Applications of Multivariate Mixed Proportional Hazard Models in Labor and Population Economics

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Chapter 1

Introduction

Duration analysis is one of the core subjects in microeconometrics and the number of available models has increased steadily over the last forty years. In labor and population economics, the Mixed Proportional Hazard (MPH) model and its multivariate extensions, the so-called Multivariate Mixed Proportional Hazard (MMPH) models, are state of the art and the most widely used models to estimate durations. This class of models provides a relatively simple parametric form and allows for two important aspects: events are random and may occur at random intervals. Those two aspects have been of key interest for the design of theoretical models in all fields of labor and population economics during the last forty years. A major leap forward was the introduction of job search theory (see Salop, 1973, Jovanovic, 1979, Mortensen, 1986 and Pissarides, 1992). This modeling approach was also highly influential to the design of theoretical models in other fields of economics, in which it is important that information arrives at random intervals and that decision are made dynamically. For example, in population economics, models of partner search or marriage duration are often based on job search theory (see Becker et al., 1976).

Apart from the fact that econometric duration analysis is closely linked to theoretical models of search and matching, another aspect has fueled its increasing popularity in labor and population economics. During the 1990s and early 2000s many countries opened up administrative data to research. These data sets typically provide individual employment histories and in many cases information on other life course events, such as birth records and marriage status. In addition, they typically cover observation periods of twenty years or longer. Their information is, in general, presented as spell data, i.e. start and end dates of a spell are given and spells are split into episodes when covariates vary during spells. Furthermore, start and end dates are normally measured on a weekly or even daily basis, which make very detailed analyses possible. In Germany, it was the labor market reforms in the early 2000s that brought new administrative data sets like the IAB Employment Sample, the Integrated Employment Biographies Sample, or the BA Employment Panel. Examples from other countries include Austria (Austrian Social Security Database), the Netherlands (Dutch Income Panel Database) or Sweden (HÄNDEL and AKSTAT). In addition to the increasing number of administrative data sets that were made available, many surveys like the National Longitudinal Survey for the United States, the British Household Panel Survey for the United Kingdom, or the Socioeconomic Panel for Germany now provide individual life course histories in spell format and information on start and end dates on a monthly basis.

As mentioned, MPH and its multivariate extensions, MMPH models, today belong to the class of most used econometric models in labor and population economics. MPH models were introduced by Lancaster (1979) and Vaupel, Manton and Stallard (1979). These models are reduced-form duration models that express transitions to a specific destination state via simple multiplicative functions. They are separable into three parts, a baseline hazard component depending solely on survival time and two nonnegative functions that depend on observable and unobservable characteristics.

In contrast to other duration models, MPH models have several advantages. Compared to Accelerated Failure Time (AFT) models (see Kalbfleisch and Prentice, 1980 for an overview on AFT models), MPH models account for changes in the hazard rate and not in survival time. MPH are therefore better suited for empirical investigations of theoretical models, because such models are normally formulated in dynamic decisions and not duration times. In contrast to so-called Cox models (see Cox, 1972), MPH models directly control for dependencies due to elapsed duration time. Such duration dependencies are of particular interest on their own. For example, human capital is often assumed to depreciate with the elapsed unemployment duration (see Kiker and Roberts, 1984). MPH models were originally developed for continuous measurement of time. The complementary log-log-transformation provides a simple parametric form of a MPH model for discrete measurement of time. For continuous measurement of time, typical parametric forms for the baseline hazard are based on the Weibull and Gompertz distribution. Recently, modeling the baseline hazards using piecewise constant exponential functions became en vogue in empirical applications. For example van den Berg and Richardson (2006), Cockx and Picchio (2012), or Osikominu (2013) employ piecewise-constant baseline hazards in order to account for duration dependencies. Such piecewise-constant baseline hazards do not specify the functional form of the baseline hazard a priori, but rather leave it to be fitted from the data. It is therefore a very flexible way to model the baseline hazard and is also often used with discrete measurement of time.

A last point in favor of MPH models is that they control for unobserved heterogeneity, which, in the concept of duration analysis, is often called frailty. Controlling for frailty is crucial, because otherwise estimates for the baseline hazard are bound to be biased. This so-called survival bias arises due to neglecting that unobserved components may drive the composition of survivors as spell duration lengthens. The number of parametric forms used to control for unobserved heterogeneity is limited, because one has to integrate over the distribution of the unobserved characteristics. Typical parametric forms are the Gamma or the Inverse-Gaussian distribution, which provide closed form expressions for the likelihood and avoid numerical integration. Heckman and Singer (1984) introduced discrete distributions with only a small number of mass points for modeling frailty. They show that such discrete distributions are more flexible than other parametric distributions. Today, discrete distributions are used in most applications of MPH and MMPH models. With regard to identification, Honoré (1993) shows that MPH models are non-parametrically identified under the assumption of independence between observed and unobserved explanatory variables. This means that unobserved heterogeneity is similar to random effects in a panel framework.

One of the first applications of MPH models in labor economics, is Lancaster (1979) who estimates the duration of finding a job for a sample of unemployed. Kreyenfeld (2000) instead provides an application of a MPH model in population economics. She estimates the duration until a first birth for a sample of East German women. As in all applications of MPH models, the authors restrict their models to one single risk and one spell per individual. However, individuals are often faced with more than just on destination state and draw decisions more than once.

Multivariate Mixed Proportional Hazard (MMPH) models provide an extension of Mixed Proportional Hazard (MPH) models with one single spell and one single risk to a multivariate setting with several risks and multiple spells per individual. In a comprehensive survey, van den Berg (2001) classifies MMPH models into three categories.

The *first category* of MMPH models refers to related unobserved determinants. This category can be further distinguished into three different scenarios with respect to the timing of spells. In the first scenario, an individual faces multiple spells that start at the same point in time and the individual is observed until the first duration is completed. Such models are known as competing-risks models, because there are multiple competing destination states and an individual may move to just one. Competing risks models allow for correlation in the unobserved heterogeneity components of the different destination states, because some unobserved characteristics influence transitions to more than just one destination state. A worker's unobserved motivation to work, for example, affects the transitions from education to employment and to unemployment. Heckman and Honoré (1989) provide nonparametric identification of competing-risks model under fairly weak conditions for just one pair of spells per individual. For example, neither restrictions on the functional form of the unobserved heterogeneity nor any exclusion restrictions have to be imposed. For models that estimate multiple observations on competing risks for each individual, identification restrictions can be further relaxed (see Abbring and van den Berg, 2003b). A prominent contribution of a competing risks model with single spells is Idson and Valletta (1996) who investigate the effect of tenure on employee retention under different labor market conditions. For a sample of unemployed, they conduct a competing risks analysis of recall and new job acceptance. Similarly, McCall (1996) employs a competing risks model in order to investigate the transitions to full-time and part-time employment for a group of unemployed. The second scenario with respect to the timing of two or more spells, is when spells do not overlap. This means there is, for example, an employment history of subsequent employment and unemployment spells. Honoré (1993) shows that in the case of such successive durations the identifying assumption of independence between observed and unobserved explanatory variables can be relaxed. Such models are mostly used in combination with other situations like competing risks. In addition to the two scenarios depicted so far, there may also be the situation of parallel spells. Related unobserved characteristics then require joint estimation of those processes. For example, van den Berg, Lindeboom and Ridder (1994) and van den Berg and Lindeboom (1998) model the successive durations of employment and unemployment spells jointly with the duration until panel attrition, while Lillard and Panis (1998) model the duration until panel attrition jointly with the durations of marriage, non-marriage and life.

The *second category* of MMPH models van den Berg (2001) lists, refers to the effect of a realized past duration on the current hazard. This effect is commonly known as "lagged duration dependence" and was introduced by Heckman and Borjas (1980). In a successive durations setup, one can assume that the second spell directly depends on a function of the duration of the first spell. Such a setup can naturally be extended to more than two spells and may also appear in combination with competing risks. The function of the duration of the first spell is often modeled by including the duration as an additional covariate. A second way to include the preceding duration are indicator functions. These may account for whether the duration falls into a particular time interval or may indicate the mere occurrence of a state. By accounting for the latter type, one can measure what is commonly called "occurrence dependence". Honoré (1993) shows that models with lagged duration dependence are nonparametrically identified under the independence of observed and unobserved heterogeneity. Horny and Picchio (2010) extend this proof to a competing risks framework. In a comprehensive study, Doiron and Gorgens (2008) estimate occurrence and lagged duration dependence effects for the three states employment, unemployment, and out of the labor force for a group of Australian school leavers. By estimating lagged duration and occurrence dependence for a group of Belgian long-term unemployed school-leavers, Cockx and Picchio (2012) account for whether short-term employment spells are stepping-stones to long-lasting jobs.

Finally, the *third category* of MMPH models refers to situations where multiple durations occur simultaneously, and where the realization of one duration variable has an effect on the hazard of the other duration variables. Obviously, the effects may occur for multiple directions and in combination with successive durations and competing risks. A prominent example is Lillard (1993) who estimates a model of joint durations of marriage and childbearing. His model allows the hazard rate of dissolving a marriage to shift due to the birth of a child, while the conception hazard rate depends directly on the hazard of dissolving a marriage. Aassve et al. (2006) extend this framework to the hazards of employment, nonemployment, union formation, union dissolution, and childbearing. However, they use only lagged endogenous outcomes as regressors. The idea of one duration having an effect on a simultaneous duration can also be thought of a dynamic treatment. Abbring and van den Berg (2003a) show that such models are nonparametrically identified given that the timing of the treatment can not be anticipated. Van den Berg and Richardson (2006) apply such a model in order to estimate whether the treatment of a labor market training affects unemployment durations in Sweden. For the case of Germany, Osikominu (2012) estimates the effects that short, job-search oriented training and long, human capital oriented training have on current unemployment durations and subsequent employment durations.

An important point for all duration models is how individuals and their respective histories are sampled. If individuals are sampled out of the stock of a certain state, left-censoring may be an issue. This means that the start date of the current spell is not observed. This presents a considerable problem, because the durations are unknown. Moreover, the few solutions that exist for this problem are all based on strong assumptions (see for example D'Addio and Rosholm, 2002a). The problem is less severe, if the spell is not observed from its start but the start date is known. In this case, one solution is to condition the likelihood contribution of such a so-called left-truncated spell on the elapsed duration (see Lancaster, 1979). Finally, stock sampling may also lead to selective samples, if only those who survived more than a minimum of time are included in the observation sample.

A second way to draw a sample is to sample individuals when they enter a certain state. Although the start date is known in this case, so-called flow samples are not necessarily random samples, if the inflow into the state depends on certain observed or unobserved characteristics. The problem is specifically severe, if one is interested in estimating lagged duration or occurrence dependence effects. Nonetheless, only few solutions for this initial conditions problem exist (Gritz, 1993, provides an exception). In a setting of employment or life course histories flow sampling may also exclude individuals who never move between states and thereby yield selective samples.

This thesis presents two examples of substantive MMPH models in labor and population economics. In particular, I analyze the following two topics. In chapter 3, I suggest a MMPH model with competing risks of exit to estimate duration dependence, lagged duration dependence and occurrence dependence effects for German prime-aged men. The effects are estimated for the three labor market states employment, unemployment and out of the labor force. Chapter 4 provides the application of a MMPH model with simultaneous durations that may influence each other jointly. I investigate the interrelated dynamics of employment, cohabitation and fertility for German women and men. A special point of this chapter is to include the current employment and nonemployment hazard rates and the union formation and union dissolution hazard rates also as regressors. The following two paragraphs sketch the main ideas and results of the two analyses.

Duration dependence, lagged duration dependence, and occurrence dependence in individual employment histories

The analysis of state dependence effects in individual employment histories provides important insights into how dynamic a labor market is. Can one or more short-term employment spells be considered as stepping stones towards permanent employment? Are single and short unemployment spells persistent or do they lead to scarring effects? Chapter 3 aims to answer these and related questions. In order to do so, I employ a MMPH model with competing risks of exit into different states. I follow Heckman and Borjas (1980) and differentiate between three forms of state dependence: duration dependence, lagged duration dependence, and occurrence dependence. The estimation is conducted using a sample of German prime-aged men that were drawn from the Integrated Biographies Sample (IEBS). The IEBS is a large and comprehensive administrative data set that provides a multitude of information on the current labor market state. However, the current labor market state is not directly given, but rather has to be identified from the data. In some cases, the identification of the three labor market states employment, unemployment and out of the labor force is a challenging task that requires heuristic assumptions. Data cleansing in general and identification of labor market states in particular are therefore an important element of the analysis in this chapter. The IEBS provides information on start and end dates on a daily basis. I therefore use a continuous framework for estimation. The model is applied to prime-aged men. This group of individuals is of interest, because it presents the largest of all subgroups among employable individuals in Germany. Furthermore, state dependence effects are supposed to vary over an individual's life course. For example, the state dependence effects due to the experience of an unemployment spell are supposed to be different for twenty and forty years old individuals. Nonetheless, measuring state dependence effects for prime-aged men has been neglected by the literature so far. Focussing on prime-aged has the drawback that the early parts of their employment histories are not observed. In comparison to Doiron and Gorgens (2008), Cockx and Picchio (2012), or Frijters et al. (2009) who all use high-school graduates whose employment histories are observed from the beginning, I therefore have to adjust for initial conditions. In order to do so, I adjust the approach of Wooldridge (2005), originally developed for panel data models, to mixed proportional hazard models. My results suggest that all forms of state dependence are present in the data. In particular, I find strong and persistent duration dependence effects for employment and unemployment. The results further show that no lagged duration dependence is present. However, the occurrence of past unemployment spells are scarring and make future unemployment more likely, while past employment spells help to find new employment, but do not help to remain employed. This means that vicious circles of unemployment and unstable employment may arise. Furthermore, I conduct simulations in order to evaluate long-run impacts of possible interventions in the labor market. The simulation results support the findings that even short unemployment spells are scarring and that short employment spells help to find new employment.

Employment, partnership and childbearing decisions of German women and men: A Simultaneous hazards approach

My second analysis focuses on the interrelated dynamics of employment, partnership and childbearing decisions of German women and men. An individual's employment history is no independent process, but rather influences and is influenced by other simultaneous processes, in particular by processes that are related to family outcomes. For example, losing a job may result in a postponement of childbearing, while, in particular, women may stop working when having children. I employ a MMPH model that accounts for simultaneous hazards in order to estimate a five-equation model for the hazards of employment, nonemployment, union formation, union dissolution, and conception. The model provides an extension of the approaches used in Lillard (1993) and Aassve et al. (2006). In comparison to the latter, I also include the hazards of employment, nonemployment as regressors for the hazards of union formation, union dissolution, and conception, and the hazards of union formation, union dissolution as regressors for the hazard of conception. The analysis is conducted for the 1960-69 cohort of German women and men using data from the study "Working and Learning in a changing world" (ALWA). Also the ALWA data set is a very comprehensive and highly precise data set, which is very well-suited for this kind of analysis. My results suggest that the current employment state has only small effects on other transitions, while the hazards of finding and losing a job have a significant impact on other transitions. Employed women with a high hazard of becoming nonemployed are less likely to have children. Nonemployed men having a low hazard of finding a job are more likely to have children. Children reduce the hazard of taking up a job for women but not for men. A novelty of the approach used in chapter 4 is the inclusion of a variable that accounts for current pregnancy. By doing so, I can show that it is current pregnancy that induces women to become nonemployed. Having (young) children however decreases the hazard of becoming nonemployed for women and also for men. Furthermore, unions become more stable if (young) children are present. On the other hand, having a partner strongly increases the likelihood of having children. Finally, unions with a high risk of splitting up tend to have a higher likelihood for having children. Although this result is surprising at first, it can be interpreted economically as an attempt to invest in partner-specific capital in order to reduce the likelihood of splitting up.

Chapter 3 and 4 provide two applications of complex and computationally intensive MMPH models that are linked via the similarity of the underlying model. The third chapter has a particular focus on the dynamics of employment histories. The fourth chapter relates these dynamics with the inherent dynamics of family processes. However, before I will come to the applications, the second chapter provides a short introduction to MMPH models. Finally, the last chapter briefly compares the two models and summarizes their results.

Chapter 2

A short introduction to Multivariate Mixed Proportional Hazard models

This chapter provides a brief introduction to Multivariate Mixed Proportional Hazard (MMPH) models. I start with establishing notations and definitions for duration models in general and then depict notational and methodological aspects of MPH and MMPH models (for more detailed expositions, see Lancaster, 1990, and van den Berg, 2001).

2.1 Some notations and definitions

Let t be a continuous random variable measuring the duration until an event occurs. Then

$$F(t) = P(T \leq t) \tag{2.1}$$

describes the cumulative density function indicating the probability that the duration until an event is smaller or equal to t. Furthermore,

$$S(t) = P(T > t) = 1 - F(t) \tag{2.2}$$

describes the survivor function, which states the probability that the duration is larger than t, i.e. $S(t)$ is the probability that no event takes place until t. Because $S(t)$ is a probability, it must hold that $0 \leq S(t) \leq 1$. Furthermore, for $t = 0$ and $t \to \infty$ it must hold that $S(0) = 1$ and $\lim_{t\to\infty} S(t) = 0$. The probability density function $f(t)$ is given as the derivative of the cumulative density function $F(t)$ and therefore directly linked to the survivor function $S(t)$. It evolves as

$$f(t) = \frac{\partial F(t)}{\partial t} = \frac{-\partial S(t)}{\partial t}, \text{ with } f(t) \geq 0, \tag{2.3}$$

i.e. $f(t)$ is minus the slope of the survivor function $S(t)$. The rate that is of key interest, is the hazard rate $h(t)$. It describes the rate for an event taking place at point t, given the probability that no event has occurred until then. It is defined as

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}, \text{ with } h(t) \geq 0. \tag{2.4}$$

One can also show that there is a one-to-one relationship between the hazard rate $h(t)$ and the survivor function $S(t)$. The survivor function $S(t)$ then reads as

$$S(t) = \exp\left(- \int_0^t h(u)\,\mathrm{d}u \right), \tag{2.5}$$

where $\int_0^t h(u)du$ describes the integrated hazard rate.

2.2 The Mixed Proportional Hazard model

A very convenient parametric specification for the hazard rate $h(t)$ is the Mixed Proportional Hazard (MPH) model, which is often used in labor and population economics. The MPH model is given as

$$h(t|x, v) = \lambda(t)\theta\left(x(t)\right)v, \tag{2.6}$$

where $\lambda(\cdot), \theta(\cdot)$, and v are nonnegative functions. $\lambda(t)$ describes the so-called baseline hazard that only depends on the elapsed duration time t. $\theta\left(x(t)\right)$ describes a systematic part that is determined by observed explanatory variables $x(t)$. The explanatory variables $x(t)$ may vary over the course of a spell. A common specification for $\theta\left(x(t)\right)$ is

$$\theta\left(x(t)\right) = \exp\left(x(t)'\beta\right), \tag{2.7}$$

where the β-coefficients shift the hazard $h(\cdot)$ in a nonlinear way. Finally, v is a person-specific and time-constant random term that accounts for unobserved heterogeneity.

Accounting for unobserved heterogeneity is necessary, because otherwise estimates for $\lambda(t)$ and $\theta\left(x(t)\right)$ are bound to be biased. If there is one single spell per individual, MPH models are nonparametrically identified given a set of assumptions of which the most crucial one requires that the distribution for the unobserved heterogeneity υ is independent of the observed characteristics $x(t)$ (see Honoré, 1993). However, this assumption can be relaxed, if there are multiple spells per individual or if the observed explanatory variables $x(t)$ vary over the course of a spell.

Given a parametric form for the baseline hazard and the distribution of υ, estimation of MPH models is typically conducted using Maximum Likelihood. The likelihood contribution of an individual i who has completed a spell, is given by

$$\begin{aligned} \mathscr{L}(t_i|x(t_i), \upsilon_i) &= h(t_i|x(t_i), \upsilon_i) \times S(t_i|x(t_i), \upsilon_i) \\ &= h(t_i|x_i(t_i), \upsilon_i) \times \exp\left(-\int_0^{t_i} h(u|x(u), \upsilon_i)\,\mathrm{d}u\right). \end{aligned} \tag{2.8}$$

In equation (2.8), the first term describes the intensity for an event taking place at time t_i and the second term corresponds to the probability of no event taking place until t_i, i.e. to the survivor rate. An individual i's spell may also be in progress, when it is sampled at a point of time c_i. In such a case, the duration is said to be right-censored and the likelihood contribution is given as

$$\begin{aligned} \mathscr{L}(c_i|x(c_i), \upsilon_i) &= S(c_i|x(c_i), \upsilon_i) \\ &= \exp\left(-\int_0^{c_i} h(u|x(u), \upsilon_i)\,\mathrm{d}u\right). \end{aligned} \tag{2.9}$$

Equation (2.9) then simply describes the probability of no event taking place until c_i. As one is typically interested in statements about effects due to observed characteristics $x(t)$, one has to integrate over the distribution of the unobserved heterogeneity υ_i. The likelihood contribution of an individual i then evolves as

$$\mathscr{L}(t_i|x(t_i)) = \int_0^{\infty} \mathscr{L}(t_i|x(t_i), \upsilon_i)\,\mathrm{d}A^*(\upsilon) \tag{2.10}$$

where A^* is the time-invariant marginal distribution of υ_i. Note that equation (2.10) does not not distinguish between censored and uncensored spells, i.e. it holds for the likelihood contributions of completed and right-censored spells.

