The Heterogeneous Effects of Training Incidence and Duration on Labor Market Transitions

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Contribution

- Develop approach to identify causal effects of dynamic assignment to treatment and dynamic decision to continue treatment in a discrete time competing risks framework accounting for selection both on observables and unobservables
- Fully model intermediate outcomes
- Based on Bayesian MCMC estimation, suggest how to estimate standard static treatment effects by simulating model along MCMC iterations and how to do inference
- Use unique administrative data to estimate the effect of Training Incidence and Duration on labor market transitions in discrete time

Preview of Results

- Implement dynamic approach that accounts for dynamic assignment of training and dynamic decision to continue training (dropout) in discrete time until and beyond planned duration.
- Identificaton of treatment effects relies on sequential randomization, no-anticipation, and support conditions conditional on observables and unobservables
- Availability of planned duration is key
- Significantly positive treatment effects on employment after the lock-in period (size in some cases larger than in the literature)
- Unobservables play an important role in understanding employment and treatment dynamics which explains the differences in results compared to the literature using static or dynamic selection on observables strategy (matching estimation) in discrete time (Lechner/Wunsch 2008; Biewen, Fitzenberger, Paul, Osikominu 2014, JOLE)
- Participants benefit from being assigned to longer programs

1. Motivation

- Public sector sponsored training important part of active labor market policy
  In 2003 total spending € 21.0 billion, Training € 5 billion
- Activation Strategy (OECD) suggested shortening program participation
- Using static or dynamic selection on observables strategy (matching estimation) in discrete time, assessment of employment differs strongly in the literature
- Robins (1997): Sequential randomization (CIA) in discrete time, estimate causal effects on transition rates using selection on observables and conditioning on history
- Eberwein, Ham, Lalonde (1997): Randomization at baseline and time-varying covariates/instruments identify causal effect on transition rates accounting for unobservables
- Timing-of-events approach of Abbring/van den Berg (2004): identification [relying on instantaneous change in hazard rate at treatment start] does not extend to discrete time data
- Heckman/Navarro (2007): Selection on unobservables and discrete time transitions, IV strategy requiring strong support conditions

- Impact heterogeneity by training duration received little attention so far (some papers use selection on observables strategy, e.g. Kluve, Schneider, Uhlendorff, Zhao 2007)
- Decision to continue training or to drop out depends upon success of job search

Modelling Training and Employment

- Job seeker: two competing risks, job or training.
- **Dynamic decision to continue or drop out while on program:** Encouraged to take job offer even during training. Not possible to be employed and take part in training at the same time!
- End of participation endogenous: 20% dropouts (see Waller, 2009) and some cases with prolonged participation.
- We know planned and actual duration of program duration (fairly unique feature of German admin data)

2. Evaluation Framework and Estimation

- Eberwein, Ham, and LaLonde (1997, EHL), Ham and LaLonde (1996): Treatment effect on transitions between unemployment and employment, dynamics selection on unobservables, randomization into treatment eligibility at a certain point of time does not allow for a selection on observables strategy
  Parametric Maximum likelihood estimates involving unobserved heterogeneity, randomization and time-varying covariates used as instruments.
  Not explicit about identification in a dynamic treatment setting.

- Robins (1997, RO), Fredriksson and Johansson (2008, FJ)

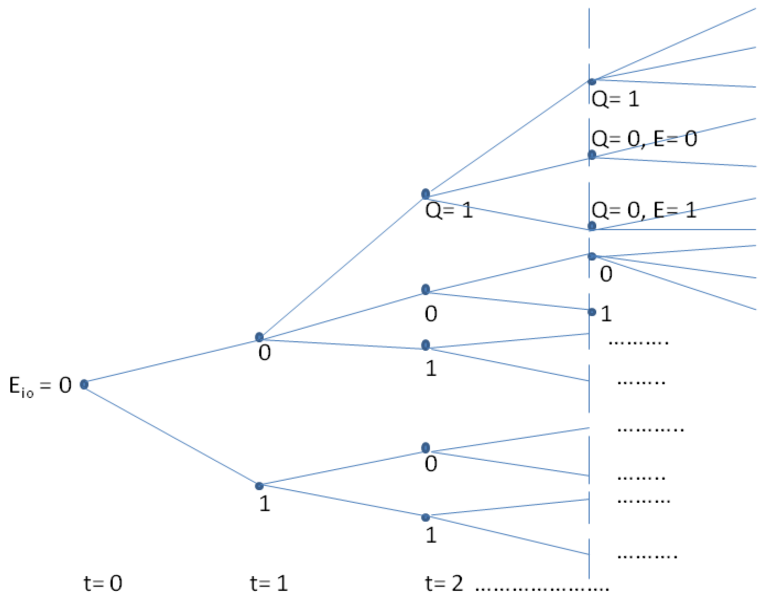
  RO's approach involves ...
  - no-anticipation assumption
  - sequential randomization assumption regarding the start or the continuation of a treatment sequence conditional on history of treatments, outcomes, covariates
  - support condition at each node in time

  RO: Reconstruct Effects on Outcomes via G-Computation Formula in dynamic setting
  FJ: Period-to-period Effects on hazard rates feed into Kaplan-Meier-type estimates

Our extensions:

- account for unobserved heterogeneity
- fully model intermediate outcomes (in contrast to Lechner 2009)
- identify effects on transition rates based on a selection on observables and unobservables strategy
- estimation of the static average effect of treatment on the treated

