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Sonderforschungsbereich 386, Paper 211 (2000)

Online unter: http://epub.ub.uni-muenchen.de/

Semiparametric Bayesian Time-Space Analysis of Unemployment Duration

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Summary

In this paper, we analyze unemployment duration in Germany with official data from the German Federal Employment Office for the years 1980-1995. Conventional hazard rate models for leaving unemployment cannot cope with simultaneous and flexible fitting of duration dependence, nonlinear covariate effects, trend and seasonal calendar time components and a large number of regional effects. We apply a semiparametric hierarchical Bayesian modelling approach that is suitable for time-space analysis of unemployment duration by simultaneously including and estimating effects of several time scales, regional variation and further covariates. Inference is fully Bayesian and uses recent Markov chain Monte Carlo techniques.

JEL classification: C11, C41 and J64

Keywords: MCMC, Semiparametric Bayesian Inference, Smoothness priors

1 Introduction

The analysis of unemployment duration presented in this paper is based on data from the IAB employment subsample, a sample from administrative data from the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung) at the German Federal Employment Office (Bundesanstalt für Arbeit). For each individual in the sample, the data provide information about the calendar start and end of unemployment spells during the years 1980-1995, the district where the individual worked prior to unemployment, and a number of personal characteristics like age, gender, nationality, education or vocational training, and periods for which a claimant receives unemployment benefits. Most unemployment studies focus on the impact of these characteristics on unemployment duration, neglecting effects of calendar time and regional heterogeneity at all or considering them only a nuisance. Given the detailed calendar time and highly disaggregated regional information of the IAB sample, our goal is a careful time-space analysis of unemployment duration. So we want to investigate temporal and small-scale regional effects jointly with the impact of other covariates. Careful incorporation and estimation of temporal and spatial effects into duration models is not only of interest in itself, it is also necessary to prevent biases in estimating the effect of personal characteristics, previous employment status, unemployment benefits, etc.

Let us provide some reasons for flexibly modelling temporal and spatial effects on unemployment duration. Looking at the development of the registered unemployment in West Germany between 1980 and 1995, the seasonal and cyclical patterns of unemployment are immediately noticeable (Figure 1). In the recessions of 1981/82 and 1992/93 unemployment in West Germany strongly increased. Although there was a long upturn after 1982, unemployment remained on a high level. In addition to the general trend, typical seasonal patterns can be seen. The number of unemployed men has a pronounced yearly peak in December. A small rise of the unemployed male population appears in the summer months. For women there is not such a great peak during the winter months, so that the "summer high" is just as pronounced as the "winter high".

The transitions from unemployment into work also depend on cyclical and seasonal effects (Schmidt, 1999). The outflow rates from unemployment are plotted against time in Figure 2. During the two recessions the fluctuation out of unemployment decreases. For males there is an absolute seasonal peak in spring and a smaller one in autumn. For females we also observe seasonal peaks in autumn and in spring, but only the peak in spring is nearly as large as for men. The seasonal pattern of the transitions out of unemployment is hence inverse to that for the stocks in Figure 1.

The monthly stock of persons receiving unemployment benefits shows similar temporal behaviour. Consequently, trend and seasonal effects of calendar time have to be adequately incorporated into duration models of unemployment.

Regional differences in unemployment rates and durations are a well known fact, too. In West Germany there are some regions with sunset industries (e.g., the Saar and the Ruhr area), that are characterised by considerable structural adjustment. As a general trend for West Germany, a so-called north-south divide exists, with particularly low unemployment rates for Bavaria and Baden-Württemberg. In addition to this overall pattern, there are further local spatial effects in special regions, often caused by high or low economic activity due to concentration effects. Firms of the same region are specialized in the same industry and use the advantages of a joint regional labor-force pool, the availability of intermediate products, the technological spill-over effects and the easy transfer of information by personal contacts. Though regional aspects of the labor market are investigated by various authors (for example, Möller, 1995, Börsch-Supan, 1990), regional effects have not been adequately included in unemployment duration models. Apart from methodological problems, a main reason has also been the lack of available small-scale regional information in many unemployment data sets such as the German Socio-economic Panel (GSOEP). In contrast, our IAB employment sample includes identifiers for small regional units. Therefore, we develop a model that allows to incorporate spatial effects on durations of unemployment where correlations among regions are considered appropriately.

Typical methodological questions that arise in such a study are: How can we include and estimate trends and seasonal components of calendar time in duration models without imposing too restrictive and rigid parametric forms, instead allowing the same flexibility as with modern semiparametric methods for Gaussian time series data such as state space modelling, local regression or spline smoothing? Can calendar time effects and duration time effects be analyzed jointly, that is how can multiple time scales be incorporated? Are there nonlinear effects of metrical covariates, for example age? How can we include regional effects of districts or labor market regions and account for spatial correlation with neighbouring districts? It is obvious that complex models are needed for simultaneously analyzing these questions.

Traditional parametric duration models are not flexible enough for exploring and answering these questions. Without any rather informative prior knowledge about specific forms of nonlinear or spatial effects, a very large number of parameters has to be introduced, making estimation either very unreliable or even impossible due to divergence or nonexistence of estimates. In this situation, non- or semiparametric approaches that do not assume certain parametric forms of various nonlinear, temporal and spatial effects, are needed. More parsimonious parametric forms may then be postulated in a second step.

In this paper, we use a semiparametric Bayesian method that allows a unified treatment of multiple time scales, linear and nonlinear effects of covariates and of spatially correlated random effects. It has been developed in the context of generalized additive mixed regression models in Fahrmeir and Lang (2001a, b) and Lang and Brezger (2001). Since unemployment duration is measured in months, we choose discrete-time duration models. In this paper we model only the transition of leaving unemployment for full-time employment. The approach is an extension of dynamic discrete-time duration models developed in Fahrmeir and Wagenpfeil (1996) and Fahrmeir and Knorr-Held (1997) to models with multiple time scales and unstructured or spatial random effects. Inference is done through recent Markov chain Monte Carlo simulations. We prefer this Bayesian method to more conventional semiparametric methods like spline smoothing via penalized likelihood (Hastie and Tibshirani, 1990) or local regression (Fan and Gijbels, 1996) for the following reasons:

(i) In contrast to the latter methods, spatial effects can be conveniently modelled and estimated using Markov random field priors.

(ii) Estimation of unknown smoothing parameters is automatically incorporated.

(iii) No approximations based on asymptotic normality assumptions or conjectures have to be made.

(iv) MCMC simulation techniques provide a rich output for flexible and sophisticated inference based on posterior samples.

(v) Predictive distributions can be computed without "plug in" methods.

After some descriptive statistics and preliminary exploratory data analysis in Section 2, we apply the Bayesian semiparametric method outlined in Section 3 for a space-time analysis of unemployment duration in West Germany from 1980-1995. The analyses are carried out separately for men and women since they show different behaviour on the labor market under several aspects. The results provide some new and refined insights compared to previous studies. In particular, effects of time and space can be investigated more thoroughly.

2 Descriptive and exploratory examination of the data

2.1 The IAB employment sample

Our analysis is based on official register data from the German Federal Labor Office, the so-called IAB employment subsample. It covers the years 1975 to 1995. A detailed description of the IAB employment subsample can be found in Bender et al. (2000). The sample contains data of one percent of all employees registered by the social insurance system within the given period of 21 years. Supplementary information on establishments and on unemployment periods in which a claimant received benefits is added to the sample. This version contains exact daily employment history of persons as recorded by the social insurance system and on periods of benefit receipt (unemployment benefit, unemployment assistance and maintenance or subsistence allowance). The basis of the IAB employment subsample is the integrated notifying procedure for health insurance, statutory pension scheme and unemployment insurance. The procedure requires that employers report all information of their employees registered by the social security system to the social security agencies. Hence, the data set allows to reproduce employment careers without the typical problems of longitudinal surveys arising in social research (e.g. panel mortality, memory gaps). Compared to unemployment spell data from the GSOEP, the data set covers a longer observation period and is much larger. Moreover, recordings on duration and calendar time of unemployment spells are more reliable, since they are not based on retrospective interviews. Thus, no heaping should arise (Kraus and Steiner 1998).

The IAB employment subsample includes workers, salaried employees and all trainees, as long as they are not exempt from the obligation to pay social insurance contributions. The characteristics sex, year of birth, nationality, marital status, number of children and qualifications, are collected for each employee recorded by social insurance. The data on employment contains information on the occupational code, the occupational status, the gross earnings, an establishment number issued by the Employment Service, the industry and the size of the establishment. In the annual averages, the IAB employment subsample includes about 200000 people in Western Germany.

The IAB employment subsample is usually only available in an anonymised version. One of the anonymisation procedures is a shift of the complete employment history of each person on the calendar time axis. This may destroy the seasonal pattern, so we use the original version of the data set. Small-scale regional information is given by the district where employed persons works, but is only available in the original version, too.

2.2 The sample of unemployment benefit recipients

Our analysis will be based on a subsample of unemployment benefit recipients of West Germany excluding West-Berlin from 1980 to 1995. Only the transition from unemployment to full-time employment will be analyzed. Men and women are always considered separately, since different behaviour on the labor market has to be expected. Only persons receiving benefits are included.

We now state some basic facts about the German unemployment benefits scheme needed later. It distinguishes between unemployment insurance benefit and unemployment assistance. To be eligible for unemployment insurance benefit, the applicant must have contributed for at least 12 months over the preceding three years to the unemployment insurance scheme. Unemployment insurance benefits can be received for up to 32 months (since July 1987), with the duration of the entitlement period depending on age and the length of contributions to the scheme. If unemployment insurance benefit is exhausted, or if the employee is not eligible for unemployment insurance benefit, he can claim unemployment assistance, which are means-tested. More details on the German compensation scheme can be found in Zimmermann (1993).

Table 1 shows absolute and relative frequencies of men and women, and of the numbers of unemployment periods and registrations, stratified by gender. Unemployment periods are defined by beginning and end of unemployment. Since additional registration of certain events like change of unemployment benefits can occur within a period, the number of registrations is higher than the number of periods. We note that there are about 59% male and 41% female registrations in the data set, and about 58% and 42% unemployment periods of men and women, respectively. The number of spells is lower than the number of people in the sample, since some people became unemployed for several times over the observation period.

Figures 3 and 4 display the age distribution of unemployment registrations for each gender, separately. The figures on the left display these distribution without weighting for the duration of unemployment. The distribution peaks for both men and women in their early/mid 20s and then decreases considerably until their late 30s. Each age cohort between 40 and 55 years makes up for a low percentage (somewhat less than 2 percent) of the sample. For age cohorts of people aged 55 to 60 years this proportion is not much higher. It becomes extremely low for cohorts above the age of 60. However, these distributions did not reflect the duration of unemployment. So let us see how much the age cohorts contribute to the sample in terms of spell length. We display the age distribution of the registrations weighted by their unemployment duration on the right-hand side of the Figures 3 and 4. Both for men and women these distributions differ a lot from the unweighted distributions: Men in their mid 20s now contribute much less to the sample, since their spell lengths are relatively short, while men aged 55 to 60 make up for a much larger share as they face particularly long unemployment spells. The weighted age distribution of women differs in a similar way from the unweighted one, though the differences are less pronounced.