2.3 Multivariate Mixed Proportional Hazard models

In a multivariate setup, multiple durations can be observed for each individual. For the sake of simplicity, I assume that, throughout this section, there are only two spells per individual. One can think of two durations t_1 and t_2 and the respective hazard rates, which are given as

$$h_1(t_1|x(t_1), \upsilon_1) = \lambda_1(t_1)\theta_1\left(x(t_1)\right)\upsilon_1 \tag{2.11}$$

$$h_2(t_2|x(t_2), \upsilon_2) = \lambda_2(t_2)\theta_2\left(x(t_2)\right)\upsilon_2. \tag{2.12}$$

Conditional on $x(t_1), x(t_2)$, the two durations t_1 and t_2 are independent, if υ_1 and υ_2 are independent. In this case the model reduces to two unrelated MPH models for the durations t_1 and t_2. Nonetheless, in most cases the unobserved components υ_1 and υ_2 have common determinants. If υ_1 and υ_2 are dependent, the likelihood contribution of an individual i is given by

$$\begin{aligned}\mathscr{L}(t_{i,1}, t_{i,2}|x(t_{i,1}), x(t_{i,2})) &= \int_0^\infty\int_0^\infty \mathscr{L}(t_{i,1}, t_{i,2}|x(t_{i,1}), x(t_{i,2}), \upsilon_{i,1}, \upsilon_{i,2})\,\mathrm{d}A^*(\upsilon_1, \upsilon_2)\\ &= \int_0^\infty\int_0^\infty f_1(t_{i,1}|x(t_{i,1}), \upsilon_{i,1})\\ &\qquad\times f_2(t_{i,2}|x(t_{i,2}), \upsilon_{i,2})\,\mathrm{d}A^*(\upsilon_1, \upsilon_2),\end{aligned} \tag{2.13}$$

where $A^*(\upsilon_1, \upsilon_2)$ is the joint distribution for the unobserved components υ_1 and υ_2. Similar to the case of just one single spell per individual, the model is identified given that υ_1, υ_2 and $x(t_1), x(t_2)$ are independent (see Honoré, 1993).

2.3.1 Competing risks

Until now, nothing has been said about the timing of the two spells. They may, for example, appear simultaneously or successively. One can think of an individual that is faced with two possible destination states of which only one may set in. This means there are two durations t_1 and t_2 that start at the same point of time but t_1 is only observed, if t_2 exceeds t_1 and t_2 is only observed, if t_1 exceeds t_2. Lancaster (1990) shows that the distribution of such an "identified minimum" does not suffice to identify the most general competing-risks model, because for every model with dependent t_1,

t_2, there is an observationally equivalent model with independent t_1, t_2. Compared with MPH models a stronger assumption on the variation in observed explanatory variables is required. If $\theta_j\left(x(t_j)\right) = \exp\left(x(t_j)'\beta_j\right)$, then a sufficient assumption for identification is that $x(t_j)$ has two continuous covariates, which affect the hazard rates $h\left(t_j|x(t_j), \upsilon_j\right)$ with different β_j, and which are not perfectly collinear. Under the assumption that the parameters are identified, the likelihood contribution of an individual i conditional on $x(t_{i,1}), x(t_{i,2}), \upsilon_{i,1}, \upsilon_{i,2}$ and provided that $t_{i,1} < t_{i,2}$ is given by

$$\begin{aligned}\mathscr{L}\left(t_{i,1}|x(t_{i,1}), \upsilon_{i,1}\right) &= h\left(t_{i,1}|x(t_{i,1}), \upsilon_{i,1}\right) \\ &\quad \times \exp\left(-\sum_{j=1,2}\int_0^{t_j} h(u|x(u), \upsilon_{i,u}))\,\mathrm{d}u\right). \qquad (2.14)\end{aligned}$$

For the case of $t_1 > t_2$ the likelihood contribution expands analogously.

2.3.2 Successive durations

A second situation occurs when spells do not overlap, i.e. when durations occur successively. In this case, the likelihood contribution of an individual i is given as in equation (2.13) and the model allows for $\lambda_1 \neq \lambda_2$, $\theta_1 \neq \theta_2$, and $\upsilon_1 \neq \upsilon_2$, i.e. no restrictions have to be imposed. A typical example would be an unemployment spell that is followed by a subsequent employment spell. In this case, one may obviously raise the question whether the duration of the preceding unemployment spell has an effect on the subsequent employment duration, i.e. if there is "lagged duration dependence". In terms of the hazards, the specification of a model that accounts for lagged duration dependence reads as

$$\begin{aligned}h_1\left(t_1|x(t_1), \upsilon_1\right) &= \lambda_1(t_1)\theta_1\left(x(t_1)\right)\upsilon_1 \\ h_2\left(t_2|t_1, x(t_2), \upsilon_2\right) &= \lambda_2(t_2)\theta_2\left(x(t_2)\right)\xi(t_1)\upsilon_2. \qquad (2.15)\end{aligned}$$

The function $\xi(t_1)$ has to be positive for every $t_1 \in [0, \infty)$, but may take on a multitude of forms. If $\xi(t_1) = \exp(t_1\gamma)$, then t_1 acts as an additional regressor and γ is a parameter accounting for lagged duration dependence. Furthermore, if $\xi(t_1) = \delta\mathbf{1}(t_1 > 0)$, where $\mathbf{1}(\cdot)$ is the indicator function, δ would account for the mere occurrence of the preceding unemployment spell, i.e for so-called "occurrence dependence". The likelihood contribution of an individual i in a model accounting for dependence due to lagged durations is given by

$$\begin{aligned}\mathscr{L}(t_{i,1},t_{i,2}|x(t_{i,1}),x(t_{i,2})) &= \int_0^\infty\int_0^\infty \mathscr{L}(t_{i,1},t_{i,2}|x(t_{i,1}),x(t_{i,2}),\upsilon_{i,1},\upsilon_{i,2})\,\mathrm{d}A^*(\upsilon_1,\upsilon_2)\\ &= \int_0^\infty\int_0^\infty f_1(t_{i,1}|x(t_{i,1}),\upsilon_{i,1})\\ &\qquad \times f_2(t_{i,2}|t_{i,1},x(t_{i,2}),\upsilon_{i,2})\,\mathrm{d}A^*(\upsilon_1,\upsilon_2).\end{aligned} \tag{2.16}$$

In addition to some normalization assumptions, Honoré (1993) shows that identification requires that second moments exist for the unobserved heterogeneity components υ_j and $j = 1, 2$.

2.3.3 Simultaneous durations

In a last scenario one may think of two durations t_1, t_2 that appear simultaneously and where t_2 has an impact on t_1. The two durations do not necessarily start at the same point of time. A necessary assumption in such models is that t_1 can not be anticipated. This means that the exact date of t_1 is unknown. However, an individual is allowed to know the determinants of the probability distribution of t_1 and to act on these. The no-anticipation assumption therefore requires that an individual, for example, does not know the exact date of a conception, but may know the probability distribution and may act on this distribution, e.g. by stopping the use of contraceptives. In terms of the hazards, the model specification reads

$$\begin{aligned}h_1\left(t_1|x(t_1),\upsilon_1\right) &= \lambda_1(t_1)\theta_1\left(x(t_1)\right)\upsilon_1\\ h_2\left(t_2|t_1,x(t_2),\upsilon_2\right) &= \lambda_2(t_2)\theta_2\left(x(t_2)\right)\phi(t_1)\upsilon_2,\end{aligned} \tag{2.17}$$

where $\phi(t_1)$ is again a nonnegative function for every $t_1 \in [0,\infty)$ that may take on different forms. In a first situation, one may think of two durations t_1 and t_2 that start at the same point in time, and the realization of t_1 has an impact on the shape of the hazard of t_2 from t_1 onwards. The data provides information on t_1 only if t_2 exceeds t_1. The duration t_1 can therefore be considered as a treatment and the causal effect of t_1 on t_2 as a "treatment effect". In such a situation, a typical functional form is $\phi(t_1) = \exp(\delta\mathbf{1}(t_1 < t_2))$, where $\mathbf{1}(\cdot)$ is again the indicator function and δ describes the treatment effect. Abbring and van den Berg (2003b) provide nonparametric identification results for these dynamic treatment effects models. They show that no exclusion restrictions are required, but that the no-anticipation assumption is necessary for identification.

In a second situation, one may again think of two durations t_1 and t_2 that not necessarily start at the same time but overlap and where t_1 has a direct impact on the shape of the hazard t_2. One possibility may be $\phi(t_1) = h_1\left(t_1|x(t_1), v_1\right)$, i.e. the current hazard of t_1 directly affects the shape of the hazard of t_2. Lillard (1993), for example, estimates the effects the hazard of a marriage duration has on the duration until conception.

In general, competing risks models can be extended to more than just two risks and successive durations to several spells per individual. Furthermore, the different forms of dependencies may also be combined in all forms one may think of. The next two chapters present two substantive applications of MMPH models in the field of labor and population economics.

Chapter 3

Duration dependence, lagged duration dependence, and occurrence dependence in individual employment histories

This chapter investigates the form and magnitude of a variety of state dependence effects for prime-aged men in Germany. I differentiate between three labor market states: employment, unemployment, and out of labor force. Results indicate that all forms of state dependence are present in the data, in particular, there is strong duration dependence in employment and unemployment. Furthermore, past unemployment experiences are scarring and make future unemployment more likely, while past employment experiences help to find new employment, but do not help to remain employed. Simulations are conducted in order to investigate the effects of possible interventions in the labor market.

3.1 Introduction

It is a well-established finding that past employment states may have a causal impact on future employment states (state dependence). Heckman and Singer (1980) were the first to distinguish state dependence in three forms, namely dependence on the current duration, dependence on the occurrence, and dependence on the duration of past labor market experiences. Most of the existing studies have focused on the effects of past unemployment (see for example Arulampalam, 2001, Arulampalam et al., 2000, 2001, Gregg, 2001, Mühleisen and Zimmermann, 1994, or Flaig et al., 1993), usually called scarring effects. Although there is an increasing number of studies that now deal with this problem (see for example Doiron and Gorgens, 2008, Cockx and Picchio, 2012, or Frijters et al., 2009), less is known about the effects of past employment experiences. Also little is known about how periods out of the labor force affect future labor market outcomes. Furthermore, most studies account for the different forms of state dependence in a very simplified manner, often because they use annual data.

Differentiating between all three forms of state dependence seems necessary for the following reasons: A first reason is that only in this way the following policy relevant reasons can be answered: Do one or more short-term employment spells help the unemployed to find permanent employment? Is a single and short unemployment period already scarring? Does the current unemployment duration has an effect on the probability of leaving unemployment? What are the cross-effects, e.g. how do past employment spells affect the risk of future unemployment? The case for considering all forms of state dependence simultaneously becomes even stronger if one considers the possibility that the different forms may influence each other. Therefore, omitting one form may result in biased estimates for the other forms. For example, omitting occurrence dependence and lagged duration dependence due to past unemployment experiences may result in biased estimates for the duration dependence of the current unemployment spell, because individuals who are long-term unemployed may also have experienced unemployment periods in the past.

The channels through which past labor market outcomes affect future labor market outcomes are various. Of particular interest are state dependence effects due to past unemployment and employment experiences each of which are generally related to another mechanism. First, in the eyes of potential employers the unemployed may be stigmatized by their unemployment duration or the occurrence of past unemployment. Second, the experience of unemployment may have led to a loss of skills or motivation. Furthermore, state dependence effects due to past employment experiences are generally related to gains in human capital and broader networks, which may help to find new employment. However, state dependence effects can also be induced by institutional features. For example, dismissal protection laws increase the employment durations for workers with permanent contracts, while they shorten the durations for workers with temporary contracts. By contrast, the absence of a possibility to offer temporary contracts to the unemployed may result in longer unemployment duration.

The goal of the present study is to provide a comprehensive analysis of the form and the magnitude of state dependence effects for the three labor market states employment, unemployment and out of the labor force. Using administrative data for Germany, these effects are investigated for a group of prime-aged men who are at the risk of becoming unemployed or of leaving the labor force during the period under observation. Prime-aged men are of particular interest as they form the largest group in the labor market and also have the highest labor market attachment. They also represent the largest group among the unemployed and are therefore a population of individuals who are most likely subject to policy measures. Furthermore, state dependence effects are supposed to vary over an individual's life course. For example, twenty-year old high-school graduates are often faced with several unemployment spells on their way to find a stable employment. For a forty-year old individual, however, the experience of an unemployment spell often presents a severe indentation to his or her career. The focus on prime-aged men is in contrast to much of the literature, which usually focuses on youth unemployment (for example, Doiron and Gorgens, 2008). The analysis of youth labor markets is appealing, as one can observe the labor market entry and hence one can measure, for example, scarring effects of early unemployment experiences. If one focuses on prime-aged men, however, most available data sets only provide the labor market histories for certain periods which are often not longer than ten years and which do not include the labor market entry. This complicates the econometric analysis of state dependence effects. For example, it is evident that one has to account for initial conditions when modeling unobserved heterogeneity.

In order to investigate the different forms of state dependence, I use a particularly rich administrative data set in this study, the Integrated Employment Biographies Sample (IEBS)[1]. The data set is based on the information from four different administrative registers and allows one to observe the employment histories on daily-basis for the period from 1992 until 2003. The availability of daily information is a major advantage over other data sets. It allows one to model the different forms of state dependence taking advantage of methods of survival analysis in continuous time (see for example, van den Berg, 2001). I distinguish between three labor market states: employment, unemployment, and out of the labor force. In order to model the six possible transition intensities jointly, I estimate a Mixed Proportional Hazard (MMPH) model with competing risk of exit. In order to distinguish between state dependence and other effects, I include a large set of observed variables and additionally account for unobserved heterogeneity. In contrast to many other studies, I also account for initial conditions. Following the idea of Wooldridge (2005), I condition the likelihood of the transition intensities on the past labor market history using a parsimonious linear specification.

My results indicate that state dependence is present for almost all states. In particular, there is strong negative duration dependence for the transitions from employment, and for the transition between unemployment and employment. Furthermore, the occurrence of past unemployment is scarring, especially if the unemployment period has occurred recently. In addition, the occurrences of past employment spells seem to be beneficial for finding new employment. The results thus indicate that there may be a vicious

[1] This study uses the factually anonymous Integrated Employment Biographies Sample (IEBS) (Years 1992-2004). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

circle of unemployment and unstable employment, where unstable employment may be considered as temporary employment or low-wage employment. The more frequent transitions between unemployment and employment were in the past, the more difficult it becomes to escape from this circle. The results are therefore in line with the literature on the segmentation of the labor market into individuals with stable employment and individuals who constantly transit between unstable employment and unemployment (see for example Stewart, 2007). Simulation of different policy interventions support these findings. They show that additional employment spells help unemployed to find new employment and that even very short additional unemployment spells are scarring.

The remainder of the chapter is structured as follows. Section 2 provides some stylized facts referring to state dependence effects in labor market outcomes and discusses some related literature. Section 3 presents the data set, it shows how labor market states are identified, and describes the sampling scheme. In addition, section 3 presents a descriptive analysis of the final sample. Section 4 then introduces the econometric model. Results are presented and discussed in section 5. Finally, section 6 shows the results of simulated policy interventions, while section 7 concludes.

3.2 Stylized facts and related literature

There are different possibilities of how past labor market outcomes may influence future labor market outcomes. Heckman and Borjas (1980) were the first to precisely define the concept of state dependence based on the theory of survival analysis and to distinguish between three forms. To start with, duration dependence refers to the dependence on the duration of the current spell. Second, occurrence dependence refers to the possibility that the occurrence of past spells may affect the probability of leaving the current state. Third, it might not only be the occurrence but also the duration of past spells that affects the probability of leaving the current labor market state. This dependency is labeled lagged duration dependence. The present section gives a short review of some stylized facts and the related literature.

Duration dependence From a theoretical point of view, transitions from employment to unemployment are generally assumed to depend negatively on the current duration (see for example Jovanovic, 1979). Mortensen (1986) shows that these effects might be due to a sorting effect. Employees, who are relatively more productive face a much lower risk of being dismissed and therefore remain longer with their current employer. The resulting survival bias is then perceived as a negative duration dependence. Also, the institutional setting may have an impact on the current employment duration. For example, protection against dismissals of those employees with permanent contracts increases employment durations in comparison to employees with temporary contracts, and therefore induces a negative duration dependence. Transitions from employment to "‘out of the labor force"’ can also be assumed to depend negatively on the current duration. However, the labor market state "out of the labor force" is more heterogenous than the labor market state "unemployment". In particular, transitions to out of the labor force and back are often planned decisions (e.g. maternity leaves). Possible relationships are therefore less obvious. Also, the literature does not provide further evidence for this type of transitions as unemployment and out of the labor force are often aggregated to one single state.

The transition from unemployment to employment is also assumed to exhibit negative duration dependence. This is the transition most studied by the literature. In general, there are two channels through which the current unemployment duration might affect the transition probability. On the one hand, Pissarides (1992) points out that long unemployment durations are accompanied by losses in human capital and therefore employment chances decrease with the time spent in unemployment. On the other hand, employers are generally not able to observe the unemployed´s productivity and motivation. They therefore use unemployment durations to infer on the productivity and motivation, as Vishwanath (1989) and Lockwood (1991) point out. In this sense, Blanchard and Diamond (1994) assume that employers rank applicants by their unemployment duration and hire the ones with the shortest durations. This means that the unemployed with longer durations are stigmatized, because always those unemployed with a shorter unemployment duration are hired.

The transition from unemployment to out of the labor force is generally assumed to depend positively on the current duration, at least in the long-run. Schweitzer and Smith (1974) point out that long unemployment durations may discourage unemployed in their search effort, and unemployed may drop from the labor force the longer they are unemployed. Although there may exist such discouragement effect, in most European countries unemployed are required to search for a job in order to receive unemployment compensation. Therefore, discouragement effects should be rather limited. Little is known about the transitions from out of the labor force to other labor market states. This is mostly due to the fact that out of the labor force is a relatively heterogeneous labor market state.

Occurrence and lagged duration dependence Many authors found evidence for the hypothesis that past unemployment causes future unemployment (for example, Arulampalam, 2001, Arulampalam et al., 2000, 2001, Gregg, 2001, Mühleisen and Zimmermann, 1994, or Flaig et al., 1993). Past unemployment experiences probably increase the current unemployment duration, because of stigmatization effects or a loss in human capital. Biewen and Steffes (2010), for the case of Germany, find evidence for such stigmatization effects. Gibbons and Katz (1991) show that past unemployment experiences increase the pressure to accept bad job matches, which in turn leads to a higher probability to end up in unemployment again. These effects may become even more pronounced with the number and duration of past unemployment experiences. Winter-Ebmer and Zweimüller (1992) also find evidence for this hypothesis. By contrast, Ehrenberg and Oaxaca (1976) suggest that a longer job search, that means a longer unemployment duration, results in a better job match and has therefore positive effects on the current employment duration.

Past employment experiences are generally assumed to increase the probability of finding a new job. Reasons for this may be that the experience of past employment spells signals a higher productivity or at least a higher motivation to work. Furthermore, past employment periods may have been used to build a network, which may help finding new employment (Ioannides and Loury, 2004). By contrast, Ljungqvist and Sargent (1998) suggest that human capital gained in previous employment periods may be firm-specific and hence not relevant for future employers. Consequentially, future employers are not willing to pay the too high reservation wage and therefore increase the unemployment duration of those searching for a job. Again, institutional features may have an impact. For example, the entitlement period of unemployment benefits depends positively on past employment experiences. As mentioned, the entitlement period may have a strong effect on the current unemployment duration and therefore may induce spurious effects of past employment experiences.

On first sight, it may be assumed that past employment experiences decrease the probability of a job loss. Although human capital gains may be firm-specific, past employment experiences result in a larger human capital and more work experience and therefore decrease the probability of becoming unemployed. Doiron and Gorgens (2008) find evidence for this hypothesis for Australian school-leavers. However, the effects probably depend on the quality and durations of past employment experiences. Boockmann and Hagen (2006) suggest that such circles may exist between temporary employment and unemployment, while Stewart (2007) shows that frequent changes between low-pay employment and unemployment create stigmatization effects and individuals therefore remain in a vicious circle of low-pay employment and unemployment. Similarly, Cockx and Picchio (2012) and Mosthaf (2011) find support for the idea that past temporary employment spells build a bridge to permanent employment for long-term unemployed.

3.3 Data and Sample Selection

3.3.1 German Integrated Employment Biographies Sample

The following empirical analysis is based on the Scientific Use File of the German Integrated Employment Biographies Sample (IEBS). The IEBS has been made available by the Research Data Center of the German Federal Employment Agency. It is a 2.2% random sample from a merged data file that integrates data from four different administrative registers.

The first register contains data on individual employment histories (*Beschäftigten-Historie*, BeH). Employment periods that are subject to social security contributions are registered by the public pension funds and then used to construct the individual's employment histories. Since employment periods that are not subject to social security contributions are not part of the data set, employment histories of self-employed individuals or lifetime civil servants are not part of the data. In total, the BeH provides information on employment spells for the period from 1992 to 2003. In addition, the register provides information on the current employer and personal characteristics.

The second register provides data on individual's histories of receipt of transfers from the unemployment insurance system (*Leistungsempfänger-Historie*, LeH), i.e. data on the receipt of unemployment benefits, unemployment assistance and income maintenance during training measures. Data on the receipt of unemployment transfers are available for the period from 1992 to 2004. In addition, relevant information of the level of unemployment benefits or assistance and further personal characteristics are provided.

The third register offers data on the histories of registered unemployment (*Arbeitsuchenden und Bewerbungsangebotsdaten*, BewA). The BewA provides information on individuals who were registered as unemployed or searched for a job at their local employment agency. Unfortunately, data from the BewA is only partly available for the period from 1992 to 1999 and completely available for the period from 2000 to 2003.

Finally, the fourth register contains data on individual histories of participation in public sponsored measures of Active Labor Market Policies (*Maßnahme-Teilnehmer-Gesamtdatenbank*, MTG), i.e. on job-creation measures (*Arbeitsbeschaffungs-Maßnahmen*), settling-in allowances (*Eingliederungszuschuss*), assistance to start an own business (*Existenzgründerzuschuss*), and further training schemes that range from vocational trainings to language courses. Again, data from the MTG is completely available only for the period from 2000 to 2004.

Merged together, the four registers provide a data set that contains labor market histories of around 1.6 million individuals. The information on start and end dates are very precise, as they are measured on daily basis. Missing information on employment spells for 2004 means that all labor market histories from the end of 2003 onwards are censored. Figure 3.1 presents the labor market history of a typical person in the IEBS. A spell is left-censored, if it is the individual´s first spell recorded by the data set and has a start date that can not be observed, i.e. the spell starts before January 1, 1992. A spell is right-censored, if it is the individual´s last spell recorded by the data set and has an end date that can not be observed, i.e. the spell ends after December 31, 2003. Periods with no information from any of the four registers may also occur, because individuals become self-employed, start to work as lifetime civil-servants, are on maternity leave, or completely withdraw from the labor market. Identification of the labor market state is particularly difficult for these periods. In particular, distinction between between periods out of the labor force and unemployment periods is often impossible. In certain cases the reason for such a gap in the labor market history can be inferred from the spells before and after the gap. Differentiating between registered unemployment and out of the labor force is particularly difficult between 1992 and 1999 as there may be periods of registered unemployment without receipt of unemployment benefits.