Identification Strategy



Estimate transition probabilities in t by path up to time t

Complete Evaluation Framework

- Reconstruct period-to-period path-dependent employment effects
- RO: G-computation formula uses sequential randomization to identify transition probability at t between unemployment and employment in counterfactual treatment regime under common support of treatment sequences
- Our strategy is to align indidviduals by time path in employment outcomes since $t = 0$ and condition on both x-variables, and unobserved heterogeneity
  $\rightarrow$ Sequential randomization as in RO conditional on observables, (un)employment history, and unobservables
  $\rightarrow$ Identify effects on discrete-time hazard rates in and out of employment constrasting treated and controls with the same observables and the same employment history (intermediate outcomes)
- Estimation is helped by time-varying covariates (Heckman and Navarro, 2007) - but insufficient support of variation

Implementation

- Two flexible dynamic probit equations with bivariate normally distributed random effects $\alpha_{i,E}$ and $\alpha_{i,Q}$: Large number of parameters (188 coefficients and (co-)variances plus random effects)
- Employment: flexible function of lagged training incidence and duration, lagged employment, elapsed duration, # quarters since inflow, observed covariates
- Participation in Training: flexible function of lagged training, elapsed duration, # quarters since inflow, observed covariates

Formally ...

Employment E_t, Training participation Q_t

Treatment Sequence $q = (0, ..., 1, ..., 1, 0, ...0)$ where $q(t) = 1$ if $q_a \leq t \leq q_b$ $q(t) = 0$ otherwise for $t = 1, ..., T$

Latent Variables

(1) $$\begin{array}{ll} E_t^* = \psi_E(t, \boldsymbol{x}_t, Q^{t-1}, E_i^{t-1}) + \alpha_E + \epsilon_{E,t} & \\ Q_t^* = \psi_Q(t, \boldsymbol{x}_t, Q^{t-1}) + \alpha_Q + \epsilon_{Q,t} & \text{if } E_t = 0 \text{ and } \{Q^{t-1} = \mathbf{0} \text{ or } Q_{t-1} = 1\} \end{array}$$

Potential Outcomes $E_t^*(q)$

(2) $$E_t^*(q) = \psi_E(t, \boldsymbol{x}_t, q^{t-1}, E^{t-1}(q)) + \alpha_E + \epsilon_{E,t}$$

where q^{t-1} denotes the first $t-1$ components $(q_1, ..., q_{t-1})$

Our adaptation of RO's assumptions ...

No-anticipation Condition (NAC):

$$E_t^*(q) = E_t^*(q') \quad \text{if} \qquad q^t = (q')^t \qquad .$$

Sequential Randomization Condition 1 (SRC.1):

$$Q_t \coprod [E_{t+1}^*(q), ..., E_T^*(q)] \mid E^t, Q^{t-1} = q^{t-1}, x^t, \alpha_E, \alpha_Q, \text{ and}$$

$$P_t \coprod [E_{t+1}^*(q), ..., E_T^*(q)] \mid E^t, Q^{t-1} = q^{t-1}, x^t, \alpha_E, \alpha_Q \quad \text{if} \quad Q^{t-1} = \mathbf{0} \text{ and } Q_t = 1\,,$$

where P_t is planned duration of a treatment sequence started in t

Sequential Randomization Condition 2 (SRC.2):

$$Q_t \coprod [\tilde{x}_{t+1}, ..., \tilde{x}_T] \mid E^t, Q^{t-1} = q^{t-1}, x^t, \alpha_E, \alpha_Q \,.$$

Support Condition (SC): $0 < P(Q_t = 1 | E_{t-1} = 0, Q^{t-1} = q^{t-1}, x^t, \alpha_E, \alpha_Q) < 1$, provided that $q^{t-1} = \mathbf{0}$ or $q^{t-1} = (0, ..., 0, 1, ..., 1)$

SRC.2 ensures (assumes) that we model all 'endogenous' intermediate outcomes.

Framework allows us to reconstruct period-to-period path-dependent employment effects

G-Computation Formula for Employment in $t + k$ conditional on employment sequence up to $t - 1$:

$$
(3) \qquad P(E_{t+k}(q') = 1 | E^t = e^t, Q = q, x^{t+k}, \alpha_E, \alpha_Q)
$$

$$
= \sum_{e' \,:\, e'(t+k)=1 \text{ and } e'^{,t}=e^t} \Pi_{l=1}^{k} P(E_{t+l} = e'(t+1) | E^{t+l-1} = e'^{,t+l-1}, Q = q', x^{t+1}, \alpha_E, \alpha_Q),
$$

Bayesian MCMC estimation (Chib 2001)

- Use of likelihood function for recursive MCMC iterations: Posterior distribution is **stationary distribution** of implied **Markov chain**.
- **Gibbs Sampler**
- Numerically robust
- Probit Model: Albert and Chib (1993): simulate latent dependent variables from truncated distributions (data augmentation).
- Random effects: data augmentation for the random effects (Zeger and Karim, 1991).
- Posterior distribution of random effects yielding best predictors / analysis of selectivity

Simulation of Treatment Effects of interest

- Raw coefficient estimates are difficult to interpret because of complex dynamic structure of the model involving many interaction effects.
- Treatment parameters of interest: Draws from the posterior distribution of these treatment effects based on the sequence of MCMC iterations: After program start, predict monthly employment recursively. Counterfactual: training switched off.
- To account for selection based on unobservables, we use the draws of the individual random effects from the MCMC estimation of the model.
- In contrast to the literature: Our estimates of the Treatment Effects account for the selection of the treated wrt unobservables
- Extends upon the literature which typically uses the estimated unconditional distribution of the individual specific effects to estimate static average treatment effects of interest based on dynamic models with unobserved heterogeneity (e.g. Ham, Li, X., and L. Shore-Sheppard 2010).

