026	0.047	0.017	0.051	-0.229	0.064	-0.207	0.082
elapsed unempl. duration	0.001	$2e^{-4}$	$-3e^{-4}$	$2e^{-4}$	0.001	$2e^{-4}$	0.001	$3e^{-4}$
elapsed unemp. duration sq.	$-1e^{-6}$	$1e^{-7}$	$7e^{-8}$	$1e^{-7}$	$-1e^{-6}$	$2e^{-7}$	$8e^{-7}$	$2e^{-7}$
days inflow to end quarter if t=0	-0.010	0.001	-0.010	0.001	-0.010	0.001	-0.010	0.002
repeated inflow	-0.030	0.044	0.052	0.064	0.037	0.061	-0.047	0.093
winter (first quarter)	0.220	0.034	0.316	0.037	0.257	0.042	0.366	0.056
spring (second quarter)	0.146	0.033	0.194	0.037	0.205	0.042	0.424	0.052
summer (third quarter)	0.135	0.032	0.173	0.034	0.152	0.041	0.240	0.052
year 99 or 2000	0.525	0.113	0.651	0.131	0.694	0.158	0.426	0.207
year 2001	0.343	0.101	0.442	0.116	0.632	0.147	0.470	0.189
year 2002	0.307	0.095	0.285	0.103	0.595	0.137	0.417	0.171
year 2003	0.081	0.095	0.080	0.097	0.224	0.134	-0.014	0.168
younger than 30	0.036	0.044	-0.183	0.053	0.012	0.060	-0.040	0.079
30-34 years old	-0.022	0.037	-0.154	0.044	-0.034	0.051	-0.021	0.064
40-44 years old	0.020	0.038	0.088	0.044	-0.028	0.053	0.101	0.060
45-49 years old	-0.064	0.044	0.056	0.048	-0.070	0.054	0.011	0.067
older than 50	-0.258	0.048	-0.235	0.059	-0.183	0.060	-0.043	0.071
no schooling degree	0.016	0.045	-0.298	0.079	-0.190	0.089	-0.331	0.140
high school (Abitur)	0.262	0.039	0.041	0.039	0.204	0.061	0.063	0.058

no vocational degree	-0.028	0.030	-0.057	0.039	-0.117	0.058	-0.144	0.074
last job: office or business jobs	0.194	0.048	0.326	0.041	0.131	0.080	0.129	0.054
last job: technician or related	0.228	0.050	0.043	0.049	0.153	0.072	0.165	0.070
last job: whitecollar job	0.111	0.040	0.114	0.044	0.183	0.059	0.280	0.061
last job: seasonal worker	-0.263	0.053	-0.111	0.061	-0.290	0.076	-0.250	0.078
last job: parttime worker	0.000	0.056	-0.039	0.042	-0.137	0.095	0.061	0.058
health problems	0.154	0.043	0.213	0.051	-0.039	0.068	0.043	0.087
at least one child	0.152	0.031	0.200	0.036	0.189	0.039	0.287	0.047
entitled to unemp. compensation	0.219	0.047	0.110	0.060	0.129	0.064	0.336	0.090
constant	-3.320	0.148	-3.349	0.194	-3.308	0.202	-3.555	0.256
Individual level variances:								
individual level variance e-equ.	0.397	0.017	0.514	0.028	0.329	0.022	0.547	0.048
individual level variance q-equ.	0.467	0.062	0.605	0.111	0.567	0.096	0.499	0.074
individual level covariance	-0.076	0.020	-0.022	0.029	-0.087	0.029	-0.101	0.039
share on individual level, e equ.	0.284	0.009	0.339	0.012	0.248	0.012	0.353	0.020
share on individual level, q equ.	0.317	0.029	0.374	0.043	0.360	0.039	0.331	0.033
correlation between equations	-0.053	0.014	-0.014	0.019	-0.060	0.019	-0.066	0.025
correl. between random effects	-0.177	0.046	-0.040	0.053	-0.202	0.063	-0.194	0.072

Appendix C

Algorithm for the MCMC Estimation

- Set starting values for the coefficient vectors η_E and η_Q, the individual specific effects ($\alpha_{i,E}$, $\alpha_{i,Q}$) 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 $E_{it} = 0$. $\mathcal{N}(\bullet)$ denotes the normal distribution.

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

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

- Step 3a: Sample the η_E vector from its multivariate normal conditional posterior distribution $\mathcal{N}(M_E, V_E)$, where $M_E = V_E(B^{-1}_{E,0} b_{E,0} + \sum_{i=1}^{N} \sum_{t=1}^{T_{i,E}} z'_{it,E}(E^*_{it,E} - \alpha_{i,E}))$ and $V_E = (B^{-1}_{E,0} + \sum_{i=1}^{N} \sum_{t=1}^{T_{i,E}} z'_{it,E} z_{it,E})^{-1}$. N is the number of persons in the data. The prior distribution of the η_E vector is given by $\mathcal{N}(b_{E,0}, B_{E,0})$.