This is in agreement with mean duration of unemployment periods classified by gender and age groups in Table 2. It becomes obvious that the younger ones, although more often unemployed, leave unemployment or change jobs significantly faster, while older unemployed have problems of finding a new job or perhaps rely on financial support from employers or the social security system and wait for early retirement.

Table 3 contains the percentages of unemployment spells cross-classified by gender and nationality. The share of foreigners is about 12% for men and 10% for women.

Figure 5 shows the distribution of the two categories of unemployment benefits for men and women. A small share of men and women receive unemployment assistance, while roughly 80 percent receive unemployment insurance. The latter share is higher for women than for men, while the opposite is true for the share of unemployment assistance recipients. This could be explained by the fact that women are more inclined to become a housewife after a period of unemployment with support from unemployment insurance.

Figure 6 displays the mean duration of unemployment for men and women in the federal states of West Germany. The horizontal straight line marks the overall mean. This indicates heterogeneity, which will be analyzed in more detail in Section 4. For males, lower mean durations in Bavaria (BAY), Baden-Württemberg (BW) and Rheinland-Pfalz (RLP) and higher mean durations in Saarland (SAL), Nordrhein-Westfalen (NRW), Bremen (BRE) and Hamburg (HAM) seem to be consistent with the so called north-south divide. For females, however, this regional heterogeneity pattern is less pronounced.

Similarly Figure 7 displays the average duration of unemployment for different sectors of the economy. Particularly striking is the low mean duration for the agricultural sector and for construction (for men only), probably caused by a large share of seasonally unemployed workers. There are also obvious differences between men and women in the sectors energy (including water supply and mining), construction and social service. Again, duration of unemployment by sector varies less for women than for men.

A first exploratory data analysis using STATA was carried out with a parametric probit model for the probability of leaving unemployment. The effects of duration time and age were modelled as smooth functions by cubic regression splines with two carefully selected knots, while calendar time was included in categorized form with a fixed seasonal pattern. Covariates like nationality, unemployment benefits etc. entered the model in effect coding. Figure 8 gives a first impression of the effects of duration time and age. While the effect of duration of the current unemployment spell looks rather similar for men and women, age effects show some difference but reflect the descriptive finding described before quite well.

Though simple parametric models are useful for a first analysis, specification of more complex models including unknown functional forms of duration time, calendar time and spatial effects as well as other continuous covariates like age is usually difficult if not impossible. Already for the simple probit model above, fitting of nonlinear effects of duration time and age requires a careful choice for the number and location of knots. With only a small number of knots, location of the knots has great influence on the fitted functional form. For the fitted curves in Figures 7 and 8, knots where chosen as quantiles to assure that about the same number of observations lies in each of the intervals defined by the knots. With more nonlinear functions, like trend and seasonal component of calendar time, and with the inclusion of effects of different sectors of the economy and a large number of spatially correlated effects of countries or districts, such a "fixed effects" parametric approach is not feasible. The next section describes a flexible semiparametric Bayesian approach for data analysis with more complex models.

3 Semiparametric Bayesian modelling and estimation of discrete-time duration models

3.1 Observation model

Since duration of unemployment as well as calendar time are measured in months, we use a discrete-time duration model, as described for example in Fahrmeir and Tutz (2001, Ch.9). Let the discrete duration time $D \in \{1, \ldots, d, \ldots\}$ denote the end of duration in month d after beginning of unemployment. In addition to duration D, a sequence of possibly time-varying covariate vectors $x_d = (x_{d1}, \ldots, x_{dk})$ is observed. Let $x_d^* = (x_1, \ldots, x_d)$ denote the history of covariates up to month d. Then the discrete hazard function is given by

$$\lambda(d, x_d^*) = P(D = d | D \geq d, x_d^*), \qquad d = 1, 2, \ldots,$$

that is the conditional probability for the end of duration being in interval d, given the interval is reached and given the history of covariates.

In economic terms, the hazard may be regarded a reduced form of the neoclassical job search model (Kiefer, 1988). It represents the product of the probability that an unemployed person receives a job offer (arrival rate, α) and the probability that this person accepts it. The latter is the probability that the offered wage (w) exceeds the individuals reservation wage (w^r)

$$\lambda(d, x_d^*) = \alpha(1 - F(w^r))$$

where $F(w)$ represents the distribution function of the wage offers.

For a sample of individuals i, $i = 1, \ldots, n$, let D_i denote duration times and C_i right censoring times. Duration data are usually given by $(d_i, \delta_i, x^*_{id_i})$, $i = 1, \ldots, n$, where $d_i = \min(D_i, C_i)$ is the observed discrete duration time, $\delta_i = 1$ if $D_i < C_i$, $\delta_i = 0$ else, is the censoring indicator, and $x^*_{id_i} = (x_{id},\ d = 1, \ldots, d_i)$ is the covariate sequence. We assume that censoring is noninformative and occurs at the end of the interval, so that the risk set R_d includes all individuals who are censored in the interval d.

We define binary event indicators y_{id}, $i \in R_d$, $d = 1, \ldots, d_i$, by

$$y_{id} = \begin{cases} 1 & \text{if } d = d_i \text{ and } \delta_i = 1 \\ 0 & \text{else.} \end{cases}$$

For $i \in R_d$, the hazard function for individual i can then be modeled by binary response models

$$pr(y_{id} = 1 | x^*_{id}) = h(\eta_{id}), \tag{1}$$

with appropriate predictor η_{id} and response function $h : R \to (0, 1)$. In other words, we model the conditional probability of leaving unemployment, given current duration d of unemployment in months, calendar time t, the region where the unemployed worked before, and other, possibly time-varying covariates. Common choices for binary response models are the grouped Cox model and probit or logit models. We prefer a probit model, because in this case the binary response model (1) can be written equivalently in terms of latent Gaussian utilities

$$U_{id} = \eta_{id} + \epsilon_{id}$$

with Gaussian errors $\epsilon_{id} \sim N(0, 1)$. Following the principle of random utility, $y_{id} = 1$ is equivalent to $U_{id} > 0$ and $y_{id} = 0$ is equivalent to $U_{id} < 0$. We will see below that the formulation of the model in terms of latent Gaussian utilities can be utilized for estimation leading to very efficient estimation algorithms.

The traditional form of the predictor is

$$\eta_{id} = f_1(d) + z'_{id}\gamma, \tag{2}$$

where the sequence $f_1(d),\ d = 1, 2, \ldots,$ of parameters represents the baseline effect, and the design vector z_{id} is some appropriate function of covariates. In general, nonparametric modelling of the function $f_1(d)$ will be required to detect and explore unknown patterns of the baseline hazard. Then (1) and (2) can be considered as the basic form of a semiparametric predictor. In many applications however, additional flexibility is needed to account for nonlinear or time-varying covariate effects and, as in our application, for further time scales, such as trend and season in calendar time, and for spatial effects of districts or labor market regions.

Based on the results of Section 2, we extend the predictor (2) to a more general semiparametric form by including effects of calendar time t, of the metrical covariate age a at the beginning of unemployment and of the labour market region s, where the unemployed has his/her domicile. This leads to a predictor of the form

$$\eta_{id} = f_1(d) + f_2(a_i) + f_3^T(t_{id}) + f_4^S(t_{id}) + f_5(s_i) + z_{id}'\gamma. \tag{3}$$

Here $f_2(a)$ is a possibly nonlinear effect of age a, f_3^T and f_4^S are a decomposition of the effect of calendar time into a time trend and seasonal component, f_5 represents the effect of labour market regions, and the term $z_{id}'\gamma$ contains the usual fixed effects of mostly categorical covariates, such as nationality, education, indicators for entitlement to unemployment benefits, etc. Note that calendar time is formally treated like a time-varying covariate.

Models with predictor (3) form the basis of our analysis. Therefrom we will discuss several extensions based on the varying coefficients framework introduced by Hastie and Tibshirani (1993). Here, the effect of a particular covariate z, say, is assumed to vary smoothly over the range of a second covariate x leading to a predictor of the form

$$\eta = \cdots + f(x)z + \cdots .$$

In other words, the term $f(x)z$ models an interaction between z and x. Covariate x is called the effect modifier of z. In a first extension of our basic model (3) the varying coefficients framework is used to model possible time-space interactions. More specifically, we subdivide calendar time into the two distinct intervals 1980 to 1990/6 and 1990/7 to 1995 and define the indicator variable $t^{90/7-95}$ whose values are one if an observation falls into the particular time period and zero otherwise. The two intervals are chosen such that we may identify possible structural breaks due to the German unification. A time space interaction is then modelled by a predictor of the form

$$\eta_{id} = \ldots + f_3^T(t_{id}) + f_4^S(t_{id}) + f_5(s_i) + f_6(s_i)t_{id}^{90/7-95} + \cdots .$$

The function f_5 corresponds now to the regional effect for the time period between 1980 and 1990/6, and f_6 can be considered as deviations from the effect in the first time period. More details can be found in Section 4.2. A second extension is based on similar methodology, see Section 4.3.

3.2 Prior assumptions

From a classical perspective, unknown functions $f_1(\cdot)$, $f_2(\cdot)$, $f_3(\cdot)$ and $f_4(\cdot)$ as well as the effects $\gamma = (\gamma_1, \ldots, \gamma_r)$ are considered as fixed and unknown, while $f_5(s)$ $s = 1, \ldots, S$ is considered as a spatially correlated random effect. Therefore the model (3) together with the binary response model (1), define a generalized additive mixed model (GAMM). Conventional non- or semiparametric methods like spline smoothing or local regression allow flexible modelling and estimation of the functions $f_j(\cdot)$, $j = 1, 2, 3, 4$ together with fixed effects γ, but are far less developed for GAMM's, where random effects, in particular correlated spatial random effects, are included.

In a Bayesian approach, as the one we will follow, all functions, more exactly the vectors $f_1 = \{f_1(d),\ d = 1, 2, \ldots\}$, $f_2 = \{f_2(a),\ a = 1, 2, \ldots\}$ etc. of *function evaluations* and parameters $\gamma = (\gamma_1, \ldots, \gamma_r)$ are considered as random variables. The observation model (1) together with (3), is understood as conditional upon these random variables, and has to be supplemented by appropriate prior distributions. For the fixed effect parameters, we will usually assume independent diffuse priors

$$p(\gamma_j) \propto const, \;\; j = 1, \ldots, r.$$

Another choice would be highly dispersed Gaussian priors.