3. Data: Panel Data Set for the Analysis

Integrated Employment Biographies Sample (IEBS)

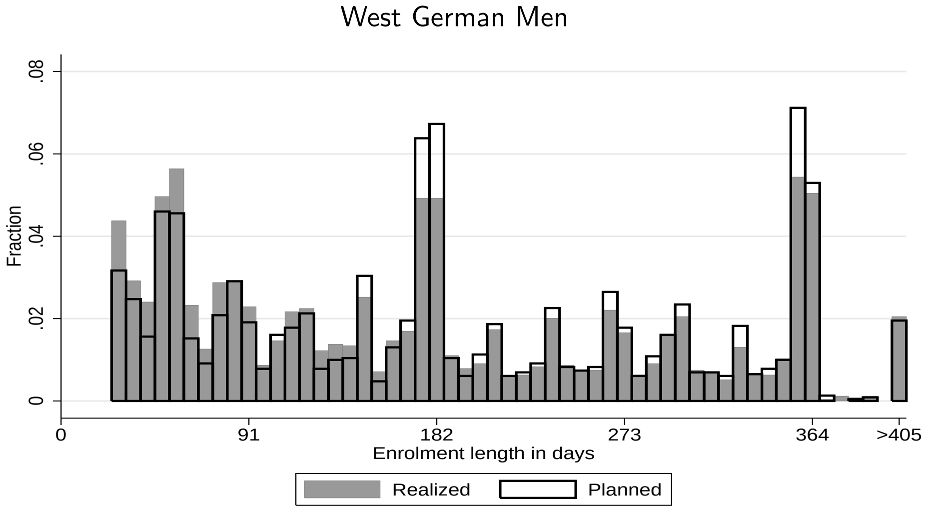
- Large and rich data set for evaluation of German ALMP.
- 2.2% random sample of individuals drawn from four administrative data sources
  - Employment register 1990–2004: Register data on employment based on social security records (daily records)
  - LH: Transfer payments by Federal Labor Office to unemployed/participants in training programs (daily records)
  - Data file on Participants in ALMP (Maßnahmeteilnehmergrunddatei, MTG): 2000–2005
  - Data file on job applicants and job searchers (Bewerberangebotsdatei und Arbeitssuchendendatei, Bewa)
- Know planned and actual length of training programs

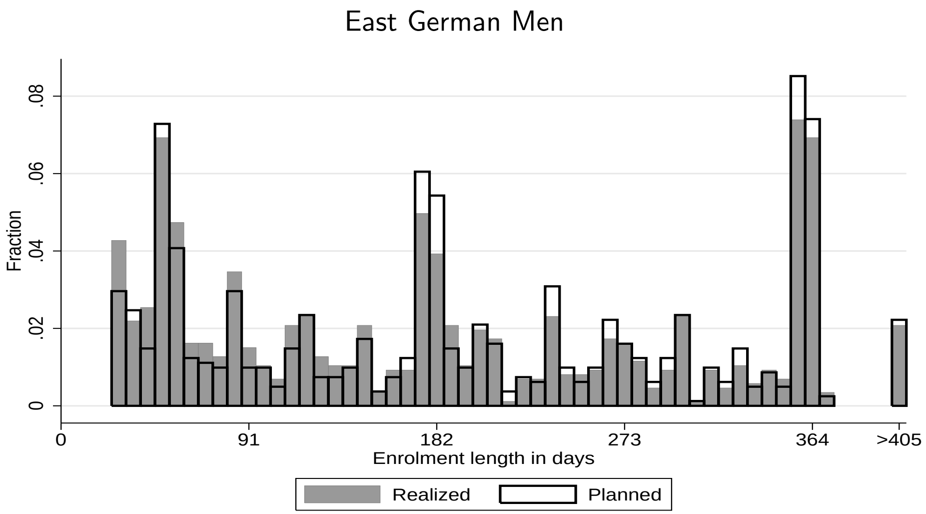
Sample for Empirical Analysis

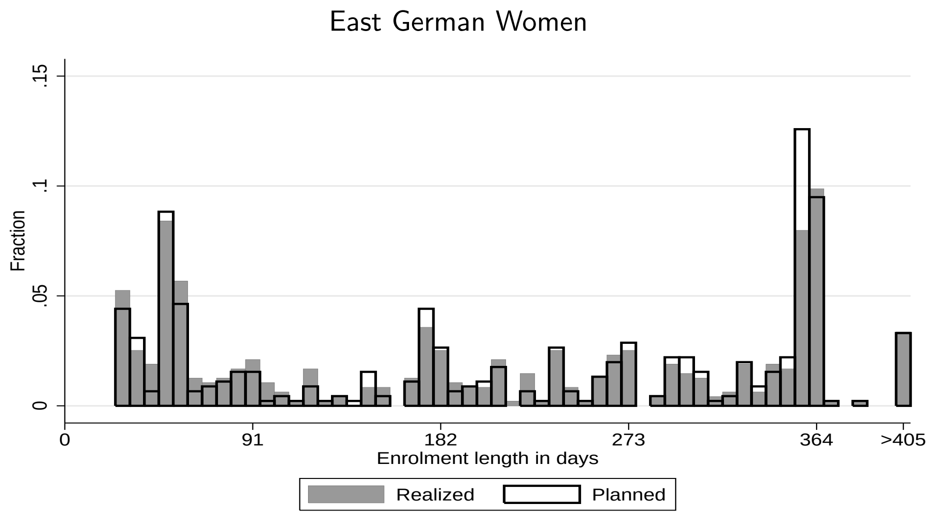
- Inflow sample into unemployment between 7/1999 and 12/2000, age 25 to 53 at entry; after continuous employment of > 124 days.
- Separate analysis by gender and region (East/West)
- Evaluate effect of first long-term training program.
- Construct employment dummy, training dummy and covariates for each month until end of 2004.