In addition to aforementioned problems, overlapping spells from one or more registers may exist. On the one hand, overlapping spells provide additional information that makes identification of the correct labor market state more reliable. For example, parallel information on registered unemployment and receipt of unemployment benefits makes the statement that the individual is unemployed more reliable. On the other hand, such overlapping spells can be a burden, because some of the overlaps contradict institutional rules and may be the result of errors. The surveys by Bernhard et al. (2006) and Jaenichen et al. (2005) present comprehensive overviews of such overlaps which contradict institutional rules and also point out possible solutions.

3.3.2 Definition of labor market states

The IEBS does not provide direct information on the current labor market state. These rather have to be identified using the information given in the four registers. In general,

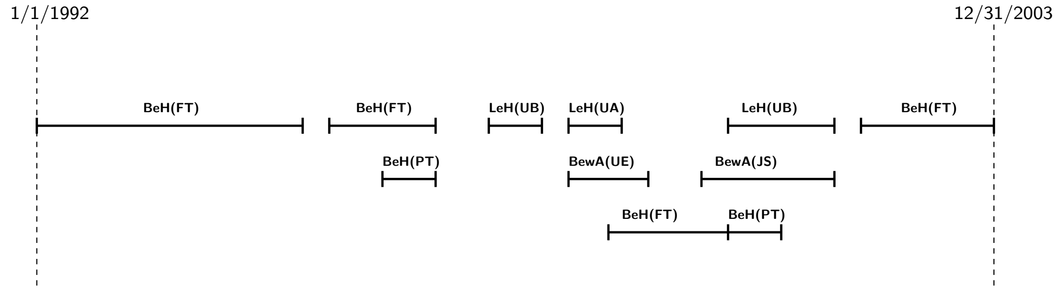

Figure 3.1: Labor market history of a typical person in the IEBS. The figure displays the labor market history of a typical individual. BeH, LeH, BewA, and MTG are the four registers of the IEBS. FT=full-time employment, PT=part-time employment, UB=receipt of unemployment benefits, UA=receipt of unemployment assistance, UE=registered unemployment, JS=job search.

the information on the current employment status suffices to identify the labor market state. The situation is more difficult for periods without information. For these periods, the labor market state is identified by making certain assumptions. The following subsection provides more details on the identification of the different labor market states.

Unemployment: In order to identify unemployment periods, the official definition for unemployment in Germany given by the Federal Statistical Office, i.e. individuals, who are registered as unemployed and do not work for more than 15 hours per week, does not suffice. In particular, the period from 1992 until 1999 does not provide complete information on registered unemployment, such that the official definition would not comprise all unemployment periods and has thus to be modified. Therefore, individuals who receive transfers from the unemployment compensation system, individuals who are registered as unemployed or at least searching for a job, or attend some form of public sponsored measures[2], and individuals who do not work for more than 15 hours per week, are considered as unemployed. This means job-creation measures and settling-in allowances are not considered as unemployment, but as employment. For the period

[2] Excluding job-creation measures (*Arbeitsbeschaffungs-Maßnahmen*), settling-in allowances (*Eingliederungszuschuss*), assistance to start an own business (*Existenzgründerzuschuss*)

from 1992 to 1999 unemployed individuals, particularly those of young age, may not appear in the data set, although they are registered as unemployed, if they are not entitled to receive transfers from the unemployment insurance system. Furthermore, individuals who quit their job without good cause disqualified themselves for transfers from the unemployment compensation system for up to twelve weeks. Unfortunately, the data set does not include information on the reason for the dismissal. For periods without information on the individual, it is therefore necessary to differentiate whether the individual is unemployed or has dropped out the labor force. In order to do this, I make the following assumptions. To begin with, periods without information on the individual and which lie between an employment period and an unemployment period, are assumed to be unemployment periods, if the individual starts to receive transfer payments or registers as unemployed within three months after the termination of a job. Second, periods with no information on the individual, which are between two unemployment periods, are assumed to be unemployment periods, if the individual starts to receive transfer payments again or renews the registration as unemployed within one month or within three months in the case of cut-off times[3]. Finally, periods that lie between an unemployment period and an employment period are assumed to be unemployment periods, if the individual starts working again within one month or within three months in the case of cut-off times.

Employment: In general, any type of employment, i.e. full-time and part-time employment, marginal employment, and also subsidized employment like job-creation measures, is considered as employment. However, if the individual is additionally registered as unemployed or receives transfers, and works less than 15 hours per week, the corresponding spell is classified as unemployment. Also, periods, with no information on the individual, between two employment periods are considered as employment, if they are

[3] Cut-off times are periods, in which the individual is prohibited to receive transfers from the unemployment compensation system. A possible reason may be to quit a job without good cause. Whether a gap is due to a cut-off time is given by the three registers that concern to periods in unemployment, i.e. LeH, BewA, and MTG, but not by the BeH.

shorter than one month.

Out of Labor Force: The general definition of an individual who is out of the labor force refers to someone who is not employed and not actively searching for a job. The data set provides information on whether the individual is employed or unemployed, but not on whether the individual actively searches for a job. Therefore, one has to rely on the information given in the data set to identify those periods as employment, or unemployment periods, or out of the labor force for which no information is present. In addition, individuals may become self-employed and may therefore not be observed in the data set. In order to account for this point, if any information about becoming self-employed is available, the individual is completely dropped from the sample. Finally, after identifying all employment and unemployment periods and accounting for self-employment, periods with no information on the individual are considered as periods out of the labor force.

Figure 3.2 provides an example for the identification of labor markets for a typical person in the IEBS.

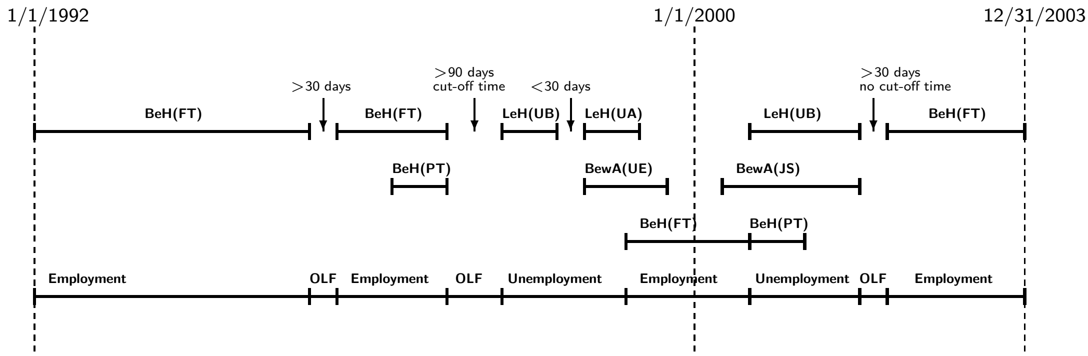

Figure 3.2: Identification of labor market states for a typical person in the IEBS. The figure displays a labor market history of a typical individual and the resultign labor market states that have to be identified from the four registers BeH, LeH, BewA, and MTG of the IEBS. FT=full-time employment, PT=part-time employment, UB=receipt of unemployment benefits, UA=receipt of unemployment assistance, UE=registered unemployment, JS=job search.

Table 3.1 presents the numbers and frequencies of transitions between all three states.

The table shows that the present identification strategy yields a relatively homogenous sample, because the frequencies change only slightly across years.

Transition	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Total
E → U	14,232	17,970	15,688	16,574	20,658	21,062	18,864	18,985	19,275	19,631	20,023	20,826	223,788
E → O	7,102	6,643	7,746	7,656	7,054	5,705	5,601	6,571	4,344	5,324	6,507	5,030	75,283
U → E	10,196	15,613	16,939	15,381	17,818	19,978	19,768	19,834	18,939	17,387	16,823	17,645	206,321
U → O	2,135	3,698	4,978	4,499	4,451	4,476	4,568	3,591	3,486	3,530	4,482	4,296	48,190
O → E	16,216	9,922	6,538	8,391	6,123	6,164	8,040	6,362	6,695	4,740	5,034	4,713	88,938
O → U	1,044	2,988	3,422	4,124	4,209	4,120	4,864	4,035	3,712	3,884	4,287	4,095	44,784
Total	50,925	56,834	55,311	56,625	60,313	61,505	61,705	59,378	56,451	54,496	57,156	56,605	687,304

Table 3.1: Transitions across years. The table presents the number of transitions of all individuals observed from 1992 until 2003.

3.3.3 Sample design

Due to large differences between employment trajectories of men and women, the following analysis focuses on prime aged men. The analysis of women's employment histories is complicated by the fact that women are much more likely to interrupt their career in order to raise children. The final sample therefore consists of men who were born between 1950 and 1970. This means the individuals are at least 22 years old when observed for the first time and at most 53 years old when observed for the last time. Prime-aged men constitute a very large subgroup in the labor market and have the lowest propensity to drop out of the labor force. Due to this high attachment to the labor market, the labor market histories of prime-aged men are often continuously observed by the four registers. Therefore, distinction between unemployment and out of the labor force is easier than for other subgroups.

The final sample consists only of those men who changed their labor market state at least once during the period from January 1, 2000 until December 31, 2003. In addition, estimation is conducted using only those spells that begin during the period under consideration. This means the final sample is similar to a flow sample, which are typically used for single-spell models. By using such a form of sample selection, the resulting sample consists of men who belong to the group of individuals who are most likely to take part in labor market policy measures. The analysis of this sample is therefore highly relevant for the analysis of labor market policies. An additional feature of this sampling mechanism is that those spells which begin prior to the first spell used for estimation can be used to construct the labor market history. Since this preceding labor market history generally covers around eight years, these histories can be used to construct regressors that account for occurrence and lagged duration dependence and that can be used to estimate state dependence effects for prime-aged men, whose labor market entry is typically not observed. Finally, this form of sampling mechanism avoids left-censoring problems, because only spells of which the start date is known enter the sample. In general, only very few authors have dealt with left-censoring issues (see for example D'Addio and Rosholm, 2002a), and their approaches require strong assumptions.

Nonetheless, sampling individuals in the way described requires some adjustments. First, right-censoring becomes more likely the later is the date at which the individual enters the sample. For example, if I used the cumulative lagged durations of the three labor market states as regressors, the cumulative lagged durations of all three labor market states of an individual, whose first spell starts on January 1, 2003 would on average be longer than the cumulative lagged durations for an individual, whose first spell starts on January 1, 2001. This means that the first spell of the first individual, who on average has longer cumulative lagged durations, is more likely to be censored than the first spell of the second individual. Therefore, longer lagged durations would erroneously result in a higher probability to be right-censored and coefficient estimates for lagged duration would be biased. In order to avoid this problem, I construct regressors referring to the lagged duration and to the occurrence of past labor market states using only the information from the last eight years of the employment history before the start of a certain spell[4].

A second point one has to account for, is the initial conditions problem. The initial

[4] The problem with the cumulative occurrence of past labor market states is the same as with the cumulative duration of past labor market states, although the effects are less strong.

conditions problem arises when using lagged outcomes as regressors because these are not exogenous with respect to unobserved characteristics. To be more precise, for the first spell of an individual in the estimation sample, the regressors that account for state dependence are based on the history of prior labor market outcomes. These outcomes, which are either not used for estimation or not observed in the data set, are certainly influenced by unobserved heterogeneity like ability or the attitude to work. Therefore, estimates for state dependence effects will be biased, if one does not take account of these prior outcomes. A description of how this is done, will be given in the next section. Figure 3.3 gives a short overview of how individuals are sampled and what parts of the individual´s history are used.

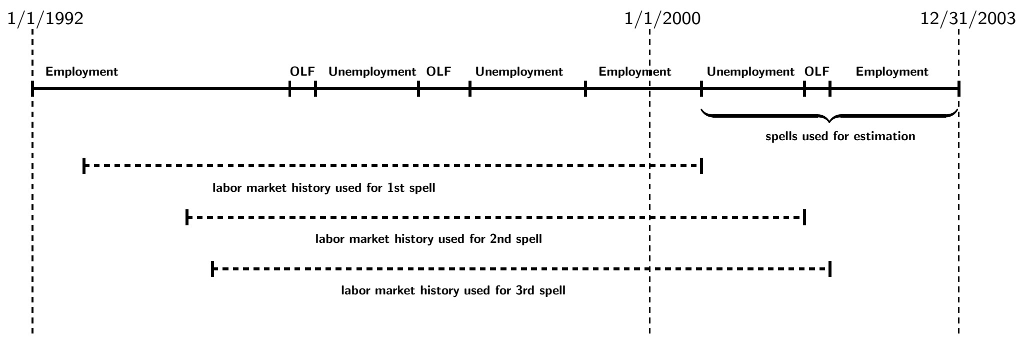

Figure 3.3: Sampling strategy. An individual enters the sample, if she transits from one state to an other after 1/1/2000. All spells that start after 1/1/2000 are used for estimation. All information on the labor market history that starts 8 years prior to a certain spell is used in order to construct variables that account for state dependence.

3.3.4 Descriptive Analysis of the Data Set

There are altogether 208,909 individuals born between 1950 and 1970, which comply with the requirements of the overall sample. Of these 69,820 individuals have spells that begin during the period from 2000 to 2003. Basic summary statistics for the final sample are presented in Table 3.2. The average duration of the sum of all spells that begin after January 1, 2000 and that are observed until December 31, 2003 is 969 days, which is a little more than two-and-a-half years. Of this average duration, on average 533 days (54.97% of the total time) are spent in employment, 317 days (32.67%) in unemployment, and 120 days (12.36%) out of labor force.

In total there are 224,709 spells, 91,977 of which are employment spells, 95,733 are unemployment spells, and 36,999 are out of the labor force spells. Although there are more unemployment than employment spells, the last spell observed is mostly spent in employment (35,788 employment spells vs 25,662 unemployment spells and 8,370 spells out of the labor force). Most of the transitions occur from unemployment to employment (58,105 transitions or 37.51% of all transitions) or vice versa (48,472 or 31.29%).
Incidence rates display the number of exits per year and type of spell. Results indicate that the individuals observed, on average, experience even more periods in unemployment than in employment. However, employment periods on average are longer and therefore individuals spend more time in employment than in unemployment.
The bottom panel of Table 3.2 shows deciles for the distribution of all three types of spells. For instance, the 10%-decile shows that 10% of all employment spells are shorter than 45 days and 90% are longer. In general, for all deciles, except the last two, employment spells are longer than unemployment spells and spells out of the labor force, while for all deciles spells out of the labor force are longer than unemployment spells. The median length of employment spells is 337 days, while that of unemployment and out of labor force spells is 152 days and 183 days respectively.
Table 3.3 provides summary statistics for some of the personal characteristics. The mean age for the year 2000 for all individuals in the estimation sample is 38.94 years. The individual's occupation can be assigned to the sectors of manufacturing or service in almost 89% of the cases, while only a small number is employed or searches employment in the other sectors. Information on individual's education shows that 18.8% of all individuals have not obtained any educational degree until the last observation.

	Origin state			Total
	E	U	O	
Number of histories starting after 01/01/2000				
Total				69,820
Time under observation (days)				
Average per person	532.88	316.64	119.82	969.34
Per cent	54.97	32.67	12.36	100.00
Maximum history length				1460
Number of spells				
Total	91,977	95,733	36,999	224,709
Right-censored	35,788	25,662	8,370	69,820
Uncensored	56,189	70,071	28,629	154,889
Destination state				
E	0	58,105	14,991	
U	48,472	0	13,638	
O	7,717	11,966	0	
Incidence rate (exits per year)				
Total	0.55	1.16	1.25	
Destination state				
E	0	0.96	0.65	
U	0.48	0	0.60	
O	0.07	0.20	0	
Duration quantiles (days)				
10%	45	27	40	
20%	103	53	60	
30%	181	79	91	
40%	257	108	123	
50%	337	152	183	
60%	539	223	274	
70%	965	347	364	
80%		576	470	
90%		1198	744	

Table 3.2: **Data overview.** E: Employment, U: Unemployment, O: Out of labor force. *Notes:* Quantiles are based on the Kaplan-Meier product limit estimator. The 80th and 90th percentile are not identified due to right-censoring.

Most individuals have passed a vocational training (67.6%), while only few individuals have obtained higher educational degrees. The overproportional number of individuals with low educational degrees is explained by the selection of only those individuals, who are not continuously employed during the period from 1992 to 2003.

	Date	***Mean***	***Standard deviation***
Explanatory variable			
Age	January 1, 2000	38.94	5.88
	last spell	41.86	5.93
Occupation	last spell		
Farming		0.041	0.199
Mining		0.003	0.058
Manufacturing		0.477	0.499
Engineering		0.057	0.232
Service		0.413	0.492
Miscellaneous		0.009	0.093
Education	last spell		
No degree		0.188	0.391
Vocational Training		0.676	0.468
High School		0.008	0.091
High School + Vocational Training		0.039	0.193
Technical College		0.028	0.166
University Degree		0.060	0.238

Table 3.3: Descriptive statistics of explanatory variables. The table presents the mean and standard deviation of selected explanatory variables.

3.4 Econometric Methods

In the next section I present the econometric method that is employed to estimate the conditional transition intensities. The methodology is similar to that used by Doiron and Gorgens (2008). However, due to a different sample design, it is necessary to account for initial conditions. This is done following an approach similar to the one suggested by Wooldridge (2005).

3.4.1 Outcome and explanatory variables

I use the labor market history of an individual i as the outcome variable of the model. The history includes two aspects: transition times and destination states. Let $T_{i,j}$ be the calendar time for the start date of the jth spell of individual i, $S_{i,j}$ be the respective type of the labor market state, i.e. whether the individual is employed (E), unemployed (U), or out of the labor force (O), and let $j = 0, 1, 2, \ldots, n_i$. This definition implies that $S_{i,j-1} \neq S_{i,j}$ and $T_{i,j-1} < T_{i,j}$, i.e. spells end when individuals switch to another state. In order to estimate conditional transition intensities, I use only spells that begin during the period $[T_{i,0}, C_i]$, where $T_{i,0}$ is the start date of the first complete spell after January 1, 2000 and C_i is a random variable, which indicates the censoring point. Observed spells with start date earlier than January 1, 2000 are used to construct the labor the history of each individual.

To clarify the discussion, it is essential to distinguish between exogenous and lagged endogenous explanatory variables in the notation. Let $X_i(t)$ be the vector of exogenous explanatory variables for individual i at time t, and $\mathbf{X}_i(t)$ be the path of exogenous explanatory variables until t. Further, define $\mathbf{Y}_i(t, s)$ to be the path of outcome variables recorded until point t, where is s is the labor market state taken at t and t is not necessarily a transition time.

It is well-known that it is difficult to separate state dependence effects from spurious dependence on past outcomes if unobserved heterogeneity is not accounted for. In order to account for unobserved heterogeneity, I therefore include random effects in the model. To this end, let V_i be a random vector that captures unobserved personal and environmental characteristics.

3.4.2 Transition intensities, right censoring and the likelihood function

As the data set provides daily information on transitions between labor market states, continuous measurement of time can be assumed. To this end, let $h(t, s|\mathbf{y}(\tilde{t}, \tilde{s}), \mathbf{x}(t), v)$ be the transition intensity for a transition from state $\tilde{s}$ to state s at time t, given that the current spell began at time $\tilde{t}$ and conditional on the labor market history, $\mathbf{y}(\tilde{t}, \tilde{s})$, the path of explanatory variables $\mathbf{x}(t)$ and the value of unobserved heterogeneity, v. Throughout the chapter lowercase letters indicate realized values of random variables. The contribution to the likelihood function of individual i conditional on $\mathbf{X}_i(C_i) = \mathbf{x}_i(c_i)$, and $V_i = v_i$, is then given by

$$\begin{aligned} \mathscr{L}\left(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{x}_i(c_i), v_i\right) = &\ \mathscr{L}\left(c_i|\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), \mathbf{x}_i(c_i), v_i\right) \\ &\times \left(\prod_{j=1}^{n_i} \mathscr{L}\left(t_{i,j}, s_{i,j}|\mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(t_{i,j}), v_i\right)\right) \\ &\times \mathscr{L}\left(\mathbf{y}_i(t_{i,0}, s_{i,0})|\mathbf{x}_i(t_{i,0}), v_i\right) \end{aligned} \tag{3.1}$$

Equation (3.1) displays the likelihood contribution using the joint distribution of all outcomes conditional on observed and unobserved heterogeneity. The first term of equation (3.1) is then the likelihood contribution for the last spell observed. For the last spell neither the transition time, nor the transition state is completely known. However, the likelihood of survival in state S_{i,n_i} up to the censoring point C_i can be given. Assuming that C_i is distributed independently from the past history and from observed and unobserved characteristics, the likelihood contribution for the last spell evolves as

$$\mathscr{L}\left(c_i|\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), \mathbf{x}_i(c_i), v_i\right) = \exp\left(-\sum_{\substack{k=E,U,O \\ k \neq s_{i,n_i}}} \int_{t_{i,n_i}}^{c_i} h(u, k|\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), \mathbf{x}_i(u), v_i)\,\mathrm{d}u\right). \tag{3.2}$$

Equation (3.2) then simply describes the probability that no transition takes place during the period $[T_{i,n_i}, C_i]$.

The second term of equation (3.1) captures the likelihood contribution of all completed spells with a start date later than January 1, 2000. Conditional on $\mathbf{Y}_i(t_{i,j-1}, s_{i,j-1}) = \mathbf{y}_i(t_{i,j-1}, s_{i,j-1})$, $\mathbf{X}_i(t_{i,j}) = \mathbf{x}_i(t_{i,j})$, and $V_i = v_i$ the likelihood contribution for the j-th spell of individual i is

$$\begin{aligned} \mathscr{L}\left(t_{i,j}, s_{i,j} | \mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(t_i), v_i\right) &= h\left(t_{i,j}, s_{i,j} | \mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(t_{i,j}), v_i\right) \\ &\times \exp\left(-\sum_{\substack{k=E,U,O \\ k \neq s_{i,j-1}}} \int_{t_{i,j-1}}^{t_{i,j}} h(u, k | \mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(u), v_i)\, \mathrm{d}u\right). \end{aligned} \tag{3.3}$$

Equation (3.3) describes the likelihood contribution for a transition of individual i from state $s_{i,j-1}$ to $s_{i,j}$ at time $t_{i,j}$. While the first term describes the intensity for a transition to state $s_{i,j}$ at time $t_{i,j}$, the second term equals the probability for surviving in the current state from $t_{i,j-1}$ until $t_{i,j}$. Obviously, individuals always face two competing destination states.