Priors for the unknown functions f_j depend upon the type of covariate. We will distinguish between metrical covariates, time scales and spatial covariates.

Consider first the effect of a metrical covariate like age a. For the moment we may distinguish roughly two main approaches for Bayesian semiparametric modelling. These are base functions approaches with adaptive knot selection (e.g. Denison et al., 1998 , Biller, 2000 and Smith and Kohn, 1996) and approaches based on smoothness priors. In the following we will focus on the latter one. Several alternatives are possible for specifying a smoothness prior for the effect of a metrical covariate. Among others, these are random walk priors (Fahrmeir and Lang, 2001a), Bayesian smoothing splines (Hastie and Tibshirani, 2000) and Bayesian P-splines (Lang and Brezger, 2001). In the following we will focus on P-splines. The basic assumption behind the P-splines approach is that an unknown smooth function f of a particular covariate x can be approximated by a spline of degree l defined on a set of equally spaced knots $\zeta_0 = x_{min} < \zeta_1 < \ldots < \zeta_{r-1} < \zeta_r = x_{max}$ within the domain of x. It is well known that such a spline can be written in terms of a linear combination of $m = r + l$ B-spline basis functions B_t, i.e.

$$f(x) = \sum_{t=1}^{m} \beta_t B_t(x).$$

The Basis functions B_t are defined locally in the sense that they are nonzero only on a domain spanned by $2 + l$ knots. It would be beyond the scope of this paper to go into the details of B-splines and their properties, see e.g. de Boor (1978). The vector $\beta = (\beta_1, \ldots, \beta_m)$ is unknown and must be estimated from the data. In a simple regression spline approach the unknown regression coefficients are estimated using standard methods for fixed effects parameters. However, a crucial point with simple regression splines is the choice of the number and the position of knots. For a small number of knots the resulting spline space may be not flexible enough to capture the variability of the data. For a large number of knots estimated curves may tend to overfit the data. As a remedy to these problems Eilers and Marx (1996) suggest a moderately large number of knots (usually between 20 and 40) to ensure enough flexibility, and to define a roughness penalty based on differences of adjacent regression coefficients to guarantee sufficient smoothness of the fitted curves. In a Bayesian approach, we replace difference penalties by their stochastic analogues, i.e. first and second order random walk models for the regression coefficients

$$\beta_t = \beta_{t-1} + u_t, \quad \beta_t = 2\beta_{t-1} - \beta_{t-2} + u_t \tag{4}$$

with Gaussian errors $u_t \sim N(0, \tau^2)$ and diffuse priors $\beta_1 \propto const$, or β_1 and $\beta_2 \propto const$, for initial values, respectively. A first order random walk penalizes abrupt jumps $\beta_t - \beta_{t-1}$ between successive states and a second order random walk penalizes deviations from the linear trend $2\beta_{t-1} - \beta_{t-2}$. Random walk priors may be equivalently defined in a more symmetric form by specifying the conditional distributions of parameters β_t given its left *and* right neighbours, e.g. β_{t-1} and β_{t+1} in the case of a first order random walk. Then, random walk priors may be interpreted in terms of locally polynomial fits. A first order random walk corresponds to a locally linear and a second order random walk to a locally quadratic fit to the nearest neighbours, see e.g. Besag et al. (1995).

The amount of smoothness is controlled by the additional variance parameter τ^2, which corresponds to the smoothing parameter in a frequentist approach. The larger (smaller) the variance, the rougher (smoother) are the estimated functions.

Consider now time scales like duration or calendar time. Depending on the particular situation we may estimate only a nonlinear time trend as for duration time, or may further split up the effect into a trend and a seasonal component as for calendar time. For the trend components we can choose the same priors as for metrical covariates. A common smoothness prior in Gaussian time series analysis for a monthly seasonal component is

$$f^S(t) = f^S(t-1) + \ldots + f^S(t-11) = u_t^S \sim N(0, \tau^2). \tag{5}$$

In contrast to conventional parametric modelling of seasonal effects by dummy variables for quarters or months, (5) allows for a flexible monthly seasonal pattern that may change over the years.

Let us now turn our attention to the labour market region indicator s. For the spatial effect $f_5(s) = (f_5(s),\ s = 1, \ldots, S)'$ we choose Markov random field priors common in spatial statistics (Besag, et al. 1991). These priors reflect spatial neighbourhood relationships. For geographical data one usually assumes that two sites or regions s and r are neighbours if they share a common boundary. Then a spatial extension of random walk models leads to the conditional, spatially autoregressive specification

$$f_5(s)|f_5(r),\ r \neq s \sim N(\sum_{r \in \partial_s} f_5(r)/N_s,\ \tau_5^2/N_s),$$

where N_s is the number of adjacent regions, and $r \in \partial_s$ denotes that region r is a neighbour of region s. Thus the (conditional) mean of $f_5(s)$ is an average of function evaluations $f_5(r)$ of neighbouring regions. Again the variance τ_5^2 controls the degree of smoothness.

For a fully Bayesian analysis, variance or smoothing parameters τ_j^2, $j = 1, 2, \ldots$, are also considered as unknown and estimated simultaneously with unknown functions or random effects. Therefore, hyperpriors are assigned to them in a second stage of the hierarchy by inverse gamma distributions

$$p(\tau_j^2) \sim IG(a_j, b_j), \quad j = 1, 2, \ldots, .$$

A common choice for a_j and b_j is very small $a_j = b_j$, for example $a_j = b_j = 0.0001$ leading to almost diffuse priors for the variance parameters. An alternative proposed, for example, in Besag et al. (1995) is $a_j = 1$ and a small value for b_j, such as $b_j = 0.005$.

Since the variances τ_j^2 act as smoothing parameters, the degree of smoothness is incorporated into a joint model together with other parameters. Posterior estimates for the smoothness are automatically provided by MCMC simulation. We consider this as a distinct advantage compared to other semiparametric approaches. For example, with a regression spline approach as in our explanatory data analysis in Section 2, the number and location of knots determines the degree of smoothness, and appropriate choice of these parameters is a delicate and nontrivial issue.

In the following, let $f = (f_1, f_2, \ldots,)$ $\tau = (\tau_j^2, j = 1, 2, \ldots,)$ and γ denote parameter vectors for function evaluations, variances and fixed effects. Then the Bayesian model is completed by the following *conditional independence assumptions*:

(i) For given covariates and parameters observations y_{id} are conditionally independent

(ii) Priors $p(f_j|\tau_j^2)$ are conditionally independent.

(iii) Priors for fixed effects, and hyperpriors for τ_j^2 are mutually independent.

3.3 Bayesian inference

Bayesian inference is based on the posterior

$$p(f, \tau, \gamma|y) \propto \ p(y|f, \gamma) \cdot p(f|\tau) \cdot p(\tau) \cdot p(\gamma)$$

where the right hand side is defined by the model assumptions.

Posterior means together with confidence intervals and other characteristics are obtained by drawing samples from the posterior by Markov chain Monte Carlo (MCMC) techniques. MCMC simulation is based on drawings from full conditionals of blocks of parameters, given the rest and the data. In a direct sampling scheme the vectors f_j, $j = 1, 2, \ldots$, of function evaluations are partitioned into smaller blocks $f_j[u, v] = (f_j(u), \ldots, f_j(v))$ and Markov chain samples from the unnormalized full conditionals $p(f_j[u, v]|\cdot)$ are generated by Metropolis-Hastings (MH) steps with conditional prior proposals as suggested by Knorr-Held (1999). Drawings from $p(\gamma|\cdot)$ can be obtained by MH steps with a random walk proposal or the weighted least squares proposal of Gamerman (1997). Updating of variance parameters τ_j^2 is done by Gibbs steps, drawing directly from inverse gamma densities. Details of the updating scheme is described in Fahrmeir and Lang (2001a). For a probit model, as considered in this paper, a useful sampling scheme can be developed on the basis of the latent variable mechanism described above, augmenting the observables y_{id} by corresponding latent utilities $U_{id} = \eta_{id} + \epsilon_{id}$ with Gaussian errors $\epsilon_{id} \sim N(0, 1)$. Posterior analysis is then based on

$$p(f, \gamma, \tau, U|y) \propto p(y|U) \cdot p(U|f, \gamma) \cdot p(f|\tau) \cdot p(\tau) \cdot p(\gamma),$$

with $p(Y|U) = \prod\limits_{i,d} p(Y_{id}|U_{id})$. Compared to the direct sampling scheme, additional drawings from full conditionals for the latent variables are necessary. However, updating of the utilities U_{id} is easy and fast, because their full conditionals are truncated standard normals, i.e. U_{id} is generated from $N(\eta_{id}, 1)$ with mean η_{id} evaluated at current values f_j and γ, subject to the constraints $U_{id} > 0$ for $y_{id} = 1$ and $U_{id} < 0$ for $y_{id} = 0$. As an advantage, full conditionals for nonlinear functions and fixed effects parameters become Gaussian, allowing computationally very efficient Gibbs sampling by updating parameter vectors of each effect in the model in one large block. Numerical efficiency is guaranteed by applying Cholesky decompositions for band matrices. The resulting MCMC scheme for generating posterior samples is then defined by drawing from the following full conditionals:

(i) Update the latent utilities U_{id} by generating samples from their truncated standard normal full conditionals.

(iii) Function evaluations f_j, $j = 1, 2, \ldots$ and fixed effects γ are generated from Gaussian full conditionals.

(iv) Samples for variances τ_j^2 are generated from inverse Gamma full conditionals.

More details on the sampling scheme can be found in Fahrmeir and Lang (2001b).

4 Time-space analysis of unemployment duration in West Germany

Based on preliminary examination of the data in Section 2, we analyse the spells of men and women separately. Only persons with full time jobs are considered. Only a small fraction of individuals is unemployed for more than 36 months. We therefore consider only durations up to 36 months, longer durations are regarded as censored. Throughout this section, the probability of leaving unemployment is being specified by probit models. We first consider a basic model with purely additive effects of space and calendar time (Section 4.1). Based on the results, we consider a model with time-space interactions (Section 4.2) and a model that allows a closer look at the effect of previous unemployment experience (Section 4.3).

4.1 The basic model

For our basic model, we choose a probit model

$$pr(y_{id} = 1 | \eta_{id}) = \phi(\eta_{id})$$

for the probability of leaving unemployment at month d, with an additive predictor

$$\eta_{id} = f_1(d) + f_2(a_i) + f_3^T(t_{id}) + f_4^S(t_{id}) + f_5(s_i) + z_{id}'\gamma. \tag{6}$$

We assume cubic P-splines with second order random walk penalties for f_1, f_2 and f_3^T, the seasonal prior (5) for f_4^S, a Markov random field prior for f_5 and diffuse priors for fixed effects.