	Male, West	Female, West	Male, East	Female, East
Individuals	17,475	12,610	9,207	4,961
Employment Spells p. P.	1.49	1.10	1.32	0.90
Unemployment Spells p. P.	2.13	1.74	2.02	1.61
Training Spells p. P.	0.11	0.13	0.17	0.19

Planned and Realized Training Durations





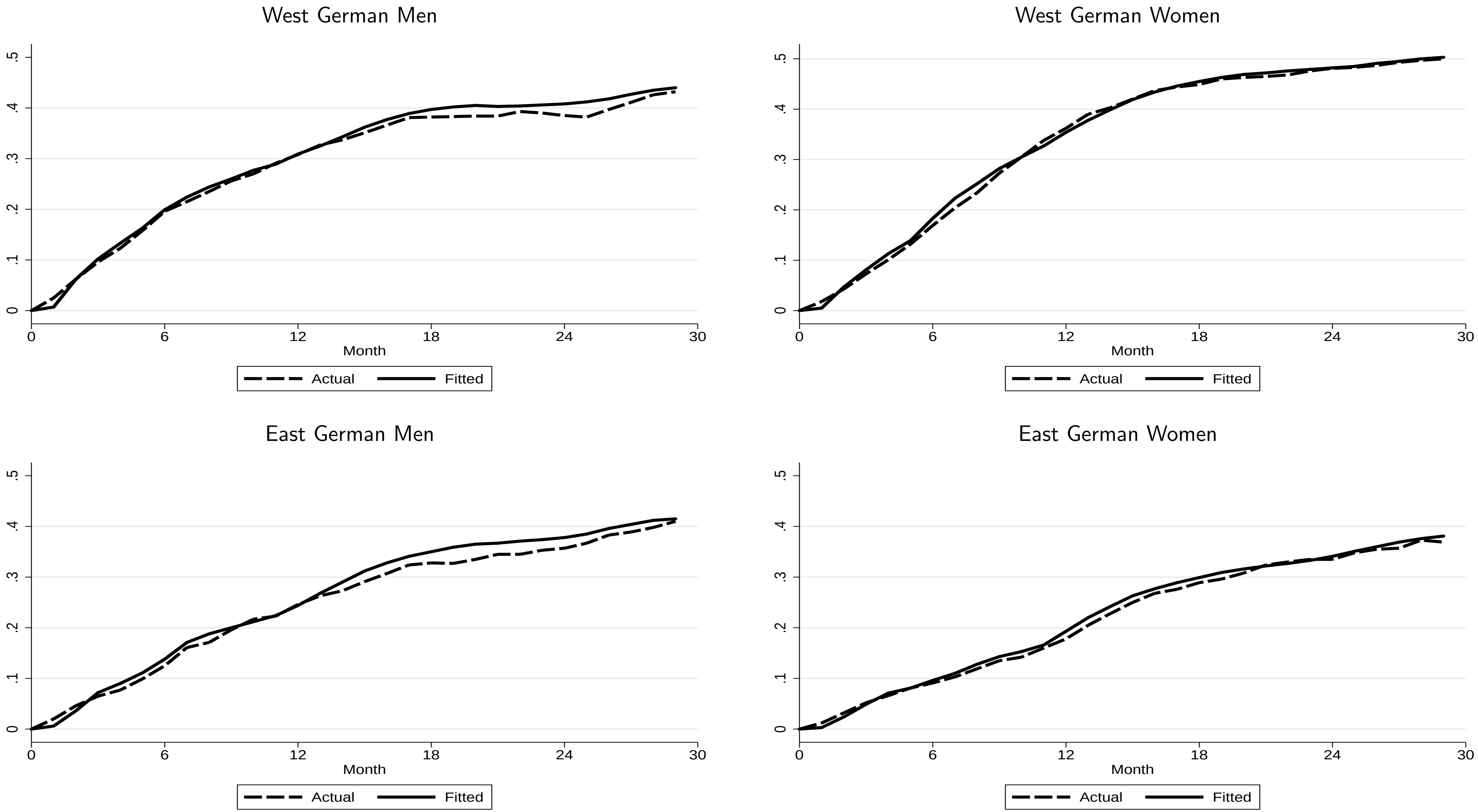


4. Empirical Results

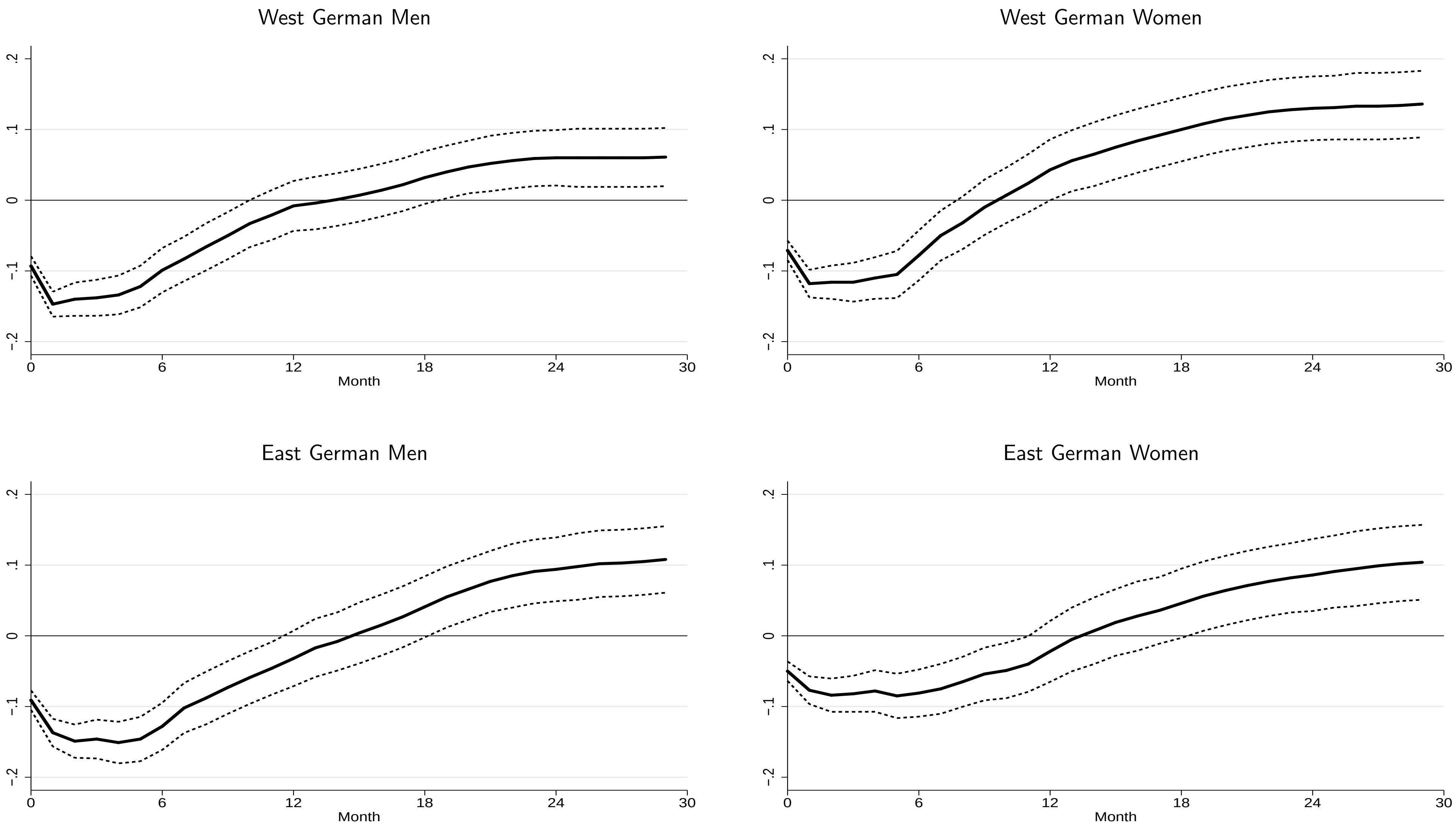
Variances and Correlation

Variable	Males		Females	
	Mean	SD	Mean	SD
West				
$\mathrm{Var}(\alpha_E)/(\mathrm{Var}(\alpha_E)+1)$	0.202	0.008	0.249	0.011
$\mathrm{Var}(\alpha_Q)/(\mathrm{Var}(\alpha_Q)+1)$	0.169	0.024	0.240	0.030
$\mathrm{Corr}(\alpha_E,\, \alpha_Q)$	0.008	0.059	0.031	0.062
East				
$\mathrm{Var}(\alpha_E)/(\mathrm{Var}(\alpha_E)+1)$	0.187	0.011	0.314	0.020
$\mathrm{Var}(\alpha_Q)/(\mathrm{Var}(\alpha_Q)+1)$	0.112	0.022	0.046	0.011
$\mathrm{Corr}(\alpha_E,\, \alpha_Q)$	-0.042	0.085	0.024	0.127