The last term in equation (3.1) captures the likelihood contribution of all spells that begin prior to January 1, 2000 conditional on observed covariates $\mathbf{X}_i(t_{i,0})$ and unobserved heterogeneity V_i. As I only estimate the transition intensities for the period $[T_{i,0}, C_i]$, it is not necessary to specify the functional form of this term. However, omitting this term would result in biased estimates, particularly estimates that refer to state dependence effects would be concerned.

3.4.3 Initial conditions and unobserved heterogeneity

In order to take account of this initial conditions problem, I follow Wooldridge (2005) and condition the likelihood contribution of individual i on $\mathbf{Y}_i(t_{i,0}, s_{i,0})$. Doing so eliminates the need to specify the last term of equation (3.1), but requires to specify the probability function of V_i conditional on $\mathbf{Y}_i(t_{i,0}, s_{i,0})$, in order to integrate out the unobserved effect

V_i. Wooldridge (2005) suggests to specify the probability function of V_i conditional on $\mathbf{Y}_i(t_{i,0}, s_{i,0})$ as a parsimonious function, so that the unobserved effect V_i conditional on $\mathbf{Y}_i(t_{i,0}, s_{i,0})$ can be integrated out easily. I therefore assume V_i to be a linear function of $\mathbf{Y}_i(t_{i,0}, s_{i,0})$ and a residual random effect U_i, whose distribution is independent of everything else. This means that the last term of equation (3.1) vanishes. Besides, integrating out V_i conditional on $\mathbf{Y}_i(t_{i,0}, s_{i,0})$ results in integrating over the unconditional distribution of the random effect U_i and estimating some additional coefficients that refer to $\mathbf{Y}_i(t_{i,0}, s_{i,0})$, i.e. to the "initial conditions". The resulting likelihood contribution of individual i is then given by

$$\mathscr{L}\left(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i)\right) = \int_{-\infty}^{\infty} \mathscr{L}\left(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i), u_i\right) \mathrm{d}A^*(u)\,, \tag{3.4}$$

where A^* is the time-invariant marginal distribution of U_i.

The support of the unconditional distribution of U_i is assumed to take on only a small number of points. This is common practice in the literature (see Heckman and Singer, 1984) and allows one to think of the points of support as different types of persons, of which each has different characteristics with regard to the six transitions. Allowing for M types of persons, equation (3.4) is given by

$$\mathscr{L}\left(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i)\right) = \sum_{m=1}^{M} \mathscr{L}\left(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i), u_m\right) \mathrm{p}_m, \tag{3.5}$$

where U_i has discrete support $\{u_1, \ldots, u_M\}$ and $\mathrm{p}_m = \mathrm{P}(U_i = u_M)$ is the corresponding probability function.

3.4.4 Parametrization and estimation

In general, the transition intensities of an individual i depend on the paths of $\mathbf{X}_i(t)$ and $\mathbf{Y}_i(t, s)$. However, estimation would become impossible including the entire paths as regressors. The literature therefore suggests to specify that a random vector $X_i(t)$, which captures the contemporaneous exogenous variables that sufficiently represent the path $\mathbf{X}_i(t)$. Higher sufficiency can be achieved by including lagged variables. With regard to the endogenous variables, it can be assumed that the path $\mathbf{Y}_i(t,s)$ affects the transition intensity only by a finite-dimensional random vector $Y_i(t)$, which summarizes the information of the path $\mathbf{Y}_i(t,s)$. Furthermore, let $Y_i^*(t_0)$ be a finite-dimensional random vector that summarizes the information of the path $\mathbf{Y}_i(t_{i,0}, s_{i,0})$. I further assume that $Y_i^*(t_0)$ captures also the effects of the path of observed heterogeneity $\mathbf{X}_i(t_{i,0})$ given at point $T_{i,0}$.

Following Heckman and Singer (1984) already a small number of support values suffices to model unobserved heterogeneity. In the following, the number of points of support is chosen to be $M = 3$. The points of support for the distribution of the unobserved effect U_i can be displayed as a $M \times 6$ random matrix

$$\begin{bmatrix} u_1^{s_E,s_U} & \cdots & u_M^{s_E,s_U} \\ \vdots & \ddots & \vdots \\ u_1^{s_O,s_U} & \cdots & u_M^{s_O,s_U} \end{bmatrix}, \tag{3.6}$$

with s_k indicating the states $k = E, U, O$. The columns can be considered as column vectors that represent the $M = 3$ types of persons and their intensity for each of the six transitions. I do not make assumptions on the location of the points of support. In particular, the correlations between the transitions are unconstrained. With $M = 3$, this results in the estimation of $3 \times 6 = 18$ parameters that relate to the support and two parameters that relate to the probability function.

Now, let $u^{\tilde{s},s}$ denote the M-dimensional row vector representing the M points of support for the transition $\tilde{s}$ to s. Further, let $z(v) = (\mathbf{1}(v = u_1), \ldots, \mathbf{1}(v = u_M))'$ be an M-dimensional vector function indicating the support points, and let $\mathbf{1}(\cdot)$ be the indicator function. Then $z(v)'u^{\tilde{s},s}$ is the component of the support that corresponds to the transition of type v from state $\tilde{s}$ to state s.

Each transition is modeled as a mixed proportional hazard model. This means that a baseline transition intensity, which is only a function of time, is multiplied by a function of observed covariates and a function of the unobserved heterogeneity. Including also the parameters that account for initial conditions ($=\delta_{\tilde{s},s}$), the transition intensity from $\tilde{s}$ to s is given by

$$h(t,s|\mathbf{y}(\tilde{t},\tilde{s}),\mathbf{x}(t),v) = \lambda_{\tilde{s},s}(t-\tilde{t};\alpha_{\tilde{s},s})\exp\left(x(t)'\beta_{\tilde{s},s}+y(\tilde{t})'\delta_{\tilde{s},s}+y^*(t_0)'\gamma_{\tilde{s},s}+z(v)'u_{\tilde{s},s}\right),$$

$$t \geq \tilde{s}, s \neq \tilde{s}, \text{and} \quad v \in \{u_1,\ldots,u_M\} \tag{3.7}$$

where $\lambda_{\tilde{s},s}(t-\tilde{t};\alpha_{\tilde{s},s})$ represents the baseline transition intensity from state $\tilde{s}$ to state s and $\alpha_{\tilde{s},s}$, $\beta_{\tilde{s},s}$, $\delta^j_{\tilde{s},s}$, and $\gamma_{\tilde{s},s}$ are parameters to estimate. The baseline transition intensities are parameterized as piecewise constant functions

$$\lambda_{\tilde{s},s}(t-\tilde{t};\alpha_{\tilde{s},s}) = \exp\left(\sum_{k=1}^{K_{\tilde{s},s}}\alpha_{k,\tilde{s},s}\mathbf{1}\left(\tau_{k-1}<t-\tilde{s}\leq\tau_k\right)\right), \tag{3.8}$$

where $\tau_0=0$, $\tau_{k-1}<\tau_k$ and $\tau_{K_{\tilde{s},s}}=\infty$. In order to identify the model $\alpha_{1,\tilde{s},s}$ is set to zero.

Finally, the unknown parameters $\alpha_{\tilde{s},s}$, $\beta_{\tilde{s},s}$, $\delta_{\tilde{s},s}$, and $\gamma_{\tilde{s},s}$ are estimated by the method of Maximum Likelihood using analytical first and second derivatives.

3.4.5 Identification

In this study I use a MPH-model with competing risks of exit that also accounts for lagged duration dependence and occurrence dependence. Cockx and Picchio (2012) provide evidence that such models are identified under fairly weak assumptions, given the data set provides multiple spells per individual and transition or time-varying exogenous regressors.

In a first step, however, it is reasonable to assume a single-risk model with just one spell per individual. Honoré (1993) proves non-parametric identification for such a model framework under the assumptions that the hazard is of a mixed proportional hazard form, the regressors vary exogenously and under an auxiliary assumption that concerns the first moments or the tail behavior of the unobserved heterogeneity. Using a similar set of assumptions, Horny and Picchio (2010) extend Honoré's (1993) proof to a competing risks framework.

Multiple spells per individual and transition (see Abbring and van den Berg, 2003b, and Picchio, 2012) as well as exogenous variation of time-varying variables (see Brinch, 2007, and Gaure et al., 2008) allow to relax these assumptions. Assuming that unobserved heterogeneity and parameters for observed variables are time-constant while exogenous variables vary across and within spells, imposes exclusion restrictions on the parameters. These exclusion restrictions allow to differentiate between variation of observed and unobserved heterogeneity. They also allow to identify parameters for endogenous variables like lagged duration dependence and occurrence dependence. Consider, for example, the unemployment rate which is exogenous to all individuals. It is obvious that the unemployment rate in 2003 affects outcomes only in 2003 and that, due to the timing of decision-making, the unemployment rate in 2001 has no effect on outcomes in 2003 except through occurrence and lagged duration dependence. The unemployment rate may therefore be used as an instrument for the variables accounting for occurrence and lagged duration dependence. Bhargava (1991) and Mroz and Savage (2006) show that time-varying exogenous regressors can be used to identify causal effects of endogenous variables also in discrete dynamic panel data models.

The model used here comprises multiple spells per individual and transition. I further condition on strictly exogenous variables like the unemployment or the growth rate. It is therefore possible to argue that the model is over-identified and that the assumption of independence between structural components and unobserved heterogeneity is not crucial to separate these two effects.

3.5 Results

3.5.1 Estimated transition intensities

Table A3.1 presents estimates for the econometric model described in the previous section. The three forms of state dependence are accounted by defining a specific set of covariates. First, occurrence dependence is controlled for using the type of the preceding spell, and the cumulative duration of all previous spells in the three labor market states. Lagged duration dependence is captured by including the duration of the preceding spell and the cumulative duration of all previous spells in the three labor market states. By differentiating between the occurrence and duration of the preceding spell and the occurrence and duration of all other previous spells, it is possible to distinguish, at least partially, between short-run and long-run effects. Finally, dependence due to the current duration is captured by the time dummies that refer to the piecewise constant functions of the baseline transition intensities. Effects that relate to initial conditions are measured by the cumulative number and duration of all previous spells in any of the three states given at point $T_{i,0}$. In total there are 292 parameters to estimate. The large number of parameters is due to the fact that each variable affects six transition intensities. A list of all covariates and whether they are time-varying is reported in Table 3.4. Results are given in table 3.5 and reported as marginal effects. All results represent the change in the probability to transit to a certain state within the first year after the start of a spell[5].

[5] Following Kyyrä (2009), the marginal effects are calculated at the mean of the large set of covariates. In the case of dummy variables, effects are calculated for a representative category.

	Variation across time
Duration dependence	
Elapsed 30-91	time-varying on a daily basis
Elapsed 91-182	time-varying on a daily basis
Elapsed 183-364	time-varying on a daily basis
Elapsed 365-546	time-varying on a daily basis
Elapsed 547-729	time-varying on a daily basis
Elapsed 730-1094	time-varying on a daily basis
Elapsed 1095-1460	time-varying on a daily basis
Occurrence dependence	
Preceding E spell	time-constant within spell
Preceding U spell	time-constant within spell
Previous cum. E spells	time-constant within spell
Previous cum. U spells	time-constant within spell
Previous cum. O spells	time-constant within spell
Lagged duration dependence	
Preceding E duration	time-constant within spell
Preceding U duration	time-constant within spell
Preceding O duration	time-constant within spell
Previous cum. E duration	time-constant within spell
Previous cum. U duration	time-constant within spell
Previous cum. O duration	time-constant within spell
Personal characteristics	
Age	time-varying on a yearly basis
Age^2	time-varying on a yearly basis
Foreigner	time-constant
Farming	time-varying on a daily basis
Mining	time-varying on a daily basis
Engineering	time-varying on a daily basis
Service	time-varying on a daily basis
Miscellaneous	time-varying on a daily basis
Voc. Train.	time-varying on a daily basis
HS degree	time-varying on a daily basis
HS + VT	time-varying on a daily basis
Tech. College	time-varying on a daily basis
Uni. degree	time-varying on a daily basis
Environmental characteristics	
Lagged GDP growth	time-varying on a monthly basis
Lagged unemployment rate	time-varying on a monthly basis
East, shortcoming in employment	time-varying on a daily basis
West, hi. urbanized + hi. U-rate	time-varying on a daily basis
West, more rural + avg. U-rate	time-varying on a daily basis
West, hi. dyn. centers + g. LMC	time-varying on a daily basis

Table 3.4: **List of covariates.** The table presents the covariates used for estimation and indicates whether they are time-varying.

Duration dependence Figure 3.4 plots the baseline transition intensity curves, which capture the current duration dependence, for the six transitions. The figure displays that generally both transitions from employment exhibit negative duration dependence. Negative duration dependence is especially strong for the transition into unemployment. There are several explanations for these findings. To begin with, higher severance payments for workers with more tenure can result in increasing dismissal costs. In addition, rising opportunity costs exist, because the worker probably becomes more valuable for a firm, the longer he is employed. Finally, Germany's strict Dismissal Protection Law can yield negative duration dependence, since dismissing workers with permanent contracts is only possible under certain circumstances resulting in high dismissal costs. While workers with temporary contracts can not be dismissed, their contracts run out at specific points of time without the possibility of continuation. This often means that workers with temporary contracts end up in unemployment within two years after the start of their employment period, while workers with permanent contracts remain employed. This conjecture is supported by the finding of two slight spikes in the baseline transition intensity at one and two years. The spikes correspond to the typical durations of temporary contracts in Germany, which normally last for one or two years.

The general course of the transition from unemployment to employment also exhibits negative duration dependence. The slight increase in the intensity between one and three months can be explained by the fact that even the high-skilled unemployed have to adjust to unemployment and generally do not find a job within the first month. The baseline hazard has no spikes at the points where the entitlement periods of unemployment benefits usually end. The negative duration dependence in unemployment is typically related to decreases in human capital or to stigmatization effects. The transition from unemployment to out of the labor force also exhibits negative duration dependence. This finding contradicts the existence of discouragement effects as proposed by Schweitzer and Smith (1974). However, the fact that there is no evidence for discouragement effects can be explained by the fact that unemployment assistance is unlimited in duration, if the unemployed remains registered as unemployed and keeps on searching for a job.

Both transition intensities from out of the labor force to employment and unemployment exhibit unclear patterns. While in the medium-run the duration dependence seems to be negative, there are strong increases in the intensity to return to the labor market at the beginning of both transitions. Such strong increases are most likely influenced by the definition of labor market states, in particular, how labor market states are identified

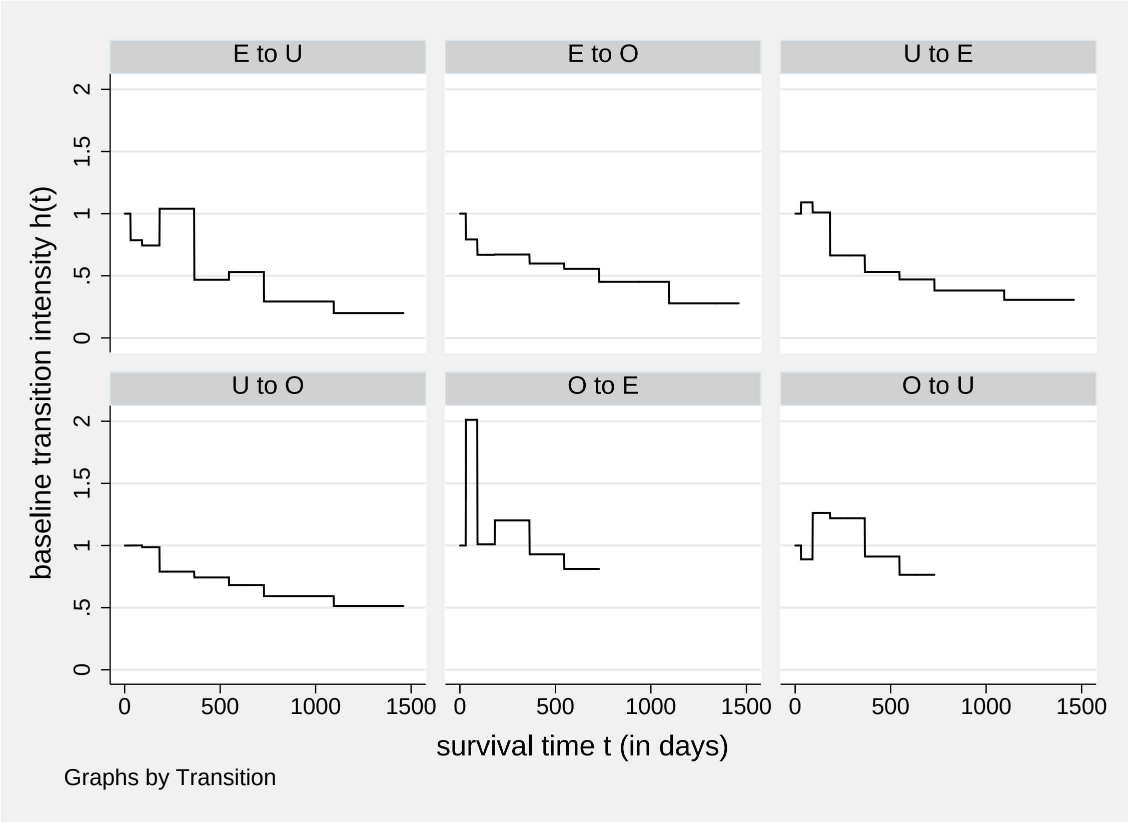

Figure 3.4: Estimated baseline transition intensities. The figure presents the estimated baseline transition intensities for the six transitions. The duration is measured in days. E: Employment, U: Unemployment, O: Out of labor force.

for periods without information. The strong increase in the transition intensity for transitions to employment can also be explained by job-to-job transitions with short sabbaticals. Negative duration dependence in the medium-run for both transitions may be due to decreases in skills or motivation. The strong and significant increases of the baseline transition intensity in the long run are again a consequence of how labor market states are defined[6].

[6] Since individuals with missing information for more than two years at the end of the observation period are dropped, all spells with more than two years of duration end up in employment or unemployment. This implies the strong and significant increase in the baseline transition intensity.

Occurrence dependence and lagged duration dependence For the transition from employment to unemployment, the estimates indicate that the occurrence of past unemployment experiences induce future unemployment. An individual who has been unemployed in the period before has a probability of ending up in unemployment within the first year that is higher by almost 16.4 percentage points compared to an individual that has been out of labor force the period before. Furthermore, an additional unemployment experience in the past increases the probability of becoming unemployed by 2.0 percentage points. These effects are large and statistically significant. Interestingly, the number of past employment spells also negatively affects the current employment duration. An additional employment experience in the past increases the probability of becoming unemployed by 0.6 percentage points. The reason for this is that individuals, who experienced many unemployment spells, by construction of the labor market states, must also have experienced many employment spells. Finally, an additional period out of the labor force has no effect on the probability of transiting from employment to unemployment. By contrast, no lagged duration dependence is found for the transition from employment to unemployment. Although some of the coefficients for lagged duration dependence are significant, the effects are rather small.

For the transition from employment to out of the labor force for individuals who were unemployed the period before, the probability of leaving the labor force within the first year is reduced by 4.5 percentage points. Furthermore, additional employment and unemployment spells reduce the probability by 0.3 percentage points, while an additional spell out of the labor force increases the probability of leaving the labor force by 0.7 percentage points. This means that past employment and unemployment periods increase the attachment to the labor market, even though the effects are small. On the other hand, individuals who have already spent time away from the labor market are more likely to leave the labor force again. As for the transition to unemployment, lagged duration dependence does not play a role.