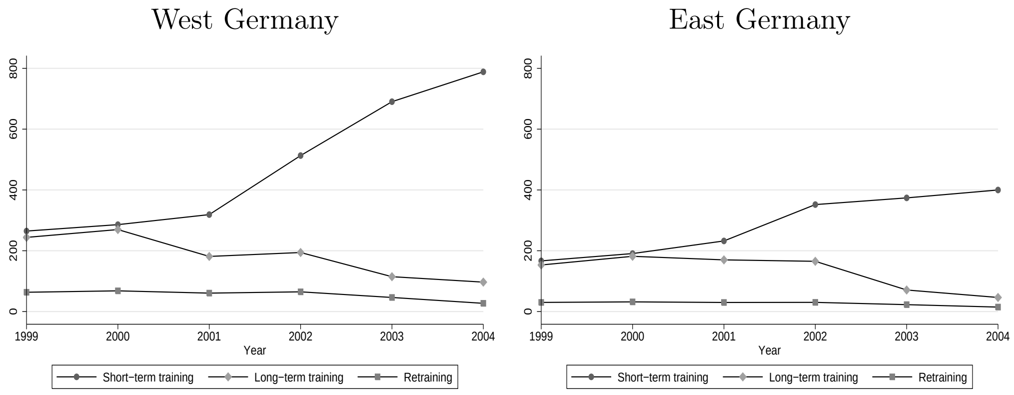
- Step 3b: If the training equation is to be estimated, sample the η_Q vector from its multivariate normal conditional posterior distribution $\mathcal{N}(M_Q, V_Q)$, where $M_Q = V_Q(B^{-1}_{Q,0} b_{Q,0} + \sum_{i=1}^{N} \sum_{t=1}^{T_{i,Q}} x'_{Q,it}(Q^*_{Q,it} - \alpha_{i,Q}))$ and $V_Q = (B^{-1}_{Q,0} + \sum_{i=1}^{N} \sum_{t=1}^{T_{i,Q}} z'_{it,Q} z_{it,Q})^{-1}$. The prior distribution of the η_Q vector is given by $\mathcal{N}(b_{Q,0}, B_{Q,0})$.

- Sample Σ^{-1} from its conditional posterior distribution $\mathcal{W}^{-1}\left(\begin{pmatrix} \sum\limits_{i=1}^{N} \alpha^2_{i,E} & \sum\limits_{i=1}^{N} \alpha_{i,E}\alpha_{i,Q} \\ \sum\limits_{i=1}^{N} \alpha_{i,E}\alpha_{i,Q} & \sum\limits_{i=1}^{N} \alpha^2_{i,Q} \end{pmatrix} + H_0,\; N + h_0 \right)$. $\mathcal{W}^{-1}$ denotes the inverse Wishart distribution. The prior distribution of Σ^{-1} is given by $\mathcal{W}^{-1}(H_0, h_0)$.

- Go to Step 1. Always use current values.

Figures

Figure 1: Entries into training programs in West and East Germany (in 1000)



Source: BA (2001, 2005); own calculations.

Tables

Table 2: Descriptive Statistics

	Male, West	Female, West	Male, East	Female, East
Individuals	16,317	12,328	8,737	4,869
Quarters per Person	16.7	17.5	14.8	15.2
Quarters Employed p. P.	6.9	6.1	5.8	4.7
Quarters Unemployed p. P.	9.8	11.4	9.0	10.5
Quarters in Training p. P.	0.28	0.32	0.46	0.57
Employment Spells p. P.	1.31	0.92	1.15	0.81
Unemployment Spells p. P.	2.00	1.61	1.87	1.55
Training Spells p. P.	0.12	0.13	0.17	0.19

Table 3: ATT aligned to end of program

	Male West		Female West		Male East		Female East	
t_after*	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	-0.028	0.015	0.024	0.017	-0.084	0.019	0.008	0.019
2	0.017	0.014	0.072	0.016	-0.024	0.018	0.046	0.019
3	0.053	0.015	0.113	0.018	0.024	0.018	0.076	0.020
4	0.064	0.014	0.117	0.017	0.050	0.017	0.091	0.019
5	0.073	0.013	0.120	0.016	0.057	0.016	0.100	0.018
6	0.087	0.013	0.128	0.016	0.080	0.017	0.114	0.019
7	0.086	0.013	0.120	0.016	0.100	0.016	0.106	0.019
8	0.083	0.015	0.115	0.017	0.115	0.018	0.104	0.020
9	0.087	0.014	0.110	0.016	0.111	0.018	0.094	0.019

*t_after: quarter after participants have left the program.

Table 4: ATT aligned to start of program

	Male West		Female West		Male East		Female East	
t_start**	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	-0.134	0.008	-0.109	0.008	-0.139	0.010	-0.086	0.010
2	-0.137	0.011	-0.110	0.012	-0.168	0.014	-0.081	0.013
3	-0.128	0.012	-0.104	0.014	-0.154	0.015	-0.073	0.015
4	-0.066	0.014	-0.032	0.016	-0.104	0.017	-0.043	0.017
5	0.004	0.014	0.049	0.016	-0.061	0.018	0.005	0.018
6	0.039	0.014	0.101	0.017	-0.012	0.018	0.047	0.019
7	0.051	0.014	0.108	0.017	0.018	0.017	0.073	0.019
8	0.076	0.014	0.122	0.016	0.063	0.017	0.101	0.019
9	0.079	0.014	0.120	0.016	0.073	0.017	0.104	0.019
10	0.089	0.014	0.126	0.017	0.099	0.017	0.106	0.019

**t_start: quarter from start of program on.