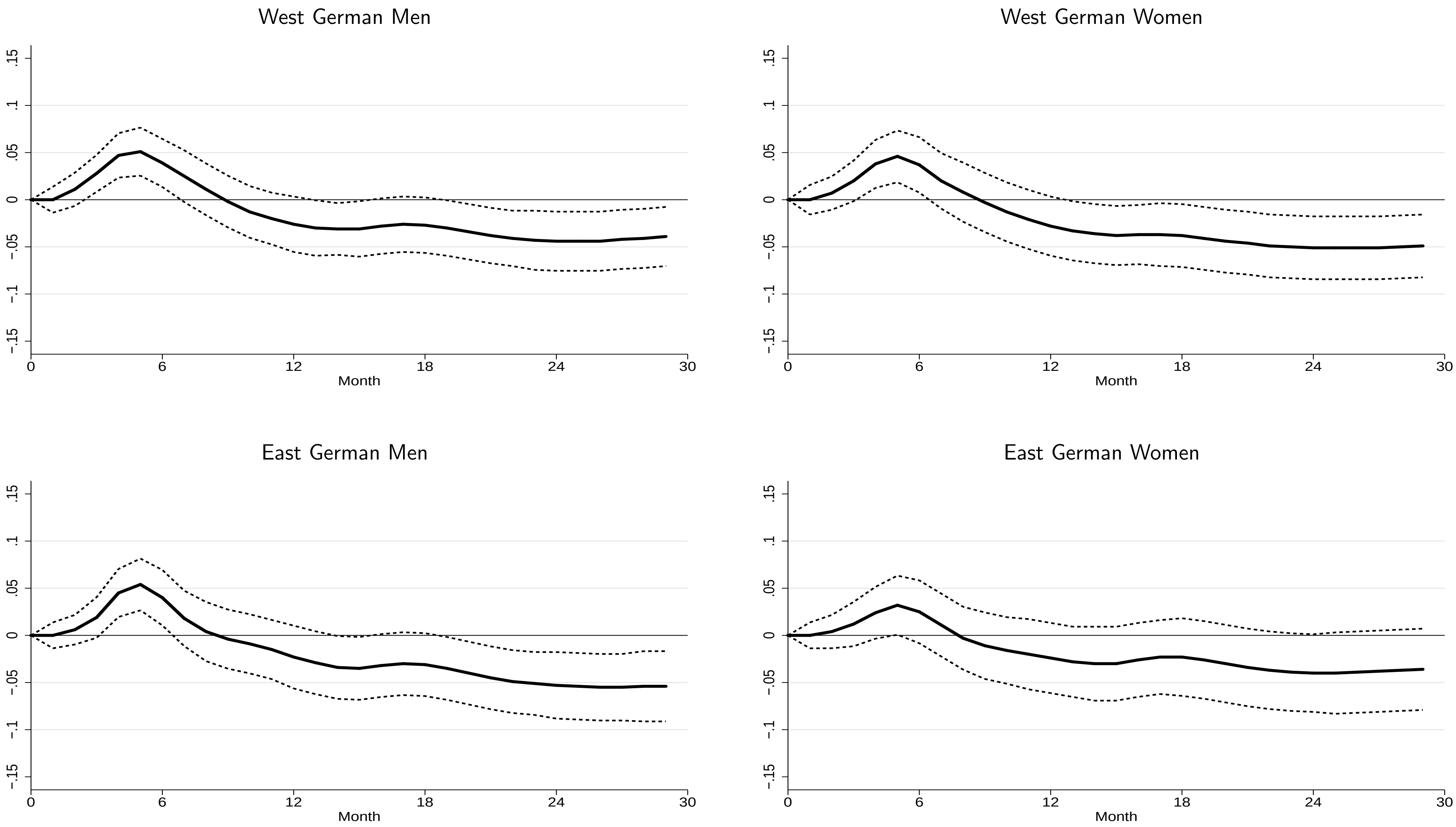
Fitted Employment Rates



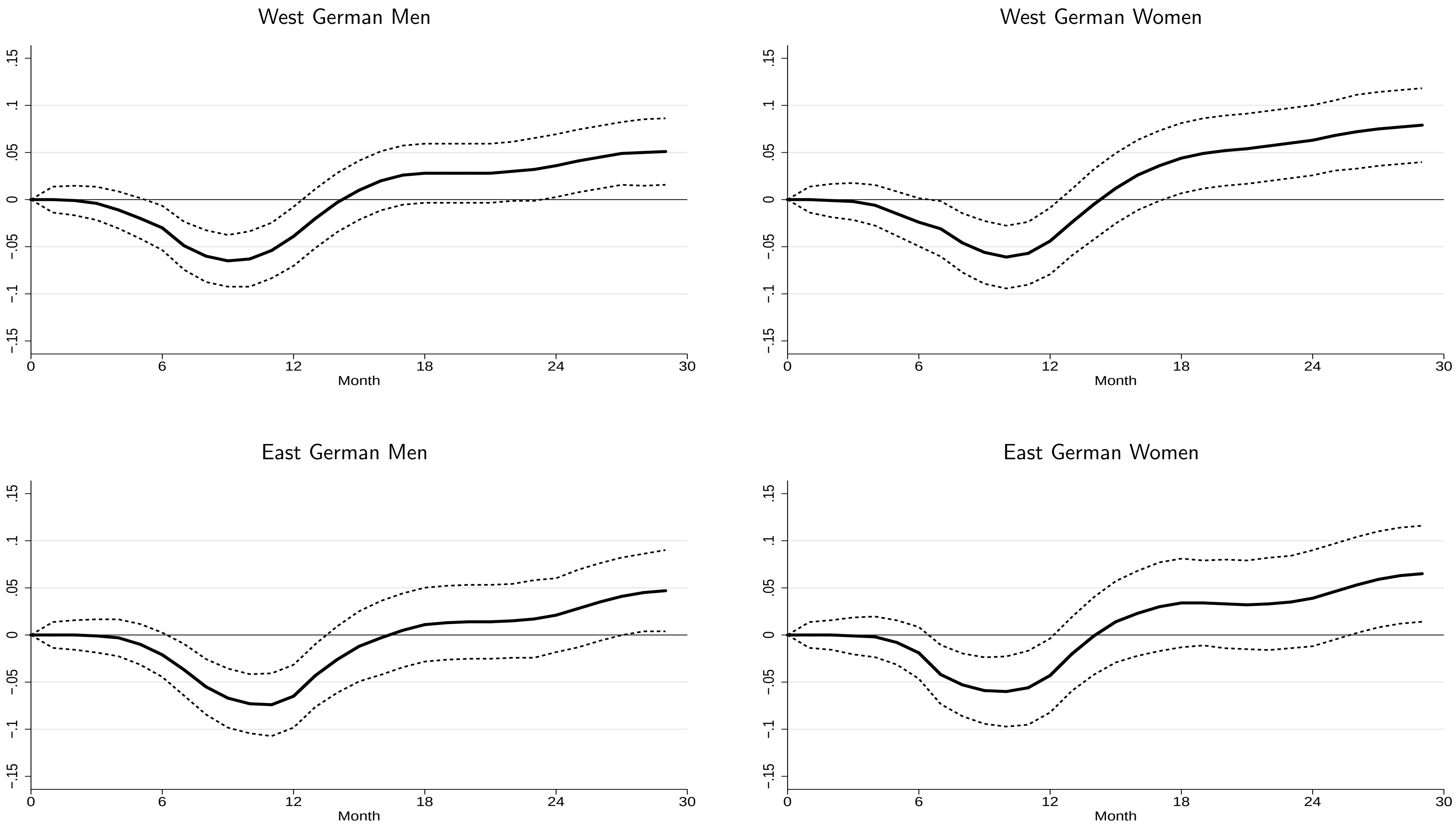
Classical ATT: Training versus No Training



ATT of Attending a Program Scheduled for 3 vs 6 Months



ATT of Attending a Program Scheduled for 12 vs 6 Months



5. Conclusions

- Develop framework for identification of treatment effects on transition rates in discrete time conditioning on observables and unobservables building on Robins (1997)
- Account for dynamic assignment of training / dynamic decision to continue training.
- Bayesian MCMC techniques enable to account for selection on both observables and unobservables in a very flexible (semiparametric) way
- Treatment effects of interest: simulation based on model parameter estimates along MCMC iterations accounting for selection

- **Methodological extensions affect results compared to the literature**:
  - Significantly positive treatment effects on employment in the medium run
  - Two years after program start, the average effect of treatment on unconditional employment rates for the treated individuals lies between six and thirteen ppoints (even for East Germany)

- **Methodological extensions allow for new results**:
  - Positive effect from being assigned to longer programs: 6 versus 3 months of planned duration result in four to five ppoints higher employment probability in the medium run
  - Positive treatment effects work mainly thru higher stability of employment (not shown)

BACKUP SLIDES

3. Evaluation Framework and Estimation

- Eberwein, Ham, and LaLonde (1997, EHL), Ham and LaLonde (1996): Treatment effect on transitions between unemployment and employment, dynamics selection on unobservables, randomization into treatment eligibility at a certain point of time does not allow for a selection on observables strategy
  Parametric Maximum likelihood estimates involving unobserved heterogeneity, randomization and time-varying covariates used as instruments.
  Not explicit about identification in a dynamic treatment setting.