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
State dependence:						
Occurrence dependence						
Previous spell (base: preceding O spell)						
Preceding E spell			0.070***	0.062***	0.173***	-0.367***
			(0.015)	(0.014)	(0.019)	(0.014)
Preceding U spell	0.164***	-0.045***				
	(0.019)	(0.006)				
Cumulative number of previous spells						
Previous cum. E spells	0.006**	-0.003**	0.017***	-0.011***	0.027***	0.008
	(0.003)	(0.001)	(0.003)	(0.002)	(0.005)	(0.005)
Previous cum. U spells	0.020***	-0.003***	0.008***	0.005***	-0.018***	0.030***
	(0.003)	(0.001)	(0.003)	(0.002)	(0.005)	(0.006)
Previous cum. O spells	-0.003	0.007***	-0.011**	0.014***	0.006	-0.040***
	(0.004)	(0.002)	(0.004)	(0.003)	(0.005)	(0.007)
Lagged duration dependence						
Duration of preceding spell						
Preceding E duration			-0.001***	0.000***	0.000	-0.003***
			(0.000)	(0.000)	(0.000)	(0.001)
Preceding U duration	0.001***	-0.000**			-0.005***	0.001***
	(0.000)	(0.000)			(0.000)	(0.000)
Preceding O duration	-0.003***	-0.000**	0.001	-0.000*		
	(0.000)	(0.000)	(0.000)	(0.000)		
Cumulative duration of previous spells (measured in months)						
Previous cum. E duration	-0.000	-0.000	-0.002***	0.000	-0.004***	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Previous cum. U duration	0.000	-0.000*	-0.004***	-0.000	-0.005***	-0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Previous cum. O duration	-0.003***	-0.001***	-0.002***	0.000	-0.005***	0.002
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Personal characteristics						
Age structure						
Age	0.001	-0.002***	-0.002	-0.002*	-0.007**	0.011***
	(0.002)	(0.000)	(0.002)	(0.001)	(0.003)	(0.003)
Nationality (base: German)						
Foreigner	-0.025***	0.004***	-0.019***	-0.001	0.018***	-0.008
	(0.005)	(0.002)	(0.006)	(0.003)	(0.006)	(0.008)
Occupation (base: manufacturing)						
Farming	0.016**	-0.006	-0.004	-0.004	-0.044**	-0.007
	(0.007)	(0.004)	(0.010)	(0.005)	(0.017)	(0.017)
Mining	-0.038	0.004	-0.178***	0.020	0.046	-0.037
	(0.036)	(0.013)	(0.051)	(0.023)	(0.050)	(0.041)

Table 3.5: (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Engineering	-0.095***	-0.001	-0.019	-0.016**	-0.006	-0.033*
	(0.016)	(0.003)	(0.013)	(0.007)	(0.011)	(0.019)
Service	-0.055***	0.005*	-0.013***	0.001	0.005	-0.016**
	(0.008)	(0.003)	(0.005)	(0.003)	(0.006)	(0.008)
Miscellaneous	0.000	0.019**	-0.044	-0.021*	-0.034	-0.047
	(0.017)	(0.009)	(0.029)	(0.012)	(0.022)	(0.032)
Education (base: no degree)						
Voc. Train.	-0.089***	-0.001	0.051***	-0.006***	-0.001	-0.058***
	(0.009)	(0.001)	(0.005)	(0.002)	(0.005)	(0.007)
HS degree	-0.081**	0.012**	0.007	-0.009	-0.017*	-0.101***
	(0.019)	(0.006)	(0.025)	(0.009)	(0.014)	(0.020)
HS + VT	-0.145***	-0.000	0.060***	-0.001	-0.015	-0.108***
	(0.016)	(0.003)	(0.010)	(0.005)	(0.010)	(0.014)
Tech. College	-0.160***	-0.010***	0.079***	-0.016	-0.017	-0.116***
	(0.018)	(0.003)	(0.012)	(0.006)	(0.011)	(0.017)
Uni. degree	-0.176***	-0.008***	0.060***	-0.012**	-0.055***	-0.168***
	(0.019)	(0.002)	(0.010)	(0.005)	(0.010)	(0.014)
Environmental characteristics						
Business cycle						
Lagged GDP growth	-0.002	-0.011***	0.037***	-0.020***	-0.015***	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.004)
Labor market situation in Germany (dynamic)						
Unemployment rate	0.033***	-0.008***	-0.035***	-0.002	-0.069***	-0.003
	(0.003)	(0.001)	(0.003)	(0.002)	(0.007)	(0.004)
Regional labor market situation in Germany (static, base: West, hi. dyn. regions + good LM-cond.)						
East, shortcoming in employment	0.096***	-0.006**	-0.060***	-0.025***	-0.044***	0.070***
	(0.012)	(0.003)	(0.008)	(0.006)	(0.011)	(0.013)
West, hi. urbanized + hi. U-rate	0.038***	0.005*	-0.092***	-0.006	-0.008	0.035***
	(0.008)	(0.002)	(0.009)	(0.004)	(0.008)	(0.013)
West, more rural + avg. U-rate	0.014**	-0.004*	-0.032***	-0.009**	-0.010	0.002
	(0.006)	(0.002)	(0.007)	(0.004)	(0.008)	(0.011)
West, hi. dyn. centers + g. LMC	0.010	0.006	-0.039***	0.005	0.004	-0.018
	(0.009)	(0.004)	(0.011)	(0.005)	(0.011)	(0.015)

Table 3.5: Results (marginal effects). Estimation results are presented as marginal effects. Marginal effects are calculated at the mean of X. Standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

For the transition from unemployment to employment, past employment spells are beneficial to become employed again. Having been employed in the preceding period increases the probability of finding a job by 7.0 percentage points and an additional employment spell increases the probability by 1.7 percentage points. Similarly, past unemployment spells also increase the probability of becoming employed, although the effects are also often smaller. A possible explanation is that those individuals who often were employed also often were unemployed. Again, there is little evidence for lagged duration dependence. It seems that human capital gained in especially long-lasting jobs is not considered to be transferable by future employers.

In general, results indicate positive effects of past employment experiences. On first sight this finding might be related to a positive signaling or network effects due to past employment experiences. This is not entirely clear, however, as nothing can be said about the quality of the subsequent job, in particular, whether it is a temporary or a permanent one.

Taking into consideration the results for the transition from employment to unemployment, the results indicate that those individuals with frequent transitions between employment and unemployment are more likely to lose their jobs again, i.e. the quality of their job matches tends to be poor. The results therefore suggest the existence of a circle of unemployment and unstable employment with exits becoming more unlikely in the presence of frequent transitions. This is consistent with a segmentation of the labor market into individuals with stable long-term employment on the one hand and individuals who frequently transit between unemployment and unstable employment on the other hand. This finding is in line with other findings in the literature. For example, Stewart (2007) finds the existence of circles between unemployment and low-wage employment, while Boockmann and Hagen (2006) suggest the possibility that circles between unemployment and temporary employment exist.

For both transitions from out of the labor force, the type of the preceding spell is an indicator for the subsequent transition state. A preceding employment spell increases the probability of moving to employment by 17.3 percentage points and decreases the probability of moving to unemployment by 36.7 percentage points compared to a preceding unemployment spell. In addition, past employment spells help to return to employment, while past unemployment spells increase the probability to become unemployed and decrease the probability to become employed. This means that an increasing number of past employment and unemployment periods increase the attachment to the labor market, while past periods out of the labor force diminish this attachment. Finally, it seems that the only transition that exhibits lagged duration dependence is the transition from out of the labor force to employment. The coefficients suggest that the cumulative durations of all labor market states decrease the probability of becoming employed. The magnitude of these effects is still small, however.

Summing up, the results show that occurrence dependence is present for all transitions, while there is only little evidence for lagged duration dependence.

Personal characteristics and labor market conditions One of the key variables with strong effects on the transition intensities is the level of qualifications. As expected, a higher educational level decreases the probability of moving from employment to unemployment. For example, the probability for a transition to unemployment is 8.9 percentage points lower for individuals with a vocational degree than for individuals without any educational degree. Moreover, for individuals with a university degree the probability is even 17.6 percentage points lower. The educational level does not only protect against unemployment, in addition, it helps the unemployed to find employment, although the magnitude is less strong. For example, having a vocational degree increases the probability of finding a job within the first year by 5.1 percentage points. However, in comparison with a vocational degree the probabilities do only change slightly for higher educational degrees. This means that in particular unskilled individuals have difficulties finding new employment.

Interestingly, also the probability for a transition from out of the labor force to unemployment decreases, if the the educational level is higher. A possible reason may be that periods of self-employment or working as a lifetime civil servant can not be distinguished from real periods out of the labor force, and individuals with an educational degree more often become self-employed or lifetime civil servants[7] than unskilled individuals. Therefore, employment periods may in some cases be erroneously assumed to be periods out of the labor force for skilled individuals, while for unskilled individuals periods out of the labor force might be extended unemployment periods but without being registered as unemployed.

The occupation only has a significant effect on the transition from employment to unemployment and vice versa. In particular, working in the sectors of engineering and the provision of services significantly decreases the probability of becoming unemployed. The probability of finding a job for someone who has worked in the sector of mining is 17.8 percentage points lower than for someone who has worked in manufacturing. This strong effect is explained by the fact that the mining sector is in strong decline in Germany.

Further personal characteristics like age or nationality also play a role for some transitions. Foreigners have a lower probability to move from employment to unemployment, but also a lower probability to move from unemployment to employment. However, these effects are small. The effect of age on all transitions is negligible, because most coefficients are insignificant and very small if significant. This result is probably due to the fact that the estimation sample is homogenous with respect to the age of the individuals.

In addition to personal characteristics, the current labor market situation and the state of the economy have strong effects on labor market outcomes. Current unemployment rates have the expected effects. For example, an increase in the unemployment rate by one percentage point results in an increase in the probability of moving from employment to unemployment by 3.3 percentage points. For the opposite transition, the probability decreases by 3.5 percentage points. Moreover, the probability of returning to employment from out of the labor force is significantly smaller if unemployment is high. Besides, the probability of losing one's job is significantly higher in regions with bad labor market conditions, while the probability of finding a job is significantly lower in these regions. Coefficients for business cycle effects also provide expected results. For example, an

[7] In Germany only individuals, who have at least passed a vocational training can become a lifetime civil servant.

increase in GDP-growth by one percentage point increases the probability of finding a job by 3.7 percentage points. Summing up, it seems that, in particular, the transitions between employment and unemployment and vice versa exhibit a pro-cyclical behavior.

Unobserved heterogeneity Table A3.1 presents results for the maximum likelihood coefficients, which include the coefficients for the distribution of unobserved heterogeneity. As already mentioned, the values of support can be considered as types of persons, who differ in their transition behavior. All values of support and the probabilities are statistically significant. The first and the third type are the most frequent ones (42.2% and 37.0%). The transition behaviors of these two types are also similar for the transitions from employment to unemployment and to out of the labor force, and from unemployment to out of the labor force. Both types have a low probability for transition from employment. However, the first type has a higher probability of moving from unemployment to employment and also from out of the labor force to employment. Therefore, the first type can be considered as the type with the best unobserved characteristics with regard to employment. The third type has, as mentioned, a low probability of moving from employment, but also a lower probability of finding employment when unemployed or being out of the labor force. Finally, the second type has a high probability of moving from employment to unemployment and out of the labor force, and a low probability of becoming employed when unemployed or being out of the labor force. The second type can therefore be considered as the type with the worst unobserved characteristics with regard to employment chances.

3.5.2 Model fit

In this section, I check how well the model fits the main characteristics of the data. In order to verify the fit of the estimated model, no simple test is available. Rather, employment histories have to be simulated and then compared to the original data. For a sample of 10.000 individuals, I conduct the simulations dynamically from the beginning of their first spell after January 1, 2000 until the end of the observational period.

	Origin state			Total
	E	U	O	
Raw data				
Time under observation (days)				
Average per person	532.88	316.64	119.82	969.34
Per cent	54.97	32.67	12.36	100.00
Maximum history length				1460
Incidence rate (exits per year)				
Total	0.55	1.16	1.25	
Destination state				
E	0	0.96	0.65	
U	0.48	0	0.60	
O	0.07	0.20	0	
Duration quantiles (days)				
25%	143	64	75	
50%	337	152	183	
75%		440	365	
Model fit				
Time under observation (days)				
Average per person	538.91	312.86	115.91	967.68
Per cent	55.69	32.33	11.98	100.00
Incidence rate (exits per year)				
Total	0.54	1.39	1.51	
Destination state				
E	0	1.18	0.82	
U	0.47	0	0.69	
O	0.07	0.21	0	
Duration quantiles (days)				
25%	127	46	52	
50%	342	121	133	
75%		344	333	

Table 3.6: **Model fit.** The table compares characteristics of simulated data and raw data. E: Employment, U: Unemployment, O: Out of labor force. *Notes:* Quantiles are based on the Kaplan-Meier product limit estimator. The 80th and 90th percentile are not identified due to right-censoring.

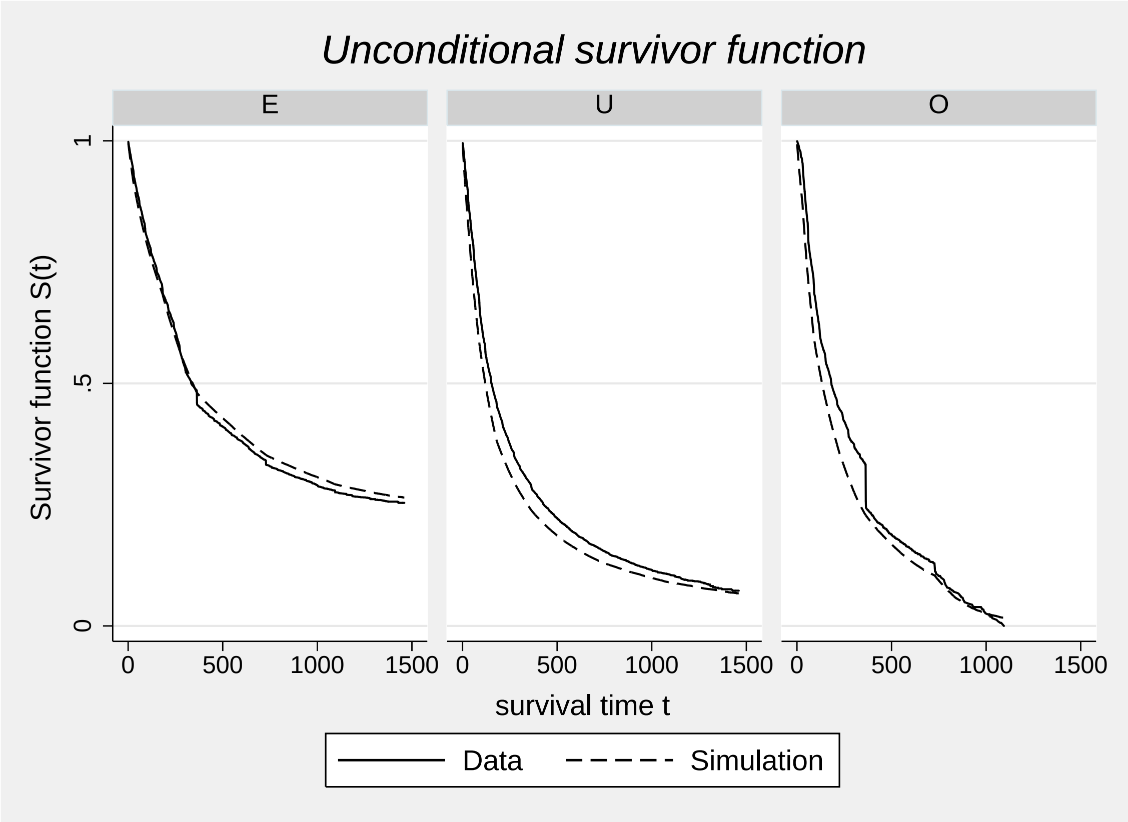

Figure 3.5: Model fit. The figure compares the unconditional survivor function of simulated data and raw data. E: Employment, U: Unemployment, O: Out of labor force.

The state of the first spell is given by the original data. For the simulations, a given set of exogenous and lagged endogenous explanatory variables is used. In a first step, I assign each individual in the sample a value of the random effect, i.e. I determine of which type the individual is. The values of the random effect are drawn from the estimated distribution of unobserved heterogeneity.

The second step is to assign to each individual its transition times and destination states. Given the set of exogenous and lagged endogenous explanatory variables, the random effect, and the estimated model, I draw the transition times for each individual from the distribution function of transition times. The destination states are then determined using the hazard ratios of the respective destination states.

After a transition has taken place, the employment history is updated to reflect the type and duration of the first spell.

Then, for the second spell transition times and destination states are assigned using the updated history. This process is repeated until the end of the observation period. The resulting data set is a random history, which is compatible with the exogenous and endogenous explanatory variables. The result of this exercise is then compared to the raw data.

In order to assess the model fit, ten histories are simulated for each individual in the sample. Table 3.6 presents summary statistics for both the simulated data and raw data. As one can see, the model fits the data relatively well for short and medium duration. In general, it tends to slightly overestimate employment durations at all quantiles and underestimate durations for spells in unemployment and out of the labor force. Figure 3.5 plots the simulated and empirical survivor functions for each state. Again, one can see that model fits well for short and medium durations, while particularly for the 80% and 90%-quantile the employment durations tend to be overestimated.

3.6 Simulation of policy interventions

Medium and long-run effects of policy interventions can differ markedly from short-term impacts in the presence of occurrence dependence. Nonetheless, evaluation of policy interventions often only looks at short-run effects. The present simulation study therefore accounts for such medium and long-run effects by simulating the effects of interventions that force transitions between labor market states at certain times in an individual's history.

Because the focus is on state dependence effects, the interventions are simulated for representative persons living in a stationary environment. I therefore fix unemployment rates and GDP growth rates at their mean value. Furthermore, simulations are conducted for individuals who have a vocational training degree and who work in the manufacturing sector. The representative individual is born between 1958 and 1962, German and lives in a highly urbanized region with high unemployment rate in the western part of Germany. I differentiate between interventions for two groups. The first group consists of individuals who were unemployed for more than three years between 1992 and 1999 and who have been unemployed for more than three months, but less than two years on January 1, 2000, i.e. the group can be considered as one of long-term unemployed. The second group consists of individuals who were employed for more than three years between 1992 and 1999, and who have been employed for more than half a year, but less than three years on January 1, 2000. The fraction of individuals varies between the two groups and the final sample for which simulations are conducted consists of 10.000 individuals.

The simulated interventions are presented graphically as the proportions of individuals in each state, measured on daily-basis. The graphs show the difference between the proportions of the treatment and the control group, that means for example the employment rate of the treatment group minus the employment rate of the control group.

Figure 3.6 shows the intervention of an employment period which last for 30 days for the group of unemployed, i.e. the treatment group experiences a 30 day employment spell from January 1, 2000 until January 31, 2000 and is then again set to unemployment. During the 30 day employment period transitions to other states are prohibited. After the employment experience the labor market history of the individual is updated in order to reflect the additional spell in unemployment. The simulations therefore display the effect of the occurrence of a 30 day employment. The intervention can be thought of a form of temporary employment. The results show that in the treatment group the employment period the unemployment rate is higher and the employment rate lower immediately after the treatment has ended. However, the situation turns round after further six months and in the long run the 30 day employment period leads to an increase in the employment rate and a decrease in the unemployment rate by around 14 percentage points, while nonparticipation is more or less unaffected. An intervention of this type may therefore help to reduce the unemployment rate, and the effects are strong even for such a short period.

Figure 3.7 presents the intervention of a 180 day employment period, again for the same group of unemployed. The simulations are conducted as above, except for a now longer employment period. In the long run results show that the 180 day employment period

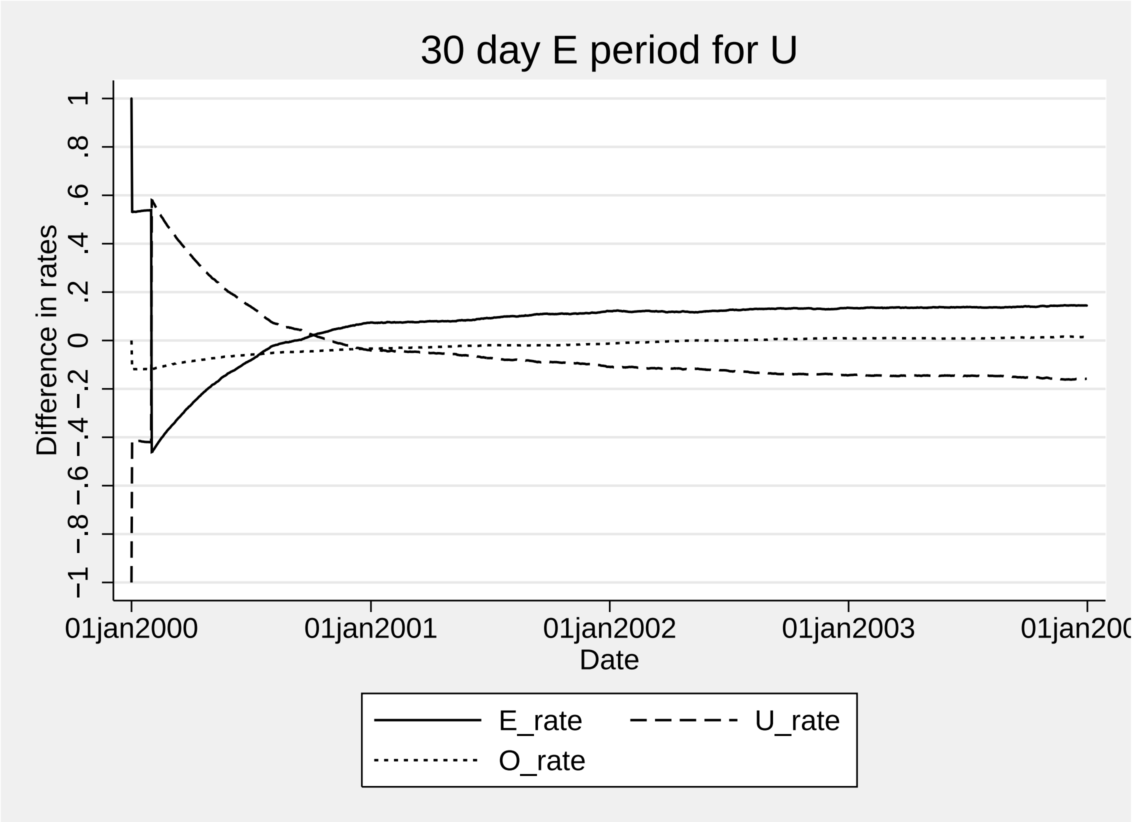

Figure 3.6: Simulated interventions: 30 days employment spell for unemployed. The figure presents a simulated intervention of a 30 days employment spell for unemployed. The differences between the treatment and the control group are given as the proportions of individuals in each state, measured on daily-basis. E: Employment, U: Unemployment, O: Out of labor force.

leads to an increase in the employment rate and a decrease in the unemployment rate by 13 and 14 percentage points. Therefore, results do practically not differ from the 30 day employment period. This reflects the absence of lagged duration dependence in the data. One has to note that the simulated intervention does not take into account direct transitions to regular employment, which are an important way for unemployed to find stable employment (see Boockmann and Hagen, 2006). For the intervention investigated, the results generally imply that an additional employment experience leads to an increase in the employment rate and a decrease in the unemployment rate and that the effects are quite strong. However, nothing can be said about the quality of the subsequent jobs.