The following categorical covariates are included in the vector z_{it} (in effect coding):

- Nationality N:

  German, Foreign (reference category)

- Education E:

  no vocational training, vocational training (reference category), university degree

- Unemployment B_d (in month d of current unemployment period):

  unemployment insurance benefit (reference category), unemployment assistance benefit

- Previous unemployment periods P_t (in month t of calendar time):

  0 (reference category), 1 or 2, 3 or more

- Economic sectors:

  Agriculture

  Manufacturing (reference category).

  Energy, water supply and mining

  Construction

  Trade

  Transport and communications

  Financial sector

  Service industry

Non-profit organizations and private households

Territorial authorities and social insurance

Results for Fixed effects

Table 4 contains posterior means, standard deviations, medians and quantiles of fixed effects of the categorical covariates for men and women, respectively. They confirm some facts already known from previous analyses with more conventional methods.

Chances for reemployment are better for Germans, and this effect is even stronger for women. The effect of education differs for men and women: Women with a university degree have significantly higher reemployment chances compared to women with vocational training and particularly with no vocational training. For men the effect is insignificant. A likely explanation is that in contrast to men, for women a higher educational attainment signals a stronger attachment to the labour market. Thus the higher their human capital, the more likely they are to stick to their job and so the lower the expected costs of turnover for the employer. For that reason the arrival rate of job offers may vary positively with the human capital of women.

The number of previous unemployment periods may signal to employers the (otherwise unobserved) talents of unemployed people. An adverse performance in the labour market signals low abilities. Moreover, people who were unemployed many times in the past may also put less effort into job search than people with no or only a few past unemployment spells. They may be discouraged as they already did not find suitable jobs in the past. For both reasons a higher number of past unemployment spells should lead to a lower arrival rate of job offers and hence has a negative effect on the hazards. However, there are other considerations that suggest that the opposite may be true: A larger number of past unemployment periods may increase the need to achieve some earnings and hence reduce the reservation wages of unemployed job searches. Furthermore, the longer people have been unemployed in the past the less time they have paid contributions to the unemployment insurance system prior to their current spell. As the entitlement length depends positively on this contribution period, a larger number of past unemployment spells is associated with shorter entitlement lengths to unemployment insurance benefits. Therefore, a larger number of past unemployment spells may be associated with lower reservation wages and so a higher probability to accept job offers. Finally, another issue are workers on recall and/or seasonally unemployed workers. In contrast to other unemployed workers, they regularly loose their jobs so that they are characterised by many past unemployment spells. Next, they are likely to return to work quickly either to their old employer or a different employer in the same sector during the next seasonal upturn. This is another reason to expect a positive association of the number of past spells and the hazard rate. Our results in the basic model suggest that the hazards rise with the number of unemployment spells. We investigate in more detail in Section 4.3 whether this is due to seasonally unemployed workers.

Positive effects of unemployment benefits compared to negative effects of unemployment assistance are in agreement with findings in previous studies, even with data from the German Socioeconomic Panel, see Fahrmeir and Knorr-Held (1997). A possible explanation is that individuals with unemployment insurance benefits had regular jobs earlier and thus get offers for a new job more easily. Next unemployment assistance benefits are means-tested. Thus the people who receive those benefits are those who are most in need. These are people who most likely concentrate characteristics that have an adverse impact on labour market performance. As far as these are unobserved like individual talents, we would expect the coefficient of the unemployment assistance receipt to pick up their negative effect on the hazards. Next, while unemployment insurance is paid only for a limited period of time, unemployment assistance may be received indefinitely. So, the incentives to leave unemployment are lower for the unemployment assistance recipients than for unemployment insurance recipients.

Table 5 shows the effects of economic sectors, where the sector energy, water supply and mining has been omitted for women, because only a small fraction of women is working there. There are significant differences between economic sectors. For both men and women transport and service sectors and particularly agriculture and construction are associated with higher reemployment chances than manufacturing. On the other side the financial sectors show negative effects for men and, in particular, for women.

Duration dependence effects

Let us first describe some recent findings on duration dependence effects by other authors. Hujer and Schneider (1996) and Steiner (1997) estimated coefficients of a set of dummies for the baseline hazard using unemployment spell data of the GSOEP-West. Hujer and Schneider find the hazards of male unemployment benefit recipients to peak in the fourth month. They decrease thereafter. Steiner cannot find any negative duration dependence for the male hazards but for female ones. Our results shed some more light on the issue. The size of the data set contributes to more precise estimates of the baseline hazard function. Moreover, in contrast to the studies above the sample size and the specific semiparametric method allows us to leave the baseline hazard flexible even for duration times that are longer than one year.

Figures 9 a) and 10 a) plot the estimated nonparametric function of duration. They demonstrate that the baseline hazards peak in the first two to three months. Thereafter the hazards tend to fall with duration. The decline is relatively steep up to the tenth month. Even after ten months of unemployment, the baseline hazards for men and women alike tend to fall. The pattern differs somewhat from other studies on unemployment duration in Germany. They suggest a negative duration dependence pattern. This may be due to supply side effects, since unemployed people may become discouraged and reduce their search effort the longer their spell lasts. It may also be due to demand side effects: people loose more and more human capital or employers regard long-term unemployment as an adverse signal of the applicant's ability. Both is associated with a lower arrival rate of job offers the longer spells last. This line of reasoning though cannot explain that the baseline hazard rises considerably during the first two to three months of duration. Maybe there is a large number of workers on recall in the sample. These may be mainly seasonally unemployed workers, who are regularly laid off and return after two to three months of unemployment to their previous employer or an employer in the same sector. Wolff (1998) showed that a similar peak of the baseline hazard of unemployment spells in Hungary is mainly caused by such workers.

Age effects

Age should influence the hazards for various reasons. The older a person gets, the shorter is the time horizon in which he/she may benefit from the offered wage (Fallon and Verry, 1988). So, older workers would have reason to accept more easily a given wage offer than younger workers. There are other considerations that would lead to opposing conclusions. For example, if employers invest in firm-specific skills of entrants, they would prefer them to stay as long as possible in the firm. Therefore, the arrival rate of job offers may decrease with age. Furthermore, since we include only a limited set of covariates the coefficients of age most likely capture the effects of some omitted covariates like the number of children or marital status. This is particularly true for women who do the bulk of housework. First, the value of one hour household production relative to one hour market work is higher for a mother than for a childless individual, and so is the reservation wage. Second, institutional constraints as the limited availability of places in creches and kindergardens as well as their opening hours may adversely affect the hazards of mothers. Third, employers may be reluctant to hire women, who they regard at risk of becoming mothers, as they presumably will be less attached to a firm than other workers. So, the arrival rate of job offers may be very low for the childbearing age-groups.

Figures 9 and 10 b) display the age effects of men and women. The function for men declines slowly and nearly linearly up to the age of 54. Then it falls rapidly up to the age 60. Thereafter the hazards rise. The slow linear decline of the hazards with age may well reflect the fact that employers prefer younger workers to older ones for the reasons discussed above. However, the age pattern for men older than 54 is certainly related to institutional rules of retirement for unemployed people. 15 years of waiting time[1] and at least 52 weeks of unemployment during the 18 months before reaching the age of 61 are necessary to retire already at this age (Lampert, 1998). There is an additional eligibility criterion of 8 years of contributory employment during the ten year period prior to reaching the age of 61. So, the incentive of unemployed people to find a job, once they are close to this retirement age should decrease substantially. This may also explain the increase in the hazards after the age of 60. Let us consider people who are still unemployed at the age of 61. These are presumably people who for some reason do not want to retire early or who do not qualify for an early old age pension. So, their incentives to find a job are higher than for the average unemployed person who is still a little younger than 61.

Not surprisingly for women older than 50 the age effects are similar to those of men[2]. In

[1]The waiting time is the sum of years of contributory employment and periods (e.g., military service) that are treated as equivalent to contributory employment.

[2]Women may retire at the age of 61 even if they have not been unemployed in the 18 months prior to reaching this age. In order to become eligible, they must have worked in contributory employment for at

sharp contrast to men though the hazards of young women decline fairly rapidly until that age of 30. Between 30 and 50 years, the age function is flat. This pattern is certainly in line with the hypothesis that the age effect captures the role of children. The likelier it is that women have children, the lower the hazard. Once that likelihood does not increase any longer the hazards are relatively stable.

Calendar time and seasonal effects

In the case of women the estimated calendar time effects (Figure 10 c) reflect fairly well and without much lag the German business cycle. Their hazards are pro-cyclical. We find a sharp decline in the transition rates to employment of unemployed women at the beginning of the 80s. They reach their trough at the start of 1983, the year in which the economy started its upturn. During the first phase of the upturn from 1983 to 1987 GDP growth never exceeded 3 percent. In that period the hazards increase somewhat. In 1988 GDP growth accelerated. It reached even more than five percent at the beginning of the 90's as a consequence of the demand shock due to German unification. By that time the female transition rates increased further and reached their pre-recession levels. The next downturn started in 1992 and again led to a sharp fall in the transition rates until the mid of 1993. The following upturn did not last for much longer than one year, so that the transition rates increased only temporarily.

The male time function (Figure 9 c) declines much more rapidly during the recessions at the start of the 80s and in 92/93 than that of women. However, the accelerated GDP growth at the end of the 80s and beginning of the 90s left the male transition rates nearly unaltered. Presumably there is a negative time trend in the transition rates of men, which does not characterise that of women. One reason for this may be the general shift of the

least 10 years after reaching the age of 41. Next, a total waiting period of 15 years is required.

economy towards service sector and the decline of some industrial sectors like mining and steel. Male workers who are dismissed in the latter industries even in boom times hardly find a job in other manufacturing, trade, transport or other service sectors.

Figures 9 and 10 d) display the seasonal effects over the entire observation period. To gain more insights about the seasonal variation during a single year Figures 9 and 10 e) show a section of the seasonal effects for 1992. For men we observe similar seasonal patterns year by year. However, the variation of the effects clearly decreased after the 1980's. In contrast to men, the size of peaks and troughs are much lower for women. This result is not very surprising, as women less frequently than men work in sectors that are affected by seasonal demand fluctuations. Moreover, apart from the troughs the seasonal pattern is less stable over time than for men.

Spatial effects

Estimated posterior means of spatial effects are shown in Figure 11. Since on average the spatial variation for women is only half of the variation for men we plotted both maps in different scales, otherwise interpretation of the effects would be difficult. Both maps show a strong spatial pattern. Chances are improved in the south and become worse in the middle and the northern part of West Germany. Particularly striking are the red spots in the west, corresponding to the Saar and the Ruhr area. These regions are known for their massive structural adjustment problems during the last two decades that are still ongoing. This becomes even more obvious with Figure 12 showing "probability maps". For a nominal level of 80 % the levels correspond to "significantly negative" (black coloured), "nonsignificant" (grey coloured), i.e. zero is within the credible interval around the estimate, and "significantly positive" (white coloured).