- Robins (1997, RO), Fredriksson and Johansson (2008, FJ) [survey in Abbring and Heckman (2007, section 3.2, AH)]
  Dynamic sequential randomization based on observables sequences of treatment, outcome, time varying covariates allows for a dynamic sequential strategy to account for selection on observables
  RO: Reconstruct Effects on Outcomes via G-Computation Formula in dynamic setting
  FJ: Period-to-period Effects on hazard rates feed into Kaplan-Meier-type estimates

- Account for unobserved heterogeneity as in Abbring and van den Berg (2003, AvdB) and Heckman and Navarro (2007, HN)
  Do not rely on identification result of AvdB in continuous time (non-anticipation up to moment of treatment) and on availability of time-varying instruments as in HN (stringent support conditions not satisfied)

Identification Strategy is Semiparametric

- Mild functional form assumptions, rich set of observed covariates and great flexibility in specification. Allow also for heterogeneity of treatment effects.

Algorithm for MCMC Estimation

Priors: $\boldsymbol{\eta}_E \sim \mathcal{N}(b_{E,0}, B_{E,0})$, $\boldsymbol{\eta}_Q \sim \mathcal{N}(b_{Q,0}, B_{Q,0})$
$\rightarrow$ large values for the variances $B_{E,0}, B_{Q,0}$: extremely diffuse priors
$(\alpha_{i,E},\, \alpha_{i,Q}) \sim \mathcal{N}(\mathbf{0}, \Sigma)$ and $\Sigma^{-1} \sim \mathcal{W}^{-1}(H_0, h_0)$, where H_0 is the inverse scale matrix, h_0 denotes the degrees of freedom and $\mathcal{W}^{-1}$ the inverse Wishart distribution.
$\rightarrow$ diffuse prior: choose a small value for h_0

- Step 0: Set starting values for the coefficient vectors $\boldsymbol{\eta}_E$ and $\boldsymbol{\eta}_Q$, the random effects $(\alpha_{i,E},\, \alpha_{i,Q})$, and the variance covariance matrix of the random effects Σ.
- Step 1a: Sample E^*_{it} from $\mathcal{N}(\boldsymbol{z}_{it,E}\boldsymbol{\eta}_E + \alpha_{i,E}, 1)$ with support $[0, \infty]$ if $E_{it} = 1$ and with support $[-\infty, 0]$ if $E_{it} = 0$.
- Step 1b: Sample Q^*_{it} from $\mathcal{N}(\boldsymbol{z}_{it,Q}\boldsymbol{\eta}_Q + \alpha_{i,Q}, 1)$ with support $[0, \infty]$ if $Q_{it} = 1$ and with support $[-\infty, 0]$ if $Q_{it} = 0$ (provided the training equation is to be estimated).

- Step 2: Sample $(\alpha_{i,E},\ \alpha_{i,Q})'$ from its bivariate normal conditional posterior distribution $\mathcal{N}(\boldsymbol{\mu}, V_{\alpha_i})$, where
$\boldsymbol{\mu} = V_{\alpha_i} \cdot \begin{pmatrix} T_{i,E} & 0 \\ 0 & T_{i,Q} \end{pmatrix} \cdot \begin{pmatrix} (\bar{E}_i^* - \bar{\boldsymbol{z}}_{i,E}\boldsymbol{\eta}_E) \\ (\bar{Q}_i^* - \bar{\boldsymbol{z}}_{i,Q}\boldsymbol{\eta}_Q) \end{pmatrix}$ 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.

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

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

- Step 4: Sample Σ^{-1} from its conditional posterior distribution

$$\mathcal{W}^{-1}\left(\begin{pmatrix} \sum_{i=1}^{N} \alpha_{i,E}^2 & \sum_{i=1}^{N} \alpha_{i,E}\alpha_{i,Q} \\ \sum_{i=1}^{N} \alpha_{i,E}\alpha_{i,Q} & \sum_{i=1}^{N} \alpha_{i,Q}^2 \end{pmatrix} + H_0,\ N + h_0\right).$$

Go to Step 1. Always use the current parameter values.

Integrate out distribution of unobserved heterogeneity to reconstruct treatment effects of interest

$ATT_1(\theta)$: Average Effect of Treatment Incidence on the Treated

assignment of treatment start plus planned duration, simulate actual duration

$$\widehat{ATT_1}(\theta) = \sum_{i:q_i \neq \mathbf{0}, p_i} [\widehat{Pr}(E_{q_{a,i}+\theta}(Q_i) = 1 | Q_{a,i} = q_{a,i}, P = p_i) - \widehat{Pr}(E_{q_{a,i}+\theta}(\mathbf{0}) = 1 | Q_{a,i} = q_{a,i})],$$

for period $\theta = 0, 1, \ldots$ since the start of the treatment, where

$$\widehat{Pr}(E_{q_{a,i}+\theta}(Q_i) = 1 | Q_{a,i} = q_{a,i}, P = p_i)$$

$$= \int \widehat{Pr}(E_{q_{a,i}+\theta}(Q_i) = 1 | Q_{a,i} = q_{a,i}, \tilde{x}^{q_{a,i}+\theta}, P = p_i, \alpha_E, \alpha_Q) \, d\hat{F}_i(\alpha_E, \alpha_Q)$$

and

$$\widehat{Pr}(E_{q_{a,i}+\theta}(\mathbf{0}) = 1 | Q_i = q_i)$$

$$= \int \widehat{Pr}(E_{q_{a,i}+\theta}(\mathbf{0}) = 1 | Q_{a,i} = q_{a,i}, \tilde{x}^{q_{a,i}+\theta}, P = p_i, \alpha_E, \alpha_Q) \, d\hat{F}_i(\alpha_E, \alpha_Q)$$