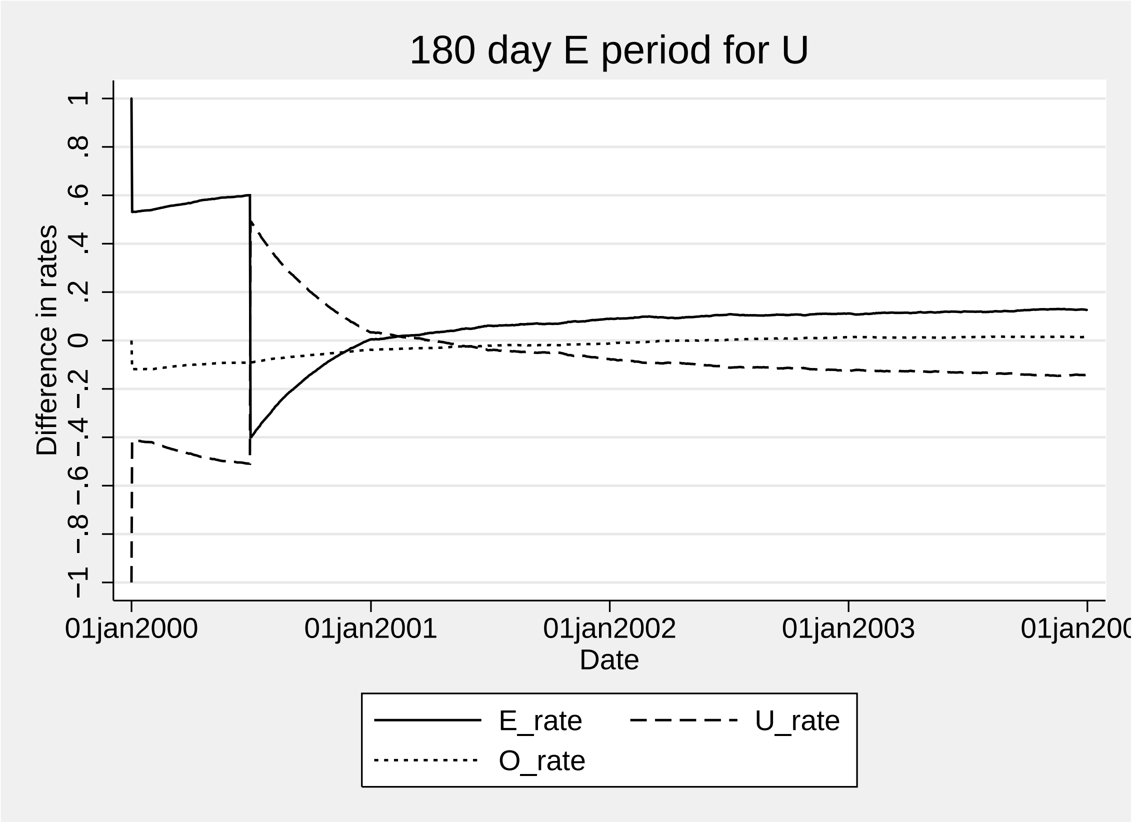

Figure 3.7: Simulated interventions: 180 days employment spell for unemployed. The figure presents a simulated intervention of a 180 days employment spell for unemployed. The differences between the treatment and the control group are given as the proportions of individuals in each state, measured on daily-basis. E: Employment, U: Unemployment, O: Out of labor force.

I also conduct simulations for the group of employed. Figure 3.8 shows the intervention of a 30 day unemployment period for the group of employed, i.e. the treatment group experiences a 30 day unemployment spell from January 1, 2000 until January 31, 2000 and is then again set to employment. Again no transitions are allowed to take place during the treatment period. A possible motivation for this kind of intervention is as follows. While the treatment and control group consist of individuals who are about to be affected by a (mass) lay-off, the control group receives a direct treatment and remains in employment and the treatment group receives the treatment only after a 30 day unemployment period.

The long-run results show that this additional employment period leads to a decrease in

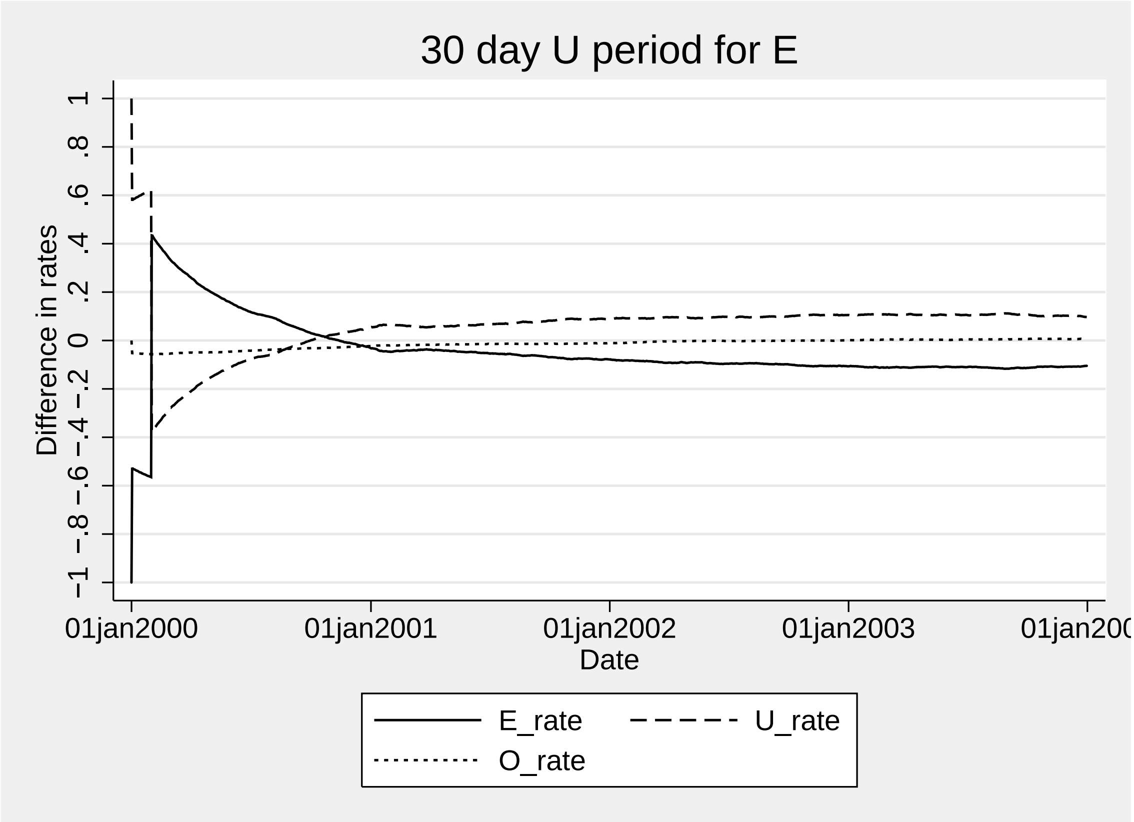

Figure 3.8: Simulated interventions: 30 days unemployment spell for employed. The figure presents a simulated intervention of a 30 days unemployment spell for employed. The differences between the treatment and the control group are given as the proportions of individuals in each state, measured on daily-basis. E: Employment, U: Unemployment, O: Out of labor force.

the employment rate by around ten percentage points, while it increases the unemployment ratio by also ten percentage points. This means that even a 30 day unemployment period has strong scarring effects. In order to measure whether the duration of an unemployment period plays a role, I simulate a 180 day unemployment period. The corresponding results are given in Figure 3.9. As can be seen directly, there is hardly any difference in the rates of each state between the 30 and 180 day unemployment intervention, which again reflects the lack of lagged duration dependence. Since even short unemployment spells seem to have severe scarring effects, the results suggest labor market policies that help employed, who are at the risk to become unemployed, before they become unemployed.

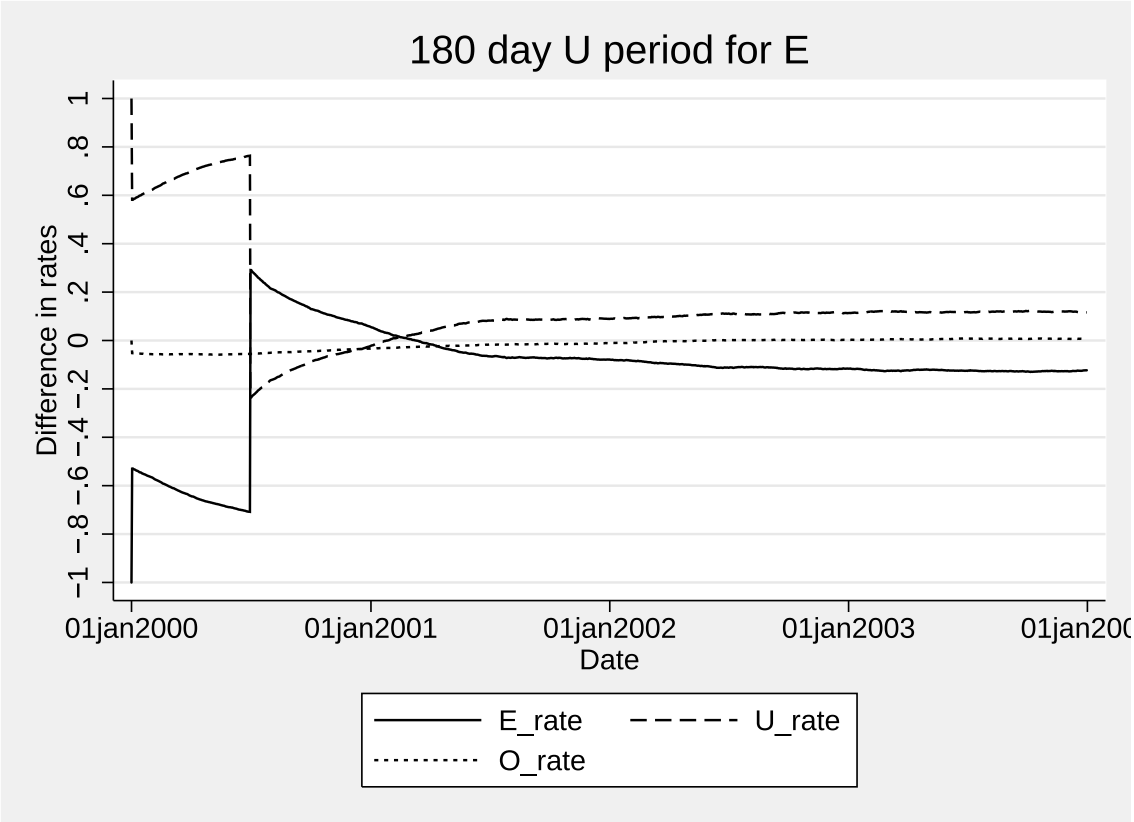

Figure 3.9: Simulated interventions: 180 days unemployment spell for employed. The figure presents a simulated intervention of a 180 days unemployment spell for employed. The differences between the treatment and the control group are given as the proportions of individuals in each state, measured on daily-basis. E: Employment, U: Unemployment, O: Out of labor force.

Summing up, the simulated interventions show that scarring effects due to past unemployment exist and are induced even by short unemployment periods. Furthermore, additional employment experiences seem to help in bringing down the unemployment rate. Finally, the effects for all interventions are very strong and they do hardly differ for the varying durations. The simulation results therefore also conform the absence of lagged duration dependence and the strong duration dependence of unemployment and employment.

3.7 Conclusion

This chapter investigates the form and magnitude of state dependence effects for prime-aged men in Germany. The empirical results can be summarized as follows. They show that employment is strongly duration dependent, which is most likely related to institutional features, in particular dismissal protection and the possibility for temporary contracts. The opposite transition is also duration dependent. The results also indicate that there is occurrence dependence. Past employment spells help the unemployed finding new employment, while past unemployment spells are scarring and increase the probability of becoming unemployed again. This may result in a circle of unemployment and unstable employment from which an exit becomes the more unlikely the more frequent the transitions between unemployment and employment were in the past. An important finding is that lagged duration dependence does not seem to influence the transitions, while occurrence dependence does. In addition to the results from occurrence dependence, this means that past employment spells are beneficial and help finding new employment, no matter how long the employment spells were. However, this also means that even short unemployment spells are scarring. The effects found are also persistent over time. Nonetheless, the preceding state plays an important role and strongly determines the transition times and destinations states, and implies that recent labor market outcomes have stronger effects than outcomes occurred earlier.

Simulating policy interventions provides evidence that even very short unemployment spells have severe scarring effects. The effects of unemployment spells with longer durations do not differ much from this finding. As already rather short unemployment spells have scarring effects, these results suggest to implement labor market policies that help those employed to find a new job, who are at the risk of becoming unemployed. Furthermore, the simulated interventions show that past employment experience strongly help to find new employment. Also for this simulation, the results imply that the duration of the intervention is not important. For labor market policies this implies that in order to find new employment, short employment periods in the past are as beneficial as longer ones. However, it is not clear whether the newly found jobs are stable ones.

The clear evidence for the different forms of state dependence also suggests that omitting variables that refer to past labor market history (occurrence and lagged duration dependence) may lead to biases in estimates that relate to duration dependence or to certain policy measures. In comparison to other papers, the results also imply that in order to analyze state dependence effects it is important to differentiate between the certain forms of state dependence and it does not suffice to condition only on the pre-period state. In particular, only by taking the different forms of state dependence into account, one can detect a vicious circle between unstable employment and unemployment.

Appendix A1: Institutional Framework

The design of the unemployment compensation system affects labor market outcomes and may be particularly relevant for the current unemployment duration (see for example Chetty, 2008 or Tatsimaros, 2010). For the period from 1998 to 2004, the German unemployment insurance system consisted of two components, unemployment benefits (*Arbeitslosengeld*) and unemployment assistance (*Arbeitslosenhilfe*). The Hartz reforms in 2005 abolished the unemployment assistance. There are now two new components of the unemployment compensation system, *Arbeitslosengeld I* (*ALG I*) and *Arbeitslosengeld II* (*ALG II*). *ALG I* is similar to unemployment benefits, although replacement ratios and entitlement periods have changed. *ALG II* combines unemployment assistance and social assistance. For the present study, only unemployment benefits as well as the former unemployment assistance and the former social assistance are relevant.

Unemployment benefits are insurance benefits with a limited entitlement period. To become eligible, the claimant first has to be registered as unemployed at his local Employment Agency. Being registered as unemployed requires that the individual is actively searching for a job of at least 15 hours a week and is available on short notice for a suitable job or a training measure. Furthermore, to receive unemployment benefits, a claimant has to be employed subject to social contributions for at least twelve months within the last two years prior to the unemployment spell. The level of unemployment benefits is calculated based on the average gross daily income over the last twelve months net of income taxes and further contributions. This amount is then multiplied by the replacement ratio, which is 67% for unemployed with dependent children and 60% without. Finally, the length of the benefit entitlement is a function that depends positively on the number of months worked prior to the unemployment spell and on the unemployed's age at the beginning of the spell.

Individuals receiving unemployment assistance have either exhausted the maximum length of unemployment benefits or they were never eligible for unemployment benefits, because they did not fulfill the minimum requirement of employment subject to social security contributions. Unemployment assistance was tax-funded and required the unemployed to pass a means-test. It was further unlimited in time and the replacement ratios were lower than in the case of unemployment benefits (57% with and 53% without children). Individuals receiving unemployment assistance were mostly long-term unemployed and therefore the suitability criteria what job the unemployed had to accept, were somewhat stricter than in the case of unemployment benefits. Unemployment benefits and unemployment assistance both allowed the unemployed to work for up to 15 hours per week. The level of the entitlement was adjusted in these cases, depending on the income from the additional employment.

In distinction to unemployment benefits and unemployment assistance, the social assistance (*Sozialhilfe*) provided a basic income protection for all individuals residing in Germany independent of their current labor market status. It was also paid as an additional income support, if the level of unemployment assistance was below some critical value. Hence, one could assume an at least marginal influence of the level of social assistance on labor market outcomes, especially for transitions from out of the labor force. Nonetheless, the level of social assistance only changed marginally during the period under consideration, so that the fact that the data does not contain information on social assistance is not a major problem.

A further institutional feature that affects unemployment and employment durations are Active Labor Market Policies (ALMPs). Such ALMPs usually provide a divesre set of measures with the goal to bring back unemployed into permanent employment. The set of ALMPs during the period from 1997 until 2003 comprised job-creation measures (*Arbeitsbeschaffungsmaßnahmen*) and settling-in allowances (*Eingliederungszuschuss*), which were forms of employment subsidies. In addition, the unemployed received financial support when they tried to become self-employed (*Existenzgründerzuschuss*). Lastly, a broad set of training measures existed that ranged from activation measures or German language courses to vocational training. Individuals, that are registered as unemployed, may receive maintenance allowance (*Unterhaltsgeld*) while participating in a public sponsored training measure.

Finally, protection against dismissal has clear effects on the employment duration, but it is also assumed that it indirectly affects unemployment duration by constraining unemployed, especially older ones, in their return to employment. The Dismissal Protection Law (*Kündigungsschutzgesetz*) protected employees with permanent contracts in Germany who had been employed for more than six months against unfair dismissal. It only applied to firms with more than five employees[8]. Although the law allowed for dismissals due to personal, behavioral, or operational reasons, it protected employees against unfair dismissal and acted as a counterbalance to a hire-and-fire policy. However, firms had the possibility to employ workers on temporary contracts in order to adjust to short-run labor demand fluctuations. The maximum duration of temporary employment was two years[9] and a subsequent contract at the same firm had to be permanent. Temporary employment was introduced to allow firms to adjust their labor force more flexibly, but also to provide bridges to permanent employment for the unemployed.

[8] For the period from 1996 to 1998, the minimum size is ten employees.

[9] There were a number of sectors, where the maximum duration was up to six or more years, e.g. academia

Appendix A2: Definition of covariates

Estimation is conducted using a large set of explanatory variables. These represent personal characteristics as well as external factors. Most of the covariates are time-varying. The following sub-section provides a short overview of the covariates used.

Age As only the year of birth is known, age is measured on a yearly basis and changes for every year on January 1. In order to account for nonlinearities, I additionally use squared age.

Education The level of education is one of the most important variables to include, as it is an indicator for the level of human capital. However, the education variable is not available for the LeH and not reliable for the BeH. In order to account for these points, some adjustments have to be made and the variable has to be imputed for periods with information from the LeH[10]. The resulting variable displays whether the individual has no degree, has passed a vocational training, finished high school, finished high school and additionally passed a vocational training, has a degree from a technical college, or a university degree.

Occupation Controlling for the individual's occupation is important, because labor market conditions differ by occupation. I therefore use a categorical variable indicating groups of occupations by a two-digit index[11] and construct six dummy-variable using only the first digit. The resulting variable differentiates between manufacturing, farming, mining, engineering, service, and miscellaneous occupations.

Nationality I also use a dummy variable that indicates whether or not the individual is a German.

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[10] Like most studies dealing with the IEBS or IABS, I follow the approach by Fitzenberger et al. (2005). I thank Aderonke Osikominu for generously providing their code.

[11] See Bundesanstalt für Arbeit (1988).

Labor market conditions In order to control for local labor market conditions, I use a set of dummy variables, that are generated from a categorical variable, which categorizes regional labor market conditions into five different groups[12]. The five categories are: Regions in Eastern Germany with an overbearing shortcoming in employment, highly urbanized regions in Western Germany with a high unemployment rate, more rural regions in Western Germany with an average unemployment rate, highly dynamical centers with favorable labor market conditions, and highly dynamical regions in Western Germany with good labor market conditions.

The overall labor market conditions are captured by monthly unemployment rates, which are made available by the Federal Employment Agency. Moreover, I use quarterly GDP growth rates published from the Federal Statistical Office to account for business cycle effects.

[12] See Blien and Hirschenauer (2005).