4.2 Time-space interactions

The basic model (6) allows to specify and to analyze the main effects of calendar time and labor market regions by an additive decomposition. To investigate non-additive spatio-temporal effects, interaction terms between calendar time and labor market regions have to be included. In this section, we specify interaction terms in form of a varying coefficient model as already mentioned at the end of Section 3.1. The entire observation period is divided into the two intervals 1980 - 1990/6 and 1990/7 - 1995. The intervals are chosen such that we may identify structural breaks due to the economic integration and unification between West-Germany and the former German Democratic Republic. We chose as the start of this process July 1990, when the German Economic, Social and Monetary Union came into force.

A model with time-space interaction is then defined by extending (6) to

$$\begin{aligned} \eta_{id} &= f_1(d) + f_2(a_i) + f_3^T(t_{id}) + f_4^S(t_{id}) + \\ & \quad f_5(s_i) + f_6(s_i) t_{id}^{90/7-95} + z_{id}'\gamma, \end{aligned} \tag{7}$$

where $t^{90/7-95}$ is a 0/1 indicator which is 1 for observations after June 1990 and zero otherwise. The additional spatial effect f_6 is the deviation from the main regional effects f_5. These time-space interactions are displayed in Figure 13 for both gender. Note that these effects do not display whether regions did better or worse than before July 1990. The reason is that we also modelled a general time trend, which is not reflected in the figure. The time-space interactions are rather deviations from this general time trend.

Let us first turn to the time-space interactions for men. Figure 13 a) shows an improvement in male exit to employment for most of the northern regions. The opposite applies to many of the southern ones. One may expect that the economic integration between West- and East-Germany had a particular impact on the regions that are close to the former German Democratic Republic. These are the border regions in the northeast and mideast.

However, their performance neither generally worsened nor improved. One reason why one might have expected an adverse effect for these areas is the high unemployment in the new federal states that emerged during the transition process. The male unemployment rate in East Germany achieved a level of more 10 percent in January 1992. Until the end of 1995 it stayed most of the time above this level. For women in East Germany the unemployment rate was about twice as high as for men. Next, wages in West-Germany were considerably higher than in East-Germany. For both reasons East-Germans may have competed with West-Germans for vacancies in the former border districts. Now regard Figure 13 b) for women. There is some indication that this competition had an adverse effect on the hazards. For nearly all districts at the former border between East- and West-Germany the interaction-effect is below average. It is not very surprising that the effect occurs for women but not for men. There are male and female dominated segments in the labour market and female unemployment rates in East Germany were twice as high as male ones. So, competition for female jobs may have increased far more than for male jobs in the former border areas.

Estimates of the remaining covariates are practically the same as in the preceding section and are therefore not presented.

4.3 Seasonality revisited

As already remarked in Section 4.1, the positive effect of higher numbers of previous unemployment periods may be caused by individuals employed in sectors with high seasonal effects such as construction or the agricultural sector. To investigate this question, we modify the influence of seasonal effects in our basic model (6) as follows. We split up the global additive seasonal component $f_4^S(t)$ into three seasonal components interacting with corresponding categories of the number of previous unemployment periods. Thus, the predictor is now

$$\eta_{id} = f_1(d) + f_2(a_i) + f_3^T(t_{id}) + f_4^{S_1}(t_{id}) \cdot P_i^1 + f_4^{S_2}(t_{id}) \cdot P_i^2 + f_4^{S_3}(t_{id}) \cdot P_i^3 + f_5(s_i) + z_{it}'\gamma.$$

Here P_{id}^1, P_{id}^2 and P_{id}^3 are 1/0 indicators for the three categories 0, 1 or 2, 3 or more previous unemployment periods of individual i. The functions $f_4^{S_j}(t)$, $j = 1, 2, 3$, are seasonally varying effects of individuals falling into one of these categories. The main effects for these categories (in effect coding) are still included in the covariate vector z_{it}. This model allows to investigate if the positive effect of 3 or more previous unemployment periods is mainly caused by effects of seasonality.

We only report on results for the variable P "previous unemployment" and the seasonal components. All other effects remain practically unchanged. The main effects for P are given in Table 6. They are more or less the same as in the basic model as the hazards rise with the number of previous spells. This implies that a larger number of previous unemployment spells is not that much a signal to employers for an adverse performance in the labour market. The reasons for the result are rather the need of such workers to renew their eligibility to unemployment insurance benefits and the fact that they are likely to be on recall. A related argument for such an outcome was that previous unemployment is also highly associated with seasonal unemployment. Our results for the interaction effects of the number of previous unemployment spells with seasonality favour this interpretation. For males and females Figures 14 a-c and 15 a-c show that the seasonality in the hazards increases considerably, the larger the number of previous spells.

5 Summary and conclusions

This paper presents a Bayesian approach for semiparametric modelling of the dependence of reemployment chances on covariates with particular emphasis on the spatio-temporal development of the labor market. Our results demonstrate that the approach is a useful and flexible tool for estimating realistically complex models. In contrast to previous studies on the duration of unemployment in West Germany, our results suggest a negative duration dependence effect. Besides, the non-parametric estimates of the age effects on the hazard also provided us with more insights than previous studies like the one of Hujer and Schneider (1996) or Steiner (1997). These studies and many others model the age effects by the coefficients of a few dummies representing age-groups or of age-polynomials of a small degree. By non-parametrically estimating such effects, we can show more clearly how retirement rules for the unemployed lead to changes in the job exit behaviour, when unemployed people come closer to the age of retirement. Moreover, we identify a rapid decline of the hazards with age for women aged younger than 30. This presumably reflects that these women become more and more likely to have young children. It may also reflect that employers are reluctant to offer jobs to these women. Previous studies also neglected cyclical effects. Our nonparametric estimates of calendar time effects show that the transition rates to full-time jobs of women are pro-cyclical and follow relatively closely the economic cycle. This is less so for men.

As has already been mentioned in the introduction, the appropriate consideration of non-linear effects of time scales, metrical covariates and spatial heterogeneity may be also important for studies with a different focus. An example are studies about the influence of unemployment benefits on reemployment chances.

In this paper possible time-space interactions are estimated through varying coefficient models. However, this approach has some limitations and can be regarded as a first step for estimating these kind of models. For example, the partition of the observed time period in the two intervals 1980-1990/6 and 1990/7-1995 is somewhat arbitrary. A more refined approach could be based on Markov random fields in space *and* time. Such an approach poses immense computational and methodological challenges. We intend to investigate this and other possible approaches in future research.

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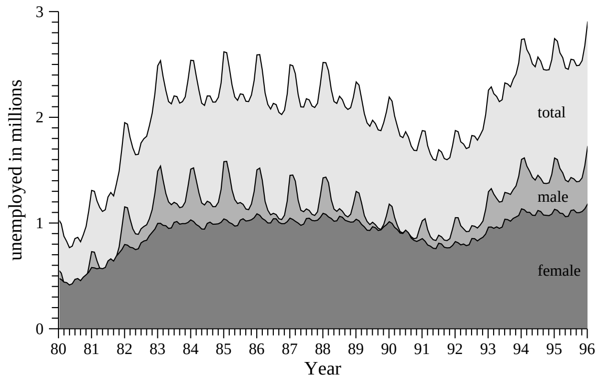

Figure 1: *Monthly stock of registered unemployed persons 1980-1995.*

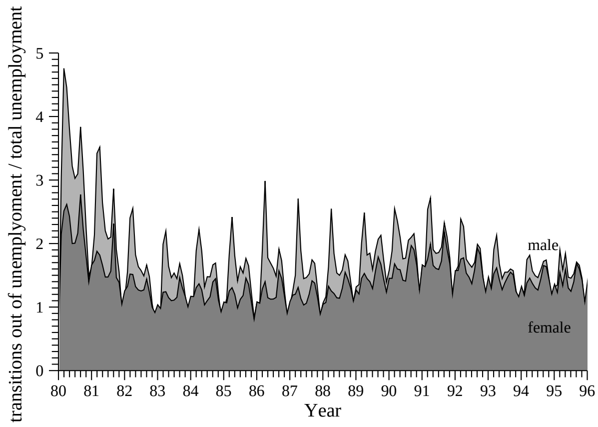

Figure 2: *Relation of the outflow from the unemployment register to the monthly stock of registered unemployed person 1980-1995.*

gender	frequency	registrations	periods
men	52067	113281	96372
in %	55.79	59.10	57.97
women	41257	78392	69884
in %	44.21	40.90	42.03
total	93324	191673	166256

Table 1: *frequencies gender.*

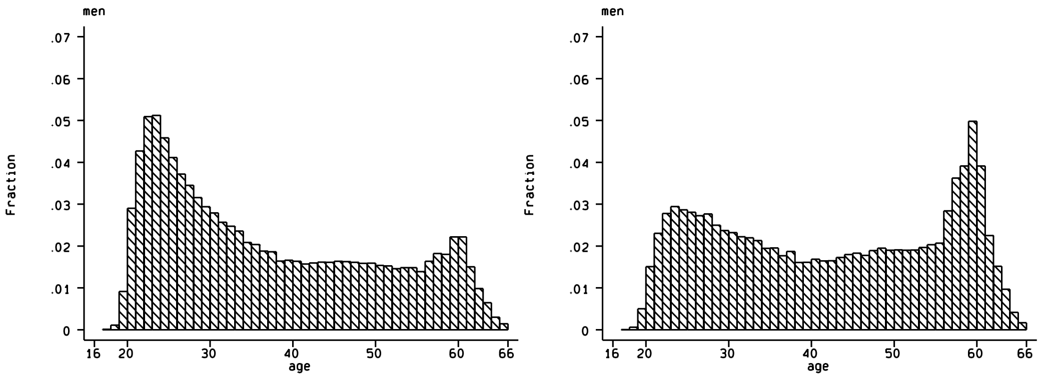

Figure 3: *Men: Distribution of age at beginning of unemployment; unweighted (left) and weighted by duration (right)*

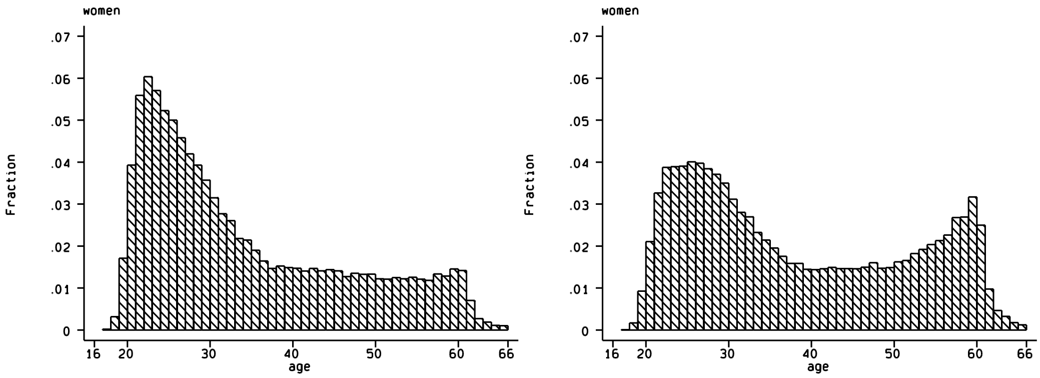

Figure 4: *Women: Distribution of age at beginning of unemployment; unweighted (left) and weighted by duration (right)*

mean duration	age < 35	$35 \leq$ age < 50	age ≥ 50
men	6.46	9.52	13.83
women	6.90	9.15	14.15