$ATT_2(\theta, p, p')$: Average Effect of Treatment Incidence assigning $P = p$ versus Incidence assigning $P = p'$ on the Treated:

$$ATT_2(\theta, p, p') = \mathrm{E}_{Q \neq \mathbf{0}}\{[E_{Q_a+\theta}(Q'(p)) - E_{Q_a+\theta}(Q'(p'))]|Q\}$$

$$\widehat{ATT_2}(\theta, p, p') = \sum_{i:q_i \neq \mathbf{0}} [\widehat{Pr}(E_{q_{a,i}+\theta}(q_{a,i}, p) = 1|Q_i = q_i) - \widehat{Pr}(E_{q_{a,i}+\theta}(q_{a,i}, p') = 1|Q_i = q_i)],$$

where

$$\widehat{Pr}(E_{q_{a,i}+\theta}(q_{a,i}, \tilde{p}) = 1|Q_i = q_i) =$$
$$\int \widehat{Pr}(E_{q_{a,i}+\theta}(Q(\tilde{p})) = 1|Q_{a,i} = q_{a,i}, \tilde{x}^{q_{a,i}+\theta}, P = \tilde{p}, \alpha_E, \alpha_Q)\, d\hat{F}_i(\alpha_E, \alpha_Q)\ .$$

Our approach extends upon the literature which typically uses the estimated unconditional distribution of the individual specific effects to estimate static average treatment effects of interest based on dynamic models with unobserved heterogeneity (e.g. Ham, Li, X., and L. Shore-Sheppard 2010).

Sensitivity Analysis: Does it make a difference?

Classical ATT Aligned to Program Start *(MCMC estimates)*

	Male West		Female West		Male East		Female East	
$t-s$	Mean	SD	Mean	SD	Mean	SD	Mean	SD
6	-0.122	0.015	-0.105	0.017	-0.146	0.016	-0.085	0.016
12	-0.021	0.018	0.024	0.021	-0.046	0.019	-0.040	0.020
18	0.022	0.019	0.092	0.023	0.027	0.022	0.036	0.024
24	0.059	0.020	0.128	0.023	0.091	0.023	0.082	0.025
30	0.061	0.021	0.136	0.024	0.108	0.024	0.104	0.027

Classical ATT Aligned to Program Start *(Simple Specification and Pooled Probit)*

	Male West		Female West		Male East		Female East	
$t-s$	Mean	SD	Mean	SD	Mean	SD	Mean	SD
6	-0.181	0.012	-0.123	0.012	-0.194	0.013	-0.125	0.016
12	-0.120	0.015	-0.051	0.016	-0.139	0.014	-0.108	0.018
18	-0.055	0.017	0.010	0.018	-0.066	0.017	-0.055	0.020
24	-0.023	0.018	0.045	0.019	-0.025	0.016	-0.025	0.024
30	-0.006	0.020	0.069	0.019	-0.003	0.020	-0.005	0.027

Detailed Estimation Results

Differences Between Treated and Untreated in Transition Rates out of Non-Employment (conditional on non–employment 'observed' in previous quarter)

$t - t_s$	Male West Mean	Male West SD	Female West Mean	Female West SD	Male East Mean	Male East SD	Female East Mean	Female East SD
0	-0.134	0.009	-0.106	0.009	-0.139	0.010	-0.073	0.010
1	-0.058	0.010	-0.034	0.010	-0.083	0.011	-0.027	0.010
2	0.011	0.009	0.026	0.010	-0.016	0.010	-0.006	0.009
3	0.039	0.008	0.071	0.009	0.009	0.009	0.013	0.008
4	0.049	0.009	0.089	0.010	0.002	0.010	0.040	0.010
5	0.023	0.009	0.064	0.011	0.028	0.011	0.034	0.011
6	0.017	0.010	0.043	0.011	0.027	0.011	0.038	0.012
7	0.013	0.009	0.034	0.011	0.023	0.010	0.031	0.011
8	0.012	0.009	0.035	0.011	0.024	0.011	0.034	0.013
9	0.006	0.010	0.028	0.011	0.029	0.013	0.028	0.013

Differences Between Treated and Untreated in Transition Rates out of Employment (conditional on employment 'observed' in previous quarter)

	Male West		Female West		Male East		Female East	
$t - t_s$	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2	-0.085	0.037	-0.089	0.040	-0.125	0.052	-0.170	0.073
3	-0.072	0.028	-0.095	0.028	-0.106	0.038	-0.143	0.059
4	-0.048	0.024	-0.071	0.025	-0.074	0.031	-0.096	0.049
5	-0.056	0.020	-0.058	0.021	-0.073	0.026	-0.095	0.041
6	-0.073	0.019	-0.058	0.020	-0.091	0.025	-0.101	0.039
7	-0.088	0.019	-0.066	0.020	-0.106	0.026	-0.107	0.036
8	-0.091	0.020	-0.068	0.020	-0.103	0.025	-0.099	0.036
9	-0.085	0.019	-0.062	0.019	-0.092	0.025	-0.091	0.034

$\rightarrow$ **Suggests that Treatment effects work mainly thru higher stability of employment**