Appendix A3: Additional Tables

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Duration dependence						
Elapsed Duration (base: elapsed 0-29 days)						
Elapsed 30-91	-0.240***	-0.232***	0.087***	0.001	0.699***	0.233***
	(0.013)	(0.031)	(0.010)	(0.027)	(0.020)	(0.020)
Elapsed 91-182	-0.296***	-0.403***	0.009	-0.014	0.010	0.198***
	(0.017)	(0.039)	(0.017)	(0.032)	(0.030)	(0.034)
Elapsed 183-364	0.039**	-0.399***	-0.410***	-0.236***	0.184***	-0.093**
	(0.020)	(0.043)	(0.023)	(0.035)	(0.028)	(0.043)
Elapsed 365-546	-0.760***	-0.513***	-0.634***	-0.297***	-0.073	-0.269***
	(0.025)	(0.053)	(0.032)	(0.043)	(0.047)	(0.053)
Elapsed 547-729	-0.635***	-0.588***	-0.753***	-0.383***	-0.210***	-0.151**
	(0.027)	(0.063)	(0.040)	(0.053)	(0.059)	(0.064)
Elapsed 730-1094	-1.226***	-0.796***	-0.963***	-0.523***	0.942***	0.795***
	(0.031)	(0.073)	(0.048)	(0.062)	(0.074)	(0.082)
Elapsed 1095-1460	-1.610***	-1.279***	-1.183***	-0.667***		
	(0.053)	(0.119)	(0.089)	(0.116)		
Occurrence dependence						
Previous spell (base: other type of spell)						
Preceding E spell			0.316***	-0.663***	0.527***	-1.155***
			(0.032)	(0.041)	(0.055)	(0.088)
Preceding U spell	0.921***	-0.738***				
	(0.032)	(0.054)				
Cumulative number of previous spells						
Previous cum. E spells	0.021*	-0.066***	0.041***	-0.106***	0.126***	0.087***
	(0.011)	(0.025)	(0.010)	(0.015)	(0.020)	(0.025)
Previous cum. U spells	0.085***	-0.075***	0.045***	0.073***	-0.074***	0.139***
	(0.011)	(0.026)	(0.011)	(0.017)	(0.022)	(0.024)
Previous cum. O spells	-0.002	0.201***	-0.001	0.154***	0.020	-0.208***
	(0.017)	(0.031)	(0.015)	(0.020)	(0.023)	(0.030)
Lagged duration dependence						
Duration of previous spell (measured in months)						
Preceding duration	-0.013***	-0.007***	0.002	-0.003	-0.025***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Preceding E duration			-0.004**	0.003	0.025***	-0.011***
			(0.002)	(0.002)	(0.003)	(0.002)
Preceding U duration	0.008***	-0.001				
	(0.002)	(0.003)				

Table A3.1: (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Cumulative duration of previous spells (measured in months)						
Previous cum. E duration	-0.001	-0.005	-0.009***	-0.001	-0.017***	0.004
	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Previous cum. U duration	0.000	-0.010*	-0.018***	-0.012***	-0.023***	-0.019***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)	(0.004)
Previous cum. O duration	-0.015***	-0.026***	-0.009***	-0.001	-0.207***	0.001
	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)	(0.005)
Personal characteristics						
Age structure						
Age	-0.008	-0.114***	-0.007	-0.055**	-0.043*	0.082***
	(0.014)	(0.012)	(0.013)	(0.024)	(0.023)	(0.030)
Age^2	0.000	0.001***	-0.000	0.001**	0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Nationality (base: German)						
Foreigner	-0.109***	0.105**	-0.081***	-0.059*	0.096***	-0.031
	(0.020)	(0.047)	(0.020)	(0.032)	(0.031)	(0.039)
Occupation (base: manufacturing)						
Farming	0.060***	-0.025	-0.032	-0.022	-0.186***	-0.196***
	(0.021)	(0.078)	(0.023)	(0.047)	(0.067)	(0.065)
Mining	-0.164	0.066	-0.592***	-0.244	0.301**	-0.132
	(0.130)	(0.294)	(0.132)	(0.166)	(0.138)	(0.194)
Engineering	-0.525***	-0.147**	-0.096***	-0.270***	-0.055	-0.174**
	(0.038)	(0.069)	(0.031)	(0.066)	(0.041)	(0.072)
Service	-0.245***	0.080**	-0.060***	-0.032	-0.003	-0.129***
	(0.013)	(0.032)	(0.012)	(0.022)	(0.021)	(0.028)
Miscellaneous	0.021	0.376***	-0.276***	-0.251**	-0.118	-0.372***
	(0.050)	(0.100)	(0.074)	(0.127)	(0.091)	(0.126)
Education (base: no degree)						
Voc. Train.	-0.459***	-0.129***	0.206***	0.035	-0.041	-0.315***
	(0.016)	(0.043)	(0.016)	(0.025)	(0.028)	(0.032)
HS degree	-0.395***	0.226*	0.009	-0.127	-0.156**	-0.585***
	(0.099)	(0.130)	(0.095)	(0.124)	(0.077)	(0.124)
HS + VT	-0.842***	-0.165**	0.242***	0.029	-0.143***	-0.647***
	(0.049)	(0.079)	(0.040)	(0.071)	(0.054)	(0.084)
Tech. College	-0.980***	-0.514***	0.310***	-0.048	-0.158**	-0.688***
	(0.059)	(0.106)	(0.047)	(0.092)	(0.062)	(0.106)
Uni. degree	-1.122***	-0.460***	0.231***	-0.040	-0.431***	-1.123***
	(0.046)	(0.072)	(0.039)	(0.070)	(0.049)	(0.085)

Table A3.1: (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Environmental characteristics						
Business cycle						
Lagged GDP growth	-0.030***	-0.318***	0.104***	-0.173***	-0.067***	-0.010
	(0.010)	(0.026)	(0.010)	(0.022)	(0.021)	(0.022)
Current labor market situation in Germany						
Unemployment rate	0.139***	-0.182***	-0.148***	-0.089***	-0.312***	-0.127***
	(0.009)	(0.020)	(0.009)	(0.017)	(0.016)	(0.018)
Regional labor market segregation in Germany (base: West, hi. dyn. regions + good LM-cond.)						
E, shortcoming in employment	0.344***	-0.141***	-0.251***	-0.470***	-0.205***	0.299***
	(0.018)	(0.050)	(0.017)	(0.033)	(0.033)	(0.041)
W, hi. urbanized + hi. U-rate	0.145***	0.096**	-0.361***	-0.229***	-0.041	0.133***
	(0.021)	(0.045)	(0.019)	(0.032)	(0.029)	(0.040)
W, more rural + avg. U-rate	0.066***	-0.094**	-0.146***	-0.197***	-0.051*	0.003
	(0.018)	(0.044)	(0.017)	(0.031)	(0.027)	(0.039)
W, hi. dyn. cent. + good LM	0.046*	0.146***	-0.153***	0.009	-0.009	-0.030
	(0.028)	(0.053)	(0.026)	(0.041)	(0.034)	(0.050)
Initial conditions						
Cumulative number of previous spells at t_0						
Previous cum. E spells at	0.045***	0.131***	0.035***	0.061***	-0.027	-0.114***
	(0.011)	(0.026)	(0.011)	(0.015)	(0.022)	(0.024)
Previous cum. U spells at	-0.045***	0.012	-0.011	-0.034*	0.045**	-0.058**
	(0.011)	(0.028)	(0.011)	(0.018)	(0.023)	(0.023)
Previous cum. O spells at	0.044**	0.014	-0.062***	-0.022	-0.014	0.175***
	(0.017)	(0.033)	(0.015)	(0.021)	(0.024)	(0.030)
Cumulative duration of previous spells at t_0 (measured in months)						
Previous cum. E duration	-0.003**	-0.005	0.006***	-0.002	0.011***	-0.001
	(0.002)	(0.004)	(0.001)	(0.003)	(0.003)	(0.004)
Previous cum. U duration	0.007***	0.011**	-0.004**	0.004	0.010**	0.024***
	(0.002)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)
Previous cum. O duration	0.013***	0.026***	0.005**	0.003	0.017***	-0.005
	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.005)

Table A3.1: (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Unobserved heterogeneity						
Type 1	-8.331***	-3.660***	-2.545***	-4.565***	-1.455***	-7.395***
	(0.300)	(0.108)	(0.294)	(0.544)	(0.491)	(0.664)
Type 2	-6.998***	-1.511***	-3.594***	-3.658***	-1.983***	-6.625***
	(0.300)	(0.000)	(0.296)	(0.533)	(0.497)	(0.669)
Type 3	-8.372***	-3.615***	-3.840***	-4.562***	-2.817***	-5.190***
	(0.303)	(0.264)	(0.288)	(0.528)	(0.501)	(0.659)
Probability of type 1	0.422***					
	(0.012)					
Probability of type 2	0.208***					
	(0.009)					
Probability of type 3	0.370***					
	(0.014)					

Table A3.1: Results (model coefficients). The table presents the model coefficients. Standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

Chapter 4

Employment, partnership and childbearing decisions of German women and men: A simultaneous hazards approach

This study investigates the interrelated dynamics of employment, cohabitation and fertility for German women and men. Using a simultaneous hazards approach due to Lillard (1993), I estimate a five-equation model with unobserved heterogeneity. One of the contributions of this study is to include the current employment and nonemployment hazard rates and the union formation and union dissolution hazard rates as regressors. My results suggest that being employed or nonemployed only has small effects on other transitions, but that employed women with a high hazard of becoming nonemployed are less likely to have children, while nonemployed men having a low hazard of finding a job are more likely to have children. Children reduce the hazard of taking up a job for women and reduce the hazard of becoming nonemployed for women and men. Children also increase the stability of unions. Having a partner strongly increases the likelihood for having children. Interestingly, unions with a high risk of splitting up are more likely to have children. Economically, this can be interpreted as an attempt to invest in partner-specific capital in order to reduce the likelihood of splitting up.

4.1 Introduction

During the last decades Germany has seen tremendous changes in employment and family outcomes. Fertility rates have dropped from 2.031 in 1970 to 1.381 children per women in 2008[1]. Women have become older at first and all subsequent births and more often do not have children at all. Socioeconomic reasons often named for this are the increased female participation in higher education and the increase in female labor force participation which has risen from 46% in 1970 to 69% in 2008[2]. Nonetheless, the overall labor market situation has changed for women and men. Germany has undergone strong fluctuations in unemployment, and jobs have become more flexible but also less stable. This holds true especially for young workers for whom an unclear employment situation often has strong effects on family planning. However, it is not only employment that has changed. There are also new forms of cohabitation. Marriage has become less important, while more and more couples cohabit without being married. Finally, marriages have become less stable which is reflected by an increasing number of divorces and which has resulted in a strong increase in the number of single-parents and patchwork-families.

The developments described above depend on processes which are generally assumed to be interrelated. For example, fertility decisions are influenced by a women's employment status, which in turn depends on whether or not there are children. The economic literature deals with many aspects of the different interrelations between employment, partnership and fertility outcomes. Authors like Lillard and Waite (1991, 1993) and Steele et al. (2005) take account of the interrelations between cohabitation and fertility. A very general finding of these papers is that children increase the stability of marriages, although stability depends on children's age. Also the interrelations between labor force participation and fertility are of interest, in particular, between fertility and female labor force participation. Typical examples are Angrist and Evans (1998), Hyslop (1999), and Michaud and Tatsiramos (2011). These studies mostly indicate that children, in

[1] See Human Fertility Database (2012)

[2] See Statistisches Bundesamt (2012b)

particular pre-school children, reduce participation rates of women. However, labor market outcomes do also affect family outcomes. Del Bono et al. (2012), for example, show that a job loss yields a postponement of childbirth for Austrian women, while Eliason (2012) indicates that a job loss results in an increase of divorce rates for Swedish men. Nonetheless, only Aassve et al. (2006) consider the three processes of employment, cohabitation or marriage, and childbirth jointly. Joint estimation however is important to identify also indirect effects and to take account of unobserved heterogeneity. For instance, a job loss may influence fertility decisions directly but also via its effects on union stability.

A further aspect, which so far has only attracted little attention is how transition risks, i.e. the risk of becoming unemployed or of exiting a union, influence other outcomes. From an economic perspective, using simultaneous hazards also as regressors provides important insights, because they take account of how expectations on one outcome may affect other outcomes. Individuals may, for example, delay or cancel cohabitation and childbirth decisions, if they work in an unstable employment and are uncertain about their future employment state. Furthermore, couples with a high risk of splitting up may postpone childbirth decisions until they have found better-suiting partners. However, children may also be used as a way to rescue their relationship. So far as I am aware, only Lillard (1993) and Lillard and Waite (1993) consider how the transition risk of one process affects the outcome of an other process. More precisely, they both use the dissolution hazard as a regressor for the fertility process for indicating that unions with a high risk of splitting up are less likely to have children.

This study adds to the literature by using hazard regression techniques in order to estimate a five-equation model which includes employment, non-employment, union formation, union dissolution, and conception. Using a hazard approach comes with the advantage that effects can often be identified more precisely. For example, children obviously reduce female labor force participation. However, for employed women children may also increase the attachment with the current job due to increased expenses. Such effects, however, cannot be identified, if the state of being employed is modeled by a simple logit or probit model. In addition to Aassve et al. (2006) I also include the current hazards of losing and finding a job as regressors for the union formation and union dissolution hazards and the conception hazard. Furthermore, also the union formation and union dissolution hazards are used as regressors for the conception hazard. In general, risks are seldom used as regressors, and if so mostly a two-step procedure not taking into account a possible dependence of unobserved heterogeneity (see for example Del Bono, 2001 who uses employment and income risks as regressors for the fertility hazard). From an econometric perspective, Lillard (1993) and Lillard and Waite (1993) provide the only exemptions who use a simultaneous hazards approach in which also the hazard of one process directly affects the hazard of a second process. In this study the framework is of a higher complexity, since five processes are used and several hazards may have an influence on one process. Using a triangular form and a small set of exogenous regressors which also include the process-specific variables accounting for state dependence, is sufficient to identify the effects.

This chapter investigates effects for the 1960-69 cohort of German women and men using data from the study "Working and Learning in a changing world" (ALWA)[3]. The data set provides retrospective information on all five processes and information is of a very high precision as it is given on a monthly basis and there is no attrition in the sample. Furthermore, the observational period is very long, because individuals are observed from primary school onwards. The data-set is therefore well-suited for this type of analysis. My results suggest that employed women with a high hazard of becoming nonemployed are less likely to have children, while nonemployed men with a low hazard of finding a job are more likely to have children. The state of employment, however, has no effect on other hazards, although employed men are less likely to split up their relationships. Furthermore, results point out that being in a union strongly increases the likelihood of having children. In contrast to economic theory and empirical findings

[3] This study uses the factually anonymous data of the Study "Working and Learning in Changing World" (ALWA). The data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

for the United States (see Lillard, 1993 and Lillard and Waite, 1993), unions with a high risk of splitting up are more likely to have children. A possible explanation for the result found, is that unions with a high risk of splitting up tend to use children as an investment in partnership-specific capital, which in turn is used to increase the stability of the current union. Such investments may have become more widespread, because separation costs have fallen and investments in partnership-specific capital have shifted from marriage to children.

By adding a binary indicator for current pregnancy, my investigation also provides new insights on interrelations between fertility and female labor force participation. In contrast to Aassve et al. (2006) and large parts of the literature, my results suggest that children reduce the likelihood of becoming nonemployed, and that only a current pregnancy increases strongly the likelihood of a transition to nonemployment. My results therefore imply that also for women children increase the attachment with their current employment. With regard to the transition of becoming employed, the results show that children and current pregnancy reduce the likelihood of becoming employed. For men, children have no effect on the transition of becoming employed, while they also decrease the hazard of becoming nonemployed.

The reminder of this chapter is structured as follows. The next two sections provide an overview of the related literature and the institutional framework during the observational period. The fourth section presents the data set and explains the sample selection. The fifth section then deals with the econometric framework. The sixth section presents and discusses empirical results. Finally, section seven concludes.

4.2 Related literature

For a long time, there has been a strong interest in the interrelation of employment and family outcomes. Fundamental theoretical contributions on this topic are Becker (1976 and 1981), Cigno (1991), and Apps and Rees (2001). Nonetheless, they all focus on interrelations of fertility and female labor force participation. With regard to the effects children have on (female) labor force participation, Angrist and Evans (1998) and Hyslop (1999) are prominent empirical examples. While the first study uses twins as an instrument in order to estimate the effect family size has on labor force participation, the latter study uses a Maximum Simulated Likelihood approach taking into account state dependence and serial correlation of unobserved heterogeneity terms. More recent studies often use simultaneous estimation approaches (see Francesconi, 2002, or Michaud and Tatsiramos, 2011) or quasi-experimental designs (see Fröhlich and Melly, 2012). All studies named here suggest that children decrease female labor force participation, but usually no effects can be found for men.

The effects of employment on fertility and cohabitation are also of great interest. Ahn and Mira (2001) show that Spanish men delay childbearing and also marriage decisions, if they are nonemployed or only have fixed-term work contracts. Gutiérrez-Domènech (2008) shows that Spanish women delay childbearing decisions, if they are employed. However, effects are mixed with regard to marriage. While older cohorts delay marriage, if they are employed, younger cohorts tend to marry at an earlier stage. The author also points out that male unemployment results in a postponement of marriage and thereby has negative effects on fertility outcomes. Del Bono (2001) finds that British women delay childbearing decisions as a consequence of unemployment experiences. She also shows that the effect is stronger for women expecting high future wages and that women who expect more favorable job opportunities in the future bring childbearing decisions forward. More recently, Del Bono et al. (2012), using firm closures as quasi-experiments, show that unemployment experiences of Austrian women result in a delay of childbearing decisions. Eliason (2012) finds that unemployment experiences also increase the risk of separation. Using data for Sweden, he shows that for men the excess divorce rate is by 13% higher if there was an unemployment experience, while effects are similar but not significant for women. For the case of Germany, Kreyenfeld (2000) provides some insight. She shows that unemployment experiences of East German women increase the hazard for a first birth.

With regard to the interrelation of cohabitation or marriage and childbearing there is a large number of studies using simultaneous estimation approaches and thereby take account of these interrelations. Lillard and Waite (1991), using data on American women and men, show that pre-school children born inside a union increase the stability of a marriage, whereas older children and children born prior to a marriage increase the probability of disruption. Steele et al. (2005) show that for British women pre-school children stabilize unions, whether born within a marriage or not. Again, effects are weaker for older children. Brien et al. (1999), using data from the National Longitudinal Study of the High School Class of 1972, point out a strong positive dependence between cohabitation, marriage and pre-marital birth for women. Lillard (1993) and Lillard and Waite (1993) show that for married couples an increase in the hazard of dissolution has strong negative effects on marital childbearing. These studies are of particular interest, because the authors point out that expectations about the future union status play a role for childbearing decisions.

Finally, Aassve et al. (2006) are the only ones who model employment, cohabitation and childbearing decisions jointly. They find that being employed has a negative effect on childbearing for women but a positive for men. Being employed also has a positive effect on union formation for women and men and on union dissolution for women. Finally, with regard to the effects of family outcomes on transitions from and to employment, results are all as one would expect.

4.3 Institutional Framework

The period of interest for the cohort under consideration is from 1975 until 2008. For this period, several policy instruments are used to support the birth and upbringing of children. During the whole period child allowances (*Kindergeld*) were provided for dependent children. The receipt of child allowances for the first child was introduced in 1975. Since then the amount has varied steadily. From 1975 onwards, the amount for the first child increased from 26€ in 1975 to 154€ in 2008. In addition to child allowances for each dependent child, a tax allowance independent of the number of children was introduced in 1989. From 1996 until today, parents have been receiving either a tax allowance or a child allowance depending on which is more advantageous.

Maternity leave (*Mutterschaftsurlaub*) has been used as an instrument to secure the job and income during the time in which an expecting mother cannot work due to her pregnancy. An expecting mother is obliged to take maternity leave from six weeks prior to a birth until eight weeks after a birth. During this period 100% of the actual wage is paid and women are not allowed to be dismissed.

With regard to other forms of support, parents receive during the first years after a birth, the sample period can be divided into three subperiods. From 1979 to 1986, employed mothers were able to receive *Mutterschaftsurlaubsgeld*, for a period away from work of up to six months during which they received 383€ (750 DM) per month. This amount was reduced to 261€ (510 DM) in 1984. The *Mutterschaftsurlaubsgeld* was introduced in order to better combine motherhood and job, but it was abolished in 1986. From 1986 to 2007, either parent could take parental leave and receive a parental allowance (*Erziehungsgeld*). The parental allowance varied from 307€ for a period of ten months in 1986 to 450€ for a period of twelve months or 300€ for a period of 24 months in 2004. While receiving parental allowances a parent was allowed to work for only up to 30 hours per week. The parental allowance was heavily criticized, as it was considered to keep young mothers away from the labor market (see for example Schönberg and Ludsteck, 2007). In 2007 the *Elterngeld* was introduced. It can be splitted between partners, is paid for up to fourteen months and depends on the prior net income. Parents receive at least a minimum amount of 300€ up to a maximum amount of 1800€. The *Elterngeld* was introduced with the goal to keep young mothers, in particular highly qualified ones, in touch with the labor market.

Despite of the increase in child and parental allowances, there was a decline in fertility rates from 1.527 births per women in 1975 to 1.381 in 2008[4], while the mean age at birth rose from 26.25 in 1975 to 30.01 in 2008[5]. This indicates that, at least at an

[4] See Human Fertility Database (2012)

[5] See Human Fertility Database (2012)

overall level, the policies were not effective in increasing fertility rates. One reason often named, is the missing compatibility of job and family for women. This issue has become more relevant because of an increasing female labor market participation[6]. In 2008, the participation of mothers was still lower than that of fathers and the proportion of part-time employment was around 70% for all women (see Statistisches Bundesamt, 2012a).

In 1977, Germany underwent a major reform of the Marriage and Family Law (*Erstes Gesetz zur Reform des Ehe- und Familienrechts*) which introduced the equal status of wife and husband in marriage and divorce. After this reform, it was no longer relevant for maintenance payments who caused a divorce. Since then the number of marriages has decreased[7], while the number of divorces has increased[8]. On the other side, other forms of cohabitation have become more popular (see for example Statistisches Bundesamt, 2011). In particular, younger couples form unions without ever getting married. This increase comes along with a rise of the number of children born out of wedlock. Moreover, the number of single mothers has increased steadily from 13.8% in 1996 to 18.8% in 2008. From a tax perspective, forms of cohabitation other than marriage have become popular despite the fact that married couples benefit from more generous tax exemptions[9]. The tax advantage of married couple is the larger the more unequal earnings are between wife and husband.

Until 2004, the German unemployment insurance system consisted of two components, unemployment benefits (*Arbeitslosengeld*) and unemployment assistance (*Arbeitslosenhilfe*). In addition to the financial support for the unemployed, several Active Labor

[6] In 1975 48.17% of all women aged 15-65 were part of the labor force, while it were 68.96% in 2008 (see Statistisches Bundesamt, 2012b).

[7] In 1975 6.7 of 1000 inhabitants have married, while it were only 4.6 in 2008 (see Statistisches Bundesamt, 2012c).

[8] In 1975 there were 1.9 of 1000 inhabitants that divorced, while it were 2.3 in 2008(see Statistisches Bundesamt, 2012c).

[9] The so-called *Ehegattensplitting* privileges those unions with only the men or women working. See for example Folkers, 2003.

Market Policies existed with the goal of bringing back unemployed into permanent employment. Beginning in 2003 the "Laws of a modern provision of services on the labor market" (*Gesetz für moderne Dienstleistungen am Arbeitsmarkt*) became effective. The reforms were conducted as a response to the enormous rise in the unemployment rate from 4.7% in 1975 to 13.0% in 2005[10]. These so-called Hartz-reforms are a heavily discussed topic in the literature (an excellent survey is Jacobi and Kluve, 2006). They included changes in occupational training programs, new forms of temporary employment, new forms of marginal employment, improvements of the matching of unemployed and firms with vacancies, and, in particular, the abolishment of unemployment assistance. There are now two new components of the unemployment compensation system, unemployment benefit I (*ALG I*) and unemployment benefit II (*ALG II*). ALG I is similar to the unemployment benefit paid before the Hartz-reform, although replacement ratios and entitlement periods have changed. ALG II combines unemployment assistance and social assistance (*Sozialhilfe*). Although the Hartz-reforms were heavily discussed, results show that, at least in some aspects, the reforms were successful (see for example Jacobi and Kluve, 2006 or Fahr and Sunde, 2006). The Hartz-reforms are also named as one reason for the drop in the unemployment rate to 8.7% in 2008[11]. However, a side-effect of the reforms was an increase in types of employment which are generally linked with a high unemployment risk, like fixed-term employment, temporary employment or part-time employment.

4.4 Data

4.4.1 Data set

For this study I use the "Working and Learning in a changing world" ("Arbeit und Leben im Wandel", ALWA) data set that was collected within the project "Qualifications, Competencies and Working Life" at the department "Education and Employment over the

[10] See Bundesagentur für Arbeit (2012)

[11] See Bundesagentur für Arbeit (2012)

Life Course" of the Institute of Employment Research (IAB). The data set was originally designed to analyze the dependencies between the employment history, educational degrees and basic skills. It is, however, a very precise and informative data set well suited for the analysis conducted here. The data set considers as its population all individuals born between 1956 and 1988 and living in Germany in July 2007. Of this population, a random sample was drawn and voluntary interviews were conducted in order to construct a retroperspective life course for each individual.