Table 2: *Mean duration versus age.*

	men	women	total
German	88.04	90.46	88.63
foreigner	11.96	9.54	11.37
total	100	100	100

Table 3: *Frequencies of nationality.*

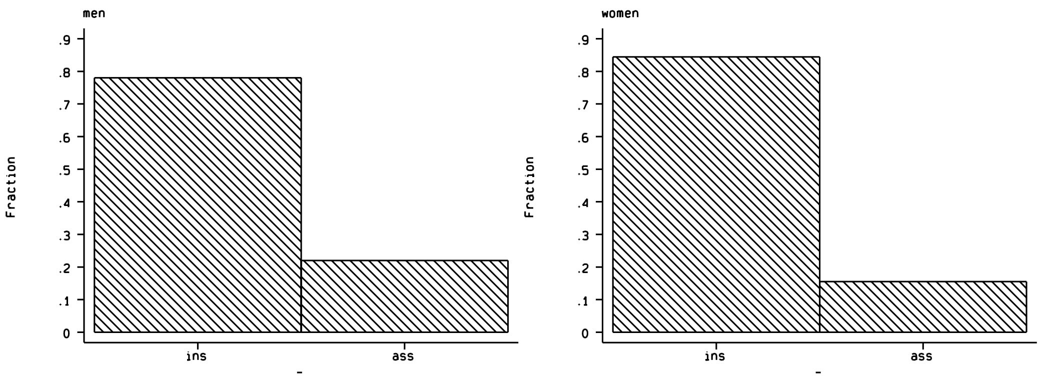

Figure 5: *Unemployment benefits.*

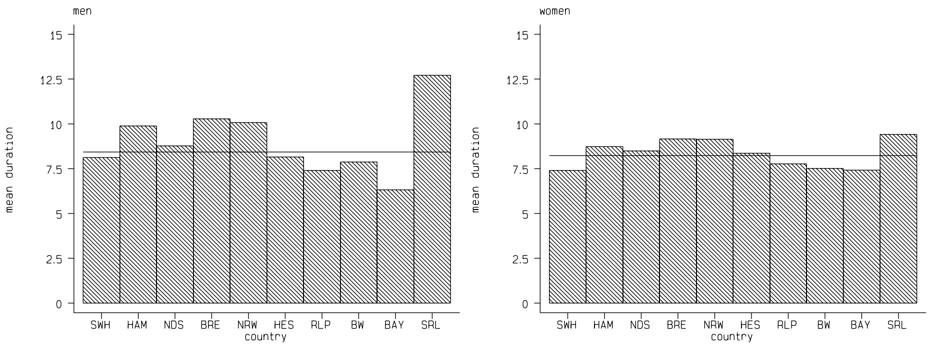

Figure 6: *Mean duration time by federal state.*

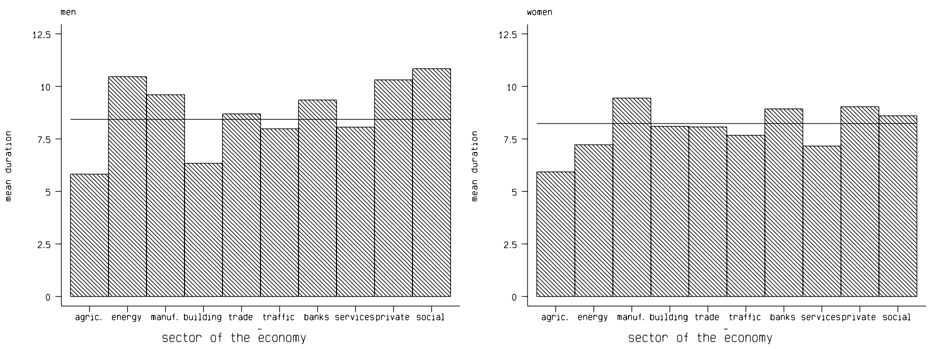

Figure 7: sectors of economy: mean duration time

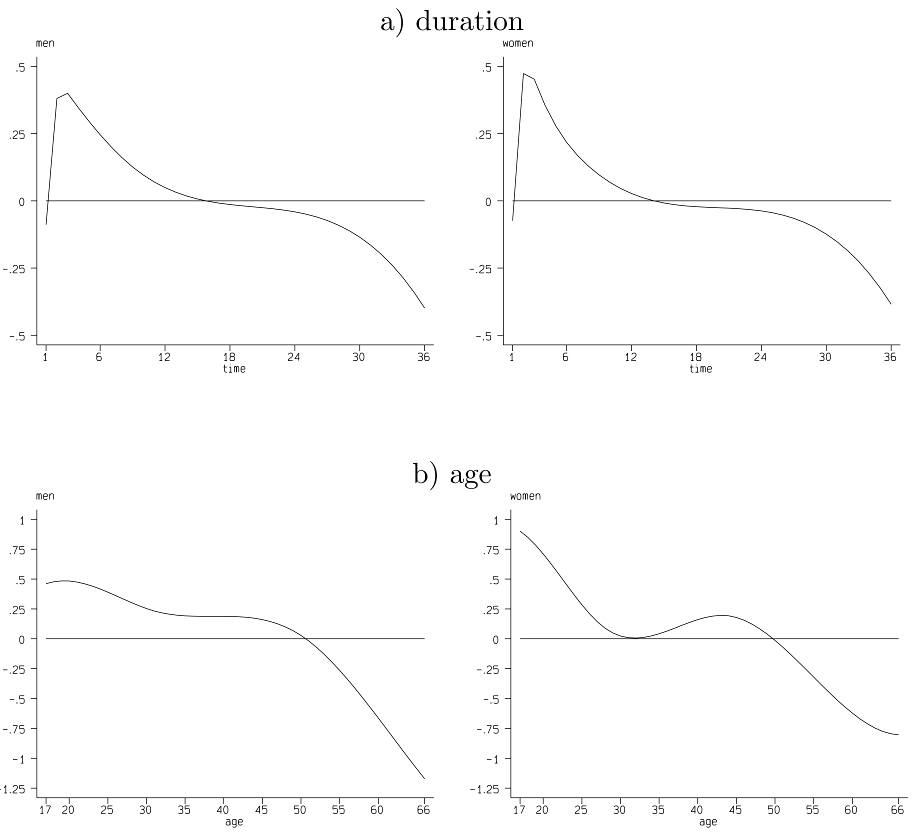

Figure 8: Estimated effects of duration time and age

a) men

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
German	0.03	0.01	0.02	0.03	0.04
foreign	-0.03	0.01	-0.04	-0.03	-0.02
no vocational training	-0.02	0.01	-0.03	-0.02	0.00
vocational training	0.03	0.01	0.02	0.03	0.04
university	-0.01	0.02	-0.04	-0.01	0.01
unemployment assistance	-0.17	0.01	-0.17	-0.17	-0.16
unemployment benefit	0.17	0.01	0.16	0.17	0.17
P=0	-0.09	0.01	-0.10	-0.09	-0.08
P=1,2	-0.01	0.01	-0.01	-0.01	0.00
P≥3	0.10	0.01	0.09	0.10	0.11

b) women

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
German	0.07	0.01	0.06	0.07	0.08
foreign	-0.07	0.01	-0.08	-0.07	-0.06
no vocational training	-0.04	0.01	-0.05	-0.04	-0.03
vocational training	-0.04	0.01	-0.05	-0.04	-0.02
university	0.07	0.02	0.05	0.07	0.10
unemployment assistance	-0.09	0.01	-0.10	-0.09	-0.09
unemployment benefit	0.09	0.01	0.09	0.09	0.10
P=0	-0.09	0.01	-0.10	-0.09	-0.08
P=1,2	-0.03	0.01	-0.04	-0.03	-0.02
P≥ 3	0.12	0.01	0.11	0.12	0.13

Table 4: *Estimates of constant parameters.*

a) men

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
agriculture	0.24	0.02	0.21	0.24	0.27
manufacturing	-0.02	0.01	-0.04	-0.02	-0.01
energy	-0.19	0.04	-0.24	-0.19	-0.14
construction	0.15	0.01	0.13	0.15	0.17
trade	-0.02	0.01	-0.04	-0.02	-0.01
transport	0.06	0.02	0.04	0.06	0.08
financial sector	-0.24	0.04	-0.29	-0.24	-0.19
service industry	0.03	0.01	0.01	0.03	0.04
private	0.01	0.03	-0.03	0.01	0.06
public	-0.01	0.02	-0.04	-0.01	0.01

b) women

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
agriculture	0.19	0.03	0.15	0.19	0.22
manufacturing	-0.15	0.01	-0.16	-0.15	-0.14
construction	-0.02	0.03	-0.06	-0.02	0.02
trade	-0.01	0.01	-0.02	-0.01	0.01
transport	0.09	0.02	0.06	0.09	0.12
financial sector	-0.18	0.03	-0.22	-0.18	-0.15
service industry	0.06	0.01	0.05	0.06	0.07
private	0.00	0.02	-0.02	0.00	0.03
public	0.02	0.02	0.00	0.02	0.04

Table 5: *Estimated effects of the sector of the economy.*

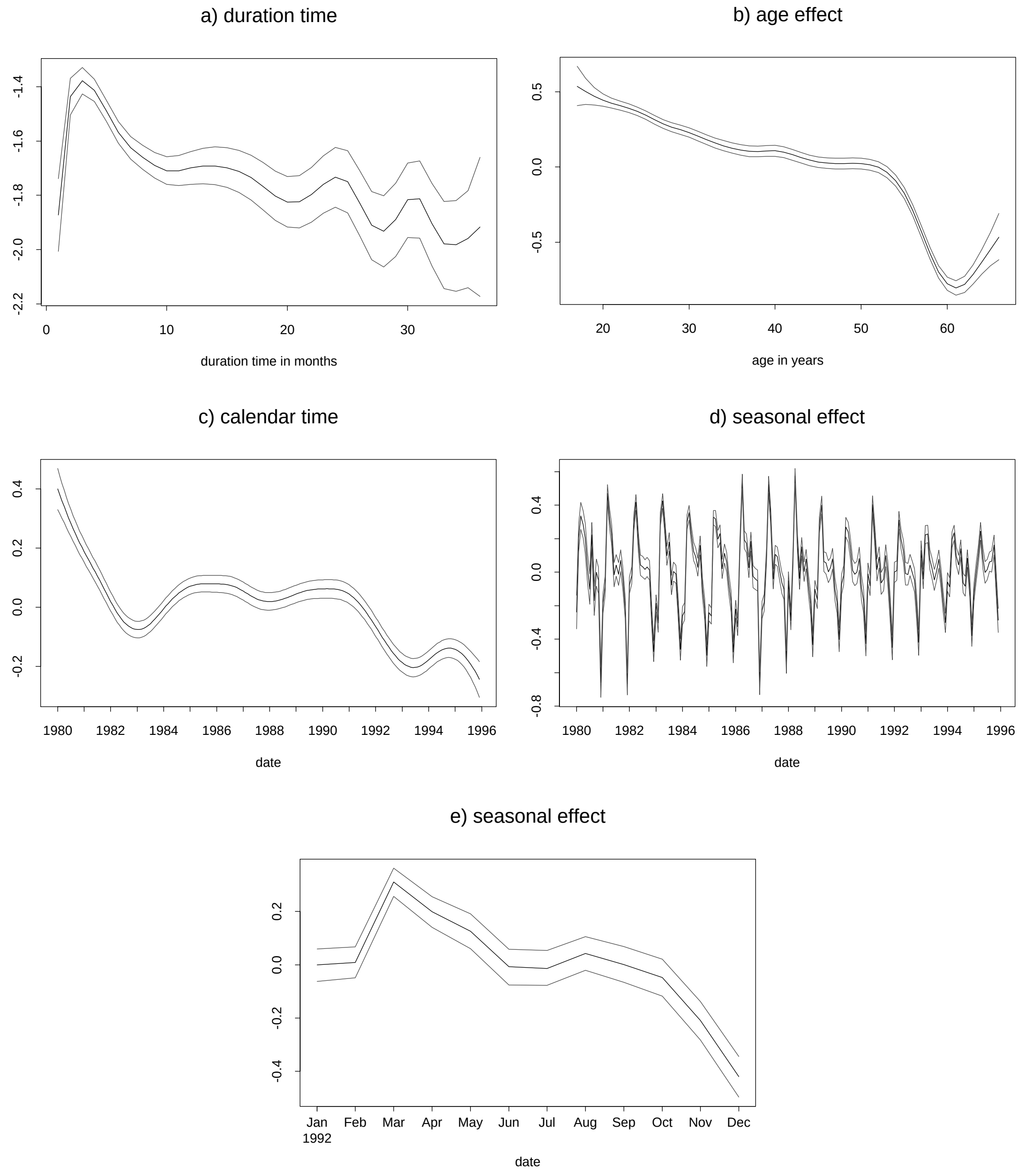

Figure 9: *Estimated nonparametric functions and seasonal effect for males. Shown is the posterior mean within 80 % credible regions.*

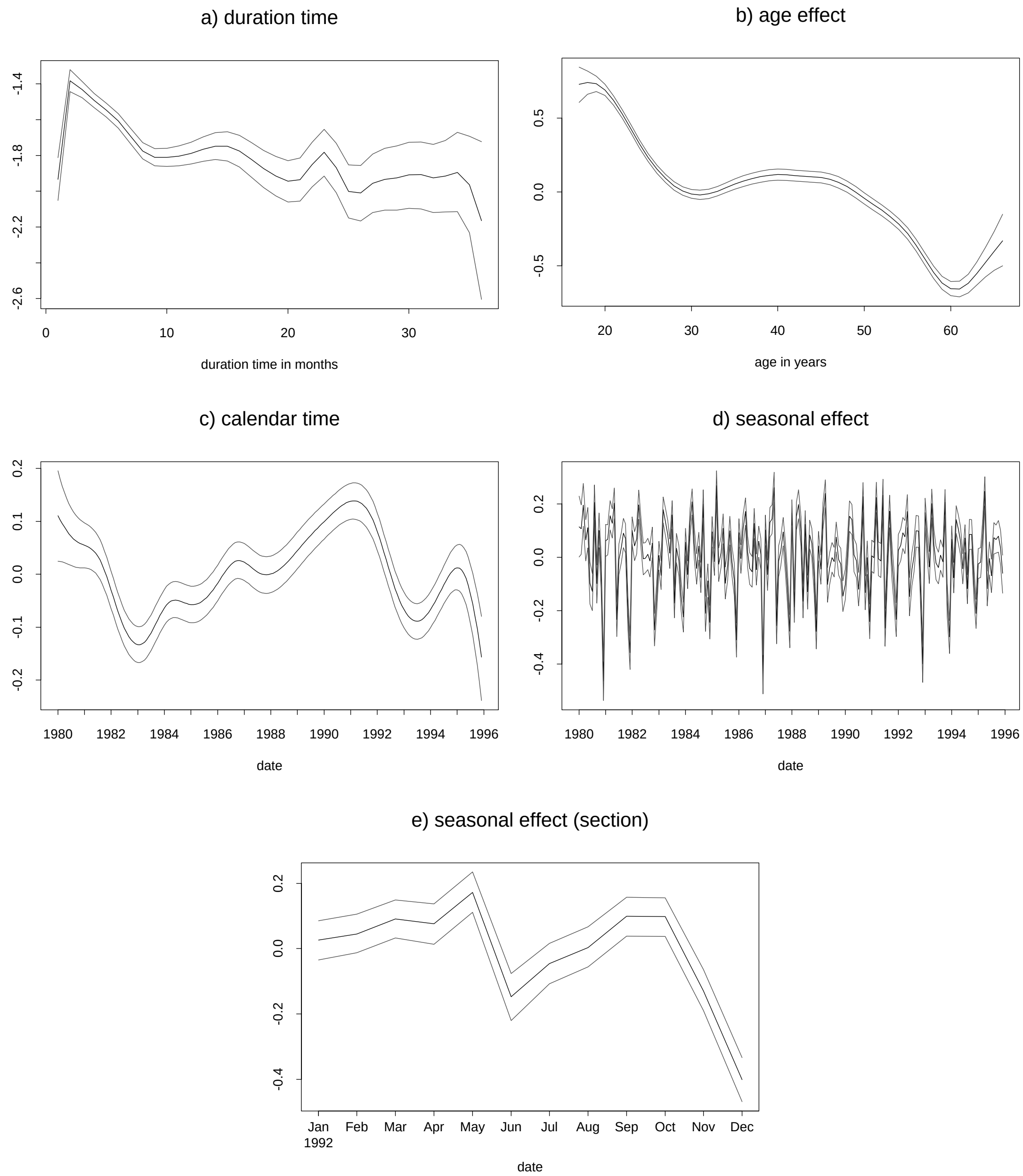

Figure 10: *Estimated nonparametric functions and seasonal effect for females. Shown is the posterior mean within 80 % credible regions.*

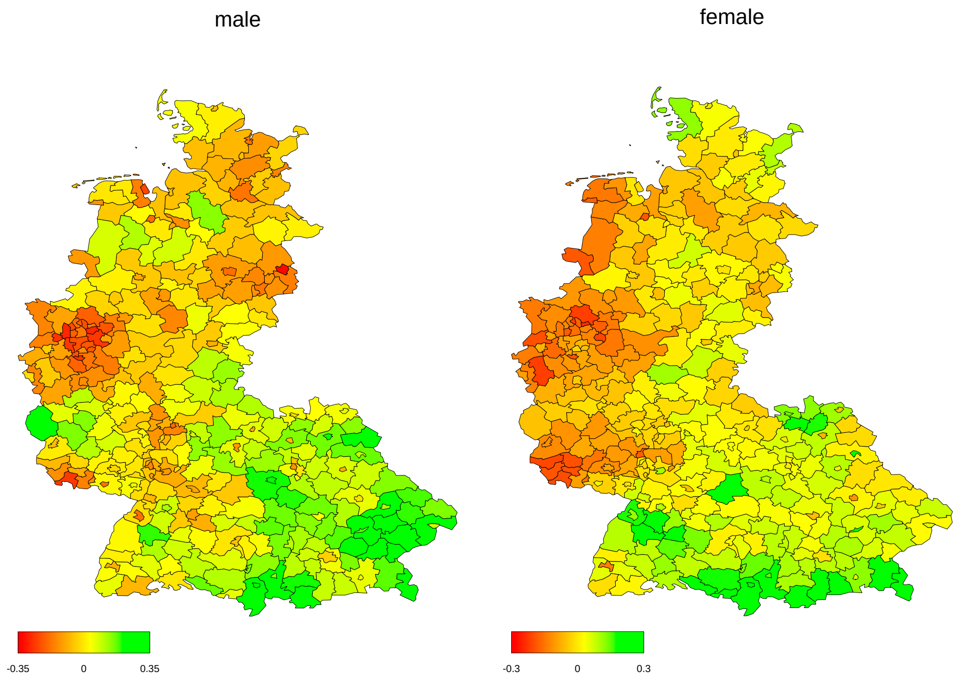

Figure 11: *Posterior mean of the spatial effects.*

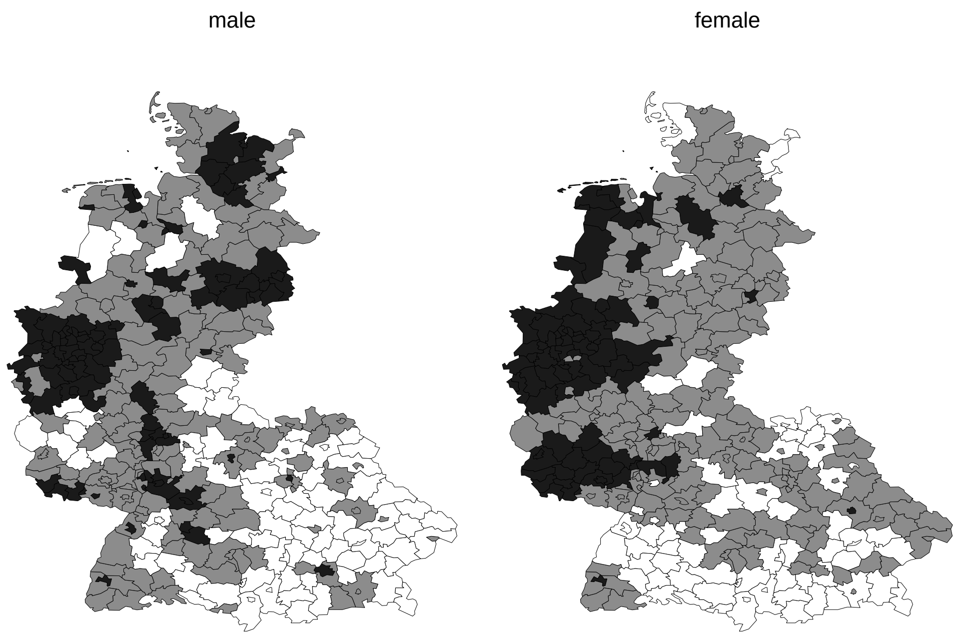

Figure 12: *Posterior "probabilities" of the spatial effects.*

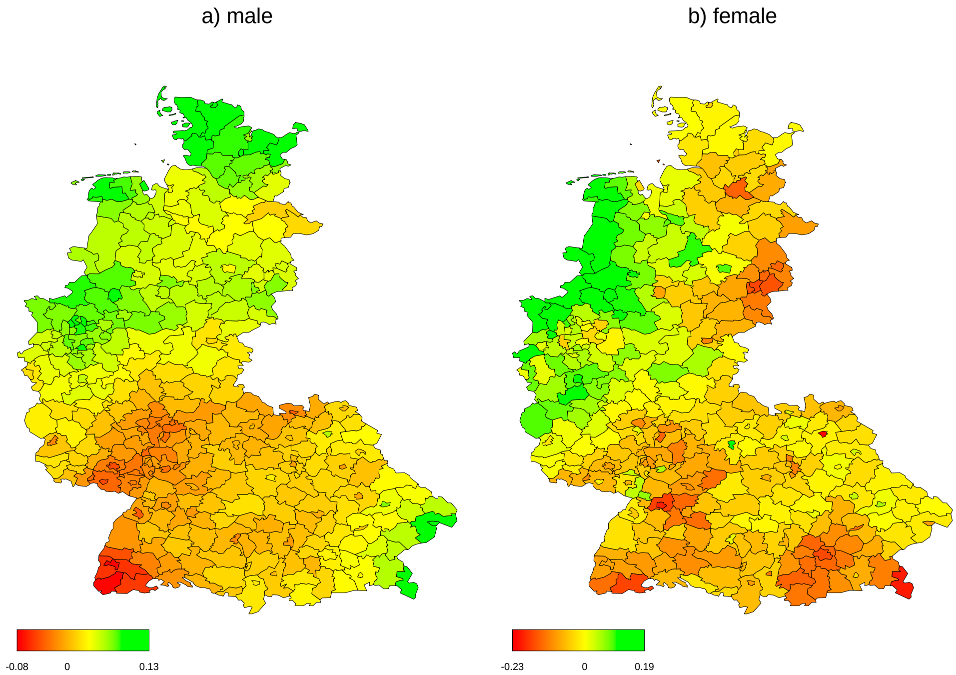

Figure 13: *Deviations from the main regional effects for males and females. Shown is the posterior mean.*

a) men

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
P = 0	-0.07	0.01	-0.08	-0.07	- 0.06
P = 1,2	0	0.01	-0.01	0	0.01
P $\geq$ 3	0.07	0.01	0.06	0.07	0.08

b) women

Variable	mean	Std.Dev.	10% quant.	median	90% quant.
P = 0	-0.08	0.01	-0.09	-0.08	-0.08
P = 1,2	-0.03	0.01	-0.04	-0.03	-0.02
P $\geq$ 3	0.11	0.01	0.10	0.11	0.12

Table 6: *Estimates of the effect of the number of previous unemployment spells.*

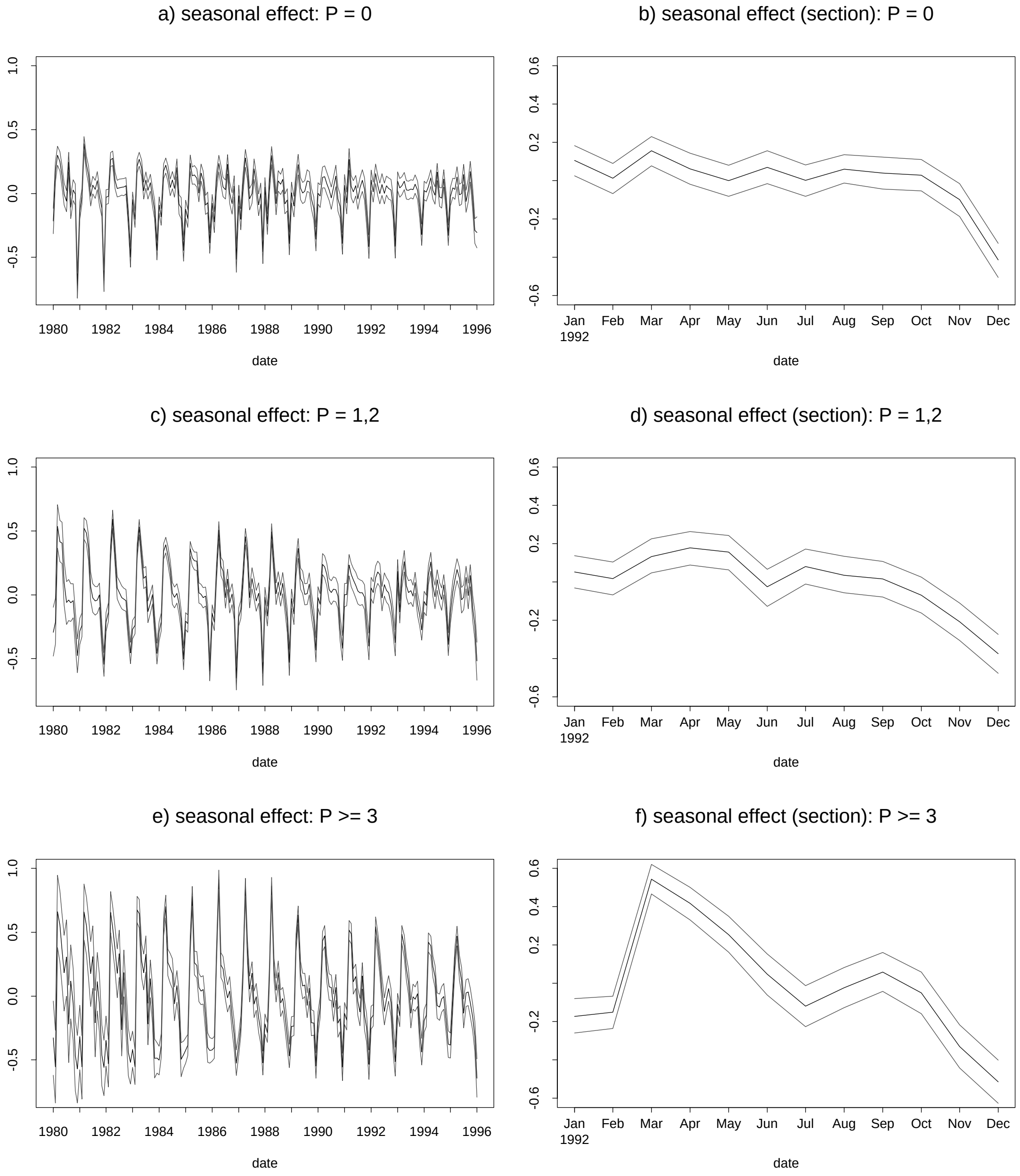

Figure 14: *Varying seasonal effects for males.*

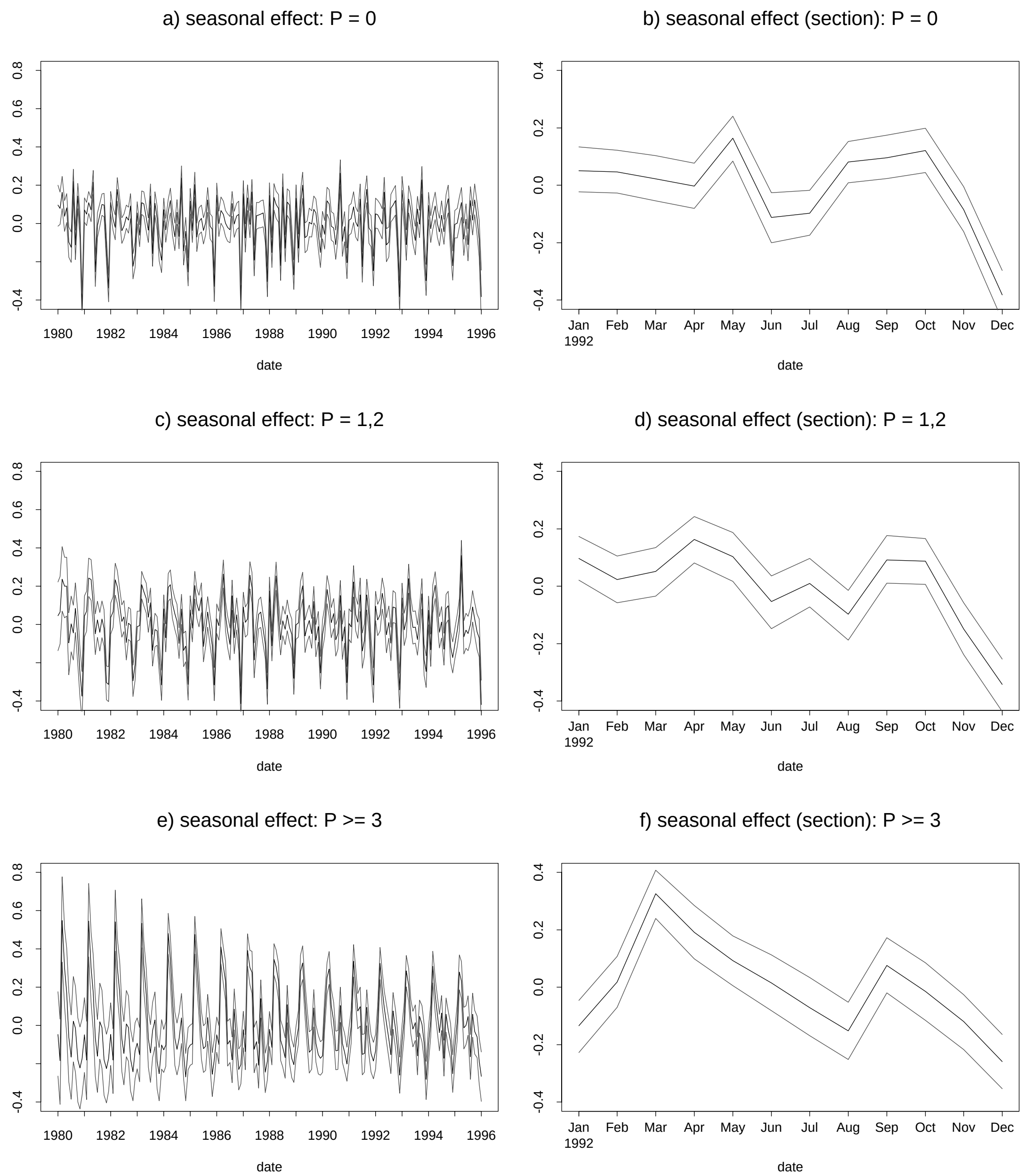

Figure 15: *Varying seasonal effects for females.*