In total, 10,404 individuals were interviewed. Of those individuals, 227 were interviewed in Turkish or Russian. I drop those 227 individuals, because they were interviewed about only a small part of their life course. As it is typical with voluntary interviews, the resulting sample is not representative for the population. Although incentives were given to promote participation in the interviews[12], the final sample overrepresents older and higher educated individuals.

The information about the life courses is given on a monthly basis and starts with the beginning of primary school. Because the information was collected retrospectively, attrition does not present a problem. The data set therefore provides highly precise information and very long life courses in comparison to survey data such as the German Socioeconomic Panel (GSOEP) or the British Household Panel (BHPS). However, a general problem with retrospective data is misreporting, in particular, of information on events that happened early in the life course. In order to reduce such measurement errors, the interviewers were instructed to inquire again, if inconsistencies in the life courses occurred (see for example Antoni et al., 2010, Antoni et al., 2011, and Gilberg et al., 2011). In general, the resulting data set provides a comprehensive and precise information source on the individual life courses.

The data set consists of different subfiles. In order to create one common event-history file, all subfiles are merged with each other and additional external covariates. The final event-history file then represents the complete life course of the individual from age 15 up to the censoring point. Information on life courses is given, as said, on a monthly basis,

[12] All participants received 15 € for taking part in the interview and could take part in a lottery.

which allows a precise examination of interrelations between employment and family outcomes. The data set provides information on birth records of every child born to a certain individual and every child once living together with this individual. Furthermore, information on all cohabiting unions of an individual are given, i.e. start and end dates as well as information on the respective union like marriage status or the age or the educational level of the partner. In addition to family outcomes, the life courses also present detailed information on the current occupational status, where the occupational status comprises schooling, further education, employment, unemployment, military or civil service, periods as housewife, and further periods. The data set also provides a large set of covariates covering employment-specific, partner-specific and child-specific information. In addition, external information, such as regional unemployment rates are merged with the life courses.

In Germany as well as in other European countries, cohabitation is an increasing form of union (see for example Köppen, 2011). In particular, cohabitation as a first form of union is common. Cohabitations may therefore precede a marriage, but may also act as a substitute. A further point which has to be taken into consideration is that there is an increasing number of non-marital births. I therefore follow Aassve et al. (2006) and use cohabitation as dependent variable. This means, all heterosexual couples living together in one household or married to each other[13] are considered as cohabiting union. The cohabitation starts when the individuals move in together and ends when they split up. This also applies to married couples for whom divorce is considered as one possible end. One generally could also assume couples as unions that do not live in the same household. However, such forms of unions are prone to misreporting and represent a weaker form of misreporting so that I do not follow this approach here.

With regard to employment and nonemployment, I consider all individuals as employed, if they are in paid employment, no matter if it is full or part-time employment. This means that also self-employed individuals are considered as employed. Women that

[13] In general, most married couples also live within the same household. However, there is a small number of individuals that begin to cohabitate after they have married. These individuals are also considered as cohabiting from the start of their marriage.

are on maternity leave (*Mutterschaftsurlaub*) are also considered as employed, while women and men that are on parental leave (*Elternzeit*) are considered as nonemployed. Nonemployment further captures periods in unemployment, education, as a housewife or househusband, and periods of military or civil service. The employment status of an individual changes if she or he moves in and out of paid employment. This means that periods of subsequent movements from one employer to an other are considered as one employment period, while, for example, moving from unemployment to schooling is considered as one nonemployment period.

Of the 10,177 individuals who were interviewed in German, I focus on the cohort of individuals born between 1960 and 1969. Cohort effects are likely to exist for female labor market participation, the duration of unions or the number of children born to an individual. In addition to all same-sex couples, I drop all nuns, monks and priests, because they neither participate in the labor market nor in the marriage market. Finally, due to the socialist regime in East Germany until 1990, labor market conditions were not comparable to West Germany at the time when most individuals entered the labor market. I therefore focus on individuals that were raised up and start their career in West Germany. This does not exclude individuals who move to East Germany after 1990.

4.4.2 Sampling design

An individuals' first employment or nonemployment process generally starts when she enters the labor market. For most individuals this point equals the date when the individual gets in touch with the labor market for the first time. However, some individuals work for a short period prior to entering university, while others register as unemployed after leaving secondary school and return to the education system only after a short time. Although these periods constitute a first contact to the labor market, they are hardly comparable to employment and nonemployment periods after the individual has left the education system for good. Such periods rather display short interruptions of education periods and mostly take place in occupations different to the ones the individuals choose later on. The goal of this study, however, is to disentangle the effects employment and nonemployment have on family outcomes. In particular, it shall be highlighted how the hazards of becoming nonemployed or finding a job influence the probabilities of having a partner or having children. The labor market entry is therefore assumed to be the start date of the first spell after the individual has left the educational institution, where she achieves or could have possibly achieved her highest degree. This also includes individuals who, for example, choose to become housewife or househusband. Nonetheless, the approach discussed so far includes few exemptions for whom the definition of the labor market entry does not fit very well. An example is an individual, who after obtaining an high school and vocational training degree, works for ten years and then chooses to go to university. In order to account for such exemptions, I set age limits until which a certain type of education form has to be started[14].

Although decisions on partnership and having children are seldom made while being in school or in education[15], individuals may form a first union or even may have children before entering the labor market. In order to account for this, the processes of union formation and conception start when the individual becomes fifteen.

Figure 4.1 presents two typical persons that both enter the labor market at age twenty. While Person A has not yet formed a union when entering the labor market, Person B has already formed a union and has conceived a child when she or he enters the labor market. Due to the fact that notably the effects employment and nonemployment have on family outcomes shall be identified, only those union formation and dissolution and conception spells are used for estimation which are in progress when the individual enters the labor market or which begin afterwards. All prior outcomes are used for construction of stocks. Finally, estimation requires a common starting point. I therefore assume the union formation, dissolution and conception spells to be quasi-left-truncated at the time of the labor market entry, i.e. I follow Lancaster (1979) and condition the likelihood contribution of the spell in progress on the probability of surviving in that state until the labor market entry. For person A in figure 4.1 this means that

[14] A precise description of the different age levels is given in the Appendix

[15] With regard to partnership, university students provide an exemption. However, only few students decide to have a child during their academic studies.

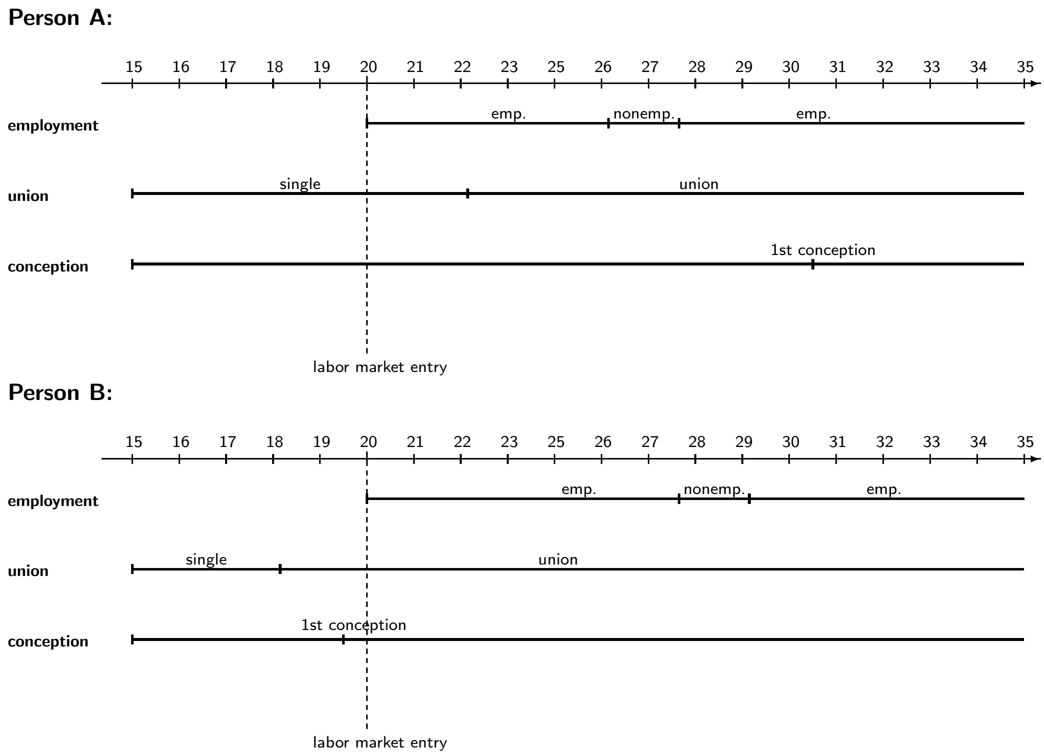

Figure 4.1: Labor market and family processes. The figure displays the histories of labor market and family processes of two typical individuals in the sample.

likelihood contributions of the union formation and the conception spell are conditioned on the probability surviving in these states since age fifteen. For person B, the likelihood contributions of the union formation process and the conception process are conditioned on the probability of surviving in the current union and not conceiving until entering the labor market.

The way a common starting date for all processes is chosen, is quite different to, for example, Aassve et al. (2006) who let all processes begin at age thirteen. However, a particularly relevant point of this chapter is to estimate how the hazards of moving from employment and nonemployment or vice versa affect the processes of union formation, dissolution and conception. Letting all processes start at age thirteen, would mean that these risk measures were influenced by whether there is a transition from unemployment to employment or from education to employment. Also the effect nonemployment itself has on conception depends on whether an individual is in education or is a housewife or househusband. The strategy of how the common starting date is chosen therefore provides a way to account for the effects of what one may call the "real" labor market risks. Nonetheless, the strategy comes with the disadvantage that the labor market entry is an endogenous starting point depending on observable and unobservable characteristics.

Furthermore, a strong desire for having children may result in having children prior to entering the labor market, which may influence the point of entering the labor market. However, such a strong desire for having children may also affect employment decisions afterwards. In order to account for such initial condition problems, I condition the process-specific unobserved heterogeneity on a set of variables consisting of the age at entry, whether the individual is employed after entering the labor market, whether she was in a union and had children, and of an interaction term accounting for whether she went to university and had children prior to entering the labor market. A more technical description of how I deal with the initial conditions is given in subsection 5.2.

4.4.3 Descriptive statistics

Table 4.1 presents some descriptive statistics for women and men born between 1960 and 1969. Results show that more women (1428) than men (1312) are part of the sample. Comparing women and men, the numbers show that the average birth year is the same for women (1964.21) and for men (1964.23) but that men are better educated than women. In particular, the proportion of men having a university degree or a degree from a technical college is higher for men (28.13%) than for women (17.57%). On average, women are more than one year younger than men when entering the labor market (20.92 vs. 22.15 years). This may be due to spending less time in education, but also due to the fact that almost all men belonging to this cohort had to do military service or civil service. Subsequently, men spent on average almost three years longer in employment than women (191.87 vs. 226.79 months) and around 50 months less in nonemployment

(71.15 vs. 21.42 months). This finding indicates that, although part-time employment is included, the employment ratio of women is significantly lower than for men in this cohort.

	female	*male*
Gender		
Frequency	1428	1312
Proportion	52.12%	47.88%
Year of birth		
Year of birth	1964.21	1964.23
Education (completed)		
Proportion No Degree	5.32%	3.13%
Proportion High School (HS)	2.24%	2.29%
Proportion Vocational Training (VT)	58.05%	52.52%
Proportion HS + VT	16.81%	13.95%
Proportion Technical College	6.51%	11.59%
Proportion University	11.06%	16.54%
Children		
Children per person	1.57	1.26
Children born while in a union	1.41	1.16
Children born while not in a union	0.16	0.10
Children born while employed	1.05	1.18
Children born while nonemployed	0.52	0.08
Proportion having no children	18.98%	35.21%
Proportion having 1 child	22.62%	23.25%
Proportion having 2 children	43.84%	33.54%
Proportion having 3 children	12.61%	6.78%
Proportion having at least 4 children	1.96%	1.22%
Age at 1st child	27.00	29.65
Age at 2nd child	29.62	32.24
Age at 3rd child	31.78	34.50
Age at 4th child	33.18	35.71
Years in E/NE until 1st child	6.29	7.76
Years in E/NE until 1st child if no NE	6.05	6.38
Years in E/NE until 1st child if NE	6.64	8.67
Years in E/NE until 1st child if no TE	6.14	7.49
Years in E/NE until 1st child if TE	6.78	8.49
Relationships		
Relationships per person	1.14	1.11
Proportion forming no union	6.58%	10.67%
Proportion forming 1 union	74.58%	69.74%
Proportion forming 2 unions	17.09%	17.61%
Proportion forming 3 or more unions	1.75%	1.98%
Age at 1st union	24.21	26.95
Age at 2nd union	30.09	33.51
Age at 3rd union	34.48	35.62
Employment		
Age at labor market entry	20.92	22.15
Number of periods employed	1.99	1.95
Number of periods nonemployed	1.46	1.29
Months spent employed	191.87	226.79
Months spent nonemployed	71.15	21.42

Table 4.1: **Descriptive statistics.** The table presents descriptive statistics for the sampled individuals. If nothing else is specified, the mean is given. E: Employment, NE: Nonemployment, TE: Temporary Employment.

Looking at relationships, it is easy to see that women are on average younger than men when forming their first union (24.21 vs 26.95). This means that women also form a union more quickly after entering the labor market (3.29 vs 4.80 years). Furthermore, one has to note that more men never enter a union until being censored (6.58% vs. 10.67%) and that the proportion of men forming two or more unions is also slightly higher (18.84% vs. 19.59%).

With regard to children the numbers show that on average men have significantly fewer children than women (1.56 vs. 1.26). This is a typical finding in the literature (see Aassve et al., 2006 for the case of the British Household Panel, BHPS) and two possible reasons can be named. First, men are, on average, older than women when having a first birth (29.65 vs. 27.00). This also holds true for further births. Therefore, the number of children not part of the data set due to right-censoring tends to be higher for men than for women. A second point may be misreporting among men. In spite of the high quality of the data set, it is a general finding that misreporting with regard to family outcomes is much higher for men than for women (for fertility histories in the BHPS see Rendall et al., 1999). This in turn may explain in parts the lower fertility rate for men.

In general, a comparison of the results for the cohort used here with official data shows that with respect to the number of children, the data set fits well. For example, women born in 1962 have on average 1.56 children. Since one of the aims of this chapter is to investigate the effects employment and nonemployment have on fertility, it is interesting to see what happens to fertility rates when individuals are nonemployed or employed in an unstable environment. Having been nonemployed for at least one month increases the duration in the labor market until the conception of a first child significantly for women (6.05 vs. 6.64 years) and even more for men (6.38 vs. 8.67 years). But it is not only nonemployment, also the expectation about the stability of a job seems to play a strong role in determining fertility. Also, having been temporarily employed for at least one month increases the duration in the labor market until the conception of a first child for women (6.14 vs. 6.78 years) and even more for men (7.49 vs. 8.49 years). Despite of this being no causal analysis, these results indicate that job stability and the expectation about it play a role for the timing of a first birth.

A further point worth mentioning is that for women, almost 20% of all births occur outside a union, while it is only around 8% of all births for men. This supports a possible misreporting among men, as it is likely that men will not report children when they are born outside a union and no union is formed afterwards.

4.5 Econometric Framework

Based on the work of Lillard (1993) two models of interrelated dynamic discrete choices are specified. In both models the discrete choices are defined over employment, nonemployment, union formation, union dissolution and conception and the dynamics are considered jointly. The five processes are specified as transition intensities, which are conditional on the time spent in the respective state, exogenous and endogenous covariates, as well as unobserved heterogeneity components that may be correlated with each other.

Model A: Inspired by Aassve et al. (2006), the set of processes is given as

$$\begin{aligned}\ln\left(h_A^E(t)\right) =& e_1T^E(t) + e_2A^E(t) + e_3X^E(t) + e_4P^E(t) + e_5P^C(t)\\ &+ e_6\mathbf{1}\{M(t)\} + e_7\mathbf{1}\{C(t)\} + v^E,\end{aligned} \tag{4.1}$$

$$\begin{aligned}\ln\left(h_A^U(t)\right) =& u_1T^U(t) + u_2A^U(t) + u_3X^U(t) + u_4P^U(t) + u_5P^C(t)\\ &+ u_6\mathbf{1}\{M(t)\} + u_7\mathbf{1}\{C(t)\} + v^U,\end{aligned} \tag{4.2}$$

$$\begin{aligned}\ln\left(h_A^M(t)\right) =& m_1T^M(t) + m_2A^M(t) + m_3X^M(t) + m_4P^M(t) + m_5P^C(t)\\ &+ m_6\mathbf{1}\{E(t)\} + m_7\mathbf{1}\{C(t)\} + v^N,\end{aligned} \tag{4.3}$$

$$\begin{aligned}\ln\left(h_A^D(t)\right) =& d_1T^D(t) + d_2A^D(t) + d_3X^D(t) + d_4P^D(t) + d_5P^C(t)\\ &+ d_6\mathbf{1}\{E(t)\} + d_7\mathbf{1}\{C(t)\} + v^D,\end{aligned} \tag{4.4}$$

$$\ln\left(h_A^C(t)\right) = c_1T^C(t) + c_2A^C(t) + c_3X^C(t) + c_4P^C(t) + c_5\mathbf{1}\{E(t)\} + c_6\mathbf{1}\{M(t)\} + v^C \tag{4.5}$$

where $\ln(h_A^s), s = E, U, M, D, C$, are the logarithms of the hazards of employment, nonemployment, union formation, union dissolution and conception. Individuals start the processes of finding employment (i.e. $\ln\left(h_A^U(t)\right)$) or entering the state of nonemployment (i.e. $\ln\left(h_A^E(t)\right)$) when entering the labor market for the first time. This means they are at risk of finding employment, if they are currently nonemployed. After finding employment, they are at risk of entering the state of nonemployment. These events may be repeated several times and an individual can only be in one of the two states at a time $T = t$, i.e. the processes are mutually exclusive. The same holds true for the processes of union formation (i.e. $\ln\left(h_A^M(t)\right)$) and union dissolution (i.e. $\ln\left(h_A^D(t)\right)$). The process of union formation is assumed to start at age 15 years, i.e. the individual is single at this age. After the individual starts her first union, she is at the risk of dissolving the union. Again these events may be repeated several times. Further, individuals are assumed to be at risk of having the first conception from age 15 years, i.e the process of conception (i.e. $\ln\left(h_A^C(t)\right)$) starts at this age. After the first conception, individuals become at risk of having a second conception and so on. Thus conceptions are specified within one hazard function.

For estimation, a common starting point is needed, which is assumed to be the date of labor market entry $T = t_0$. As the processes of union formation, union dissolution and conception start prior to t_0, only those spells are used that are in progress or start after t_0 and the likelihood contribution of the spell in progress is conditioned on the probability of survival until t_0.

For all the processes the baseline transition intensity is modeled as a piecewise constant function. More precisely, $T^s(t)$ is a $(K^s \times 1)$-vector of binary indicator variables whose coefficients are allowed to differ between the K^s time intervals. Denoting the interval bounds for process $S = s$ as τ_k^s, the binary indicator variable for the kth interval is defined as

$$T^s(t) = \mathbf{1}\left\{\tau_{k-1}^s < t - \tilde{t}^s \leq \tau_k^s\right\}, \quad k = 2, \ldots, K_s \quad \text{and} \quad s = (E, U, M, D, C),$$

where $\tilde{t}^s$ is the start date of the current spell of the respective process. Modeling the elapsed duration as a piecewise constant function is a flexible way to account for duration dependence. Doing so also allows to account for possible nonlinearities. Age effects $A^s(t)$ are specified similarly in order to capture possible nonlinearties.

In addition to age effects, I include controls for the stock of each event $P^s(t)$ accounting for occurrence and lagged duration dependence effects. While the stock of children is implemented as dummy variables, the stock of partners and the stocks for employment and nonemployment is specified as the cumulative occurrence. For the processes of employment and nonemployment, I also include the cumulative durations in employment and nonemployment. Furthermore, the stock of children enters all five processes, while the other stocks only enter the respective pair of mutually exclusive processes. Furthermore, I include endogenous binary variables $\mathbf{1}\{E(t)\}$ accounting for the employment status and $\mathbf{1}\{M(t)\}$ for the cohabitation status. $\mathbf{1}\{E(t)\}$ enters the processes of union formation and dissolution and the process of conception, while $\mathbf{1}\{M(t)\}$ enter the process of conception and the processes of employment and nonemployment. Finally, $\mathbf{1}\{C(t)\}$ is a binary indicator that displays whether the individual or his respective partner is currently pregnant. This indicator enters the processes of employment, nonemployment, union formation and union dissolution.

I also condition the processes on a set of exogenous covariates $X^j(t)$. This set of covariates differs between the five processes. The ALWA data set includes a rich set of exogenous covariates. Furthermore environmental covariates like the unemployment rate or the growth rate are included.

In this study, I do not account for the order of conception or for the order of the union. However, it is clear that results may depend on the order of birth. The transition to the first union and first birth probably differs from later transitions. Likewise there is a large strand of the literature focusing on first unions and births (see for example Le Goff, 2002 or Billari and Philipov, 2004). Also transitions from school to employment may be different to transitions from unemployment to employment. Like Aassve et al. (2006), I do not take account of the order because of the already high complexity of the model. Furthermore, several authors have argued that cohabitation and marriage differ in their effects on childbirth (see for example Steele et al. 2005). Also nonemployment tends to be a rather heterogenous state that may include unemployed individuals as well as housewives or -husbands. A similar issue concerns employment. Francesconi (2002), for example, points out that women working part-time are more likely to have children than women working full-time. Nonetheless, the already complex structure of both models requires to collapse part-time work and full-time work into one employment state. The same holds true for nonemployment and cohabitation.

Model B: In addition to Model A, the processes for union formation, union dissolution and conception include the logarithm of the employment and nonemployment hazard. The process of conception additionally includes the logarithm of the union formation and dissolution hazards. These are interrelated with the state dummies because, e.g., the hazard of becoming nonemployed only matters if the person is employed. The five processes evolve as follows:

$$\ln\left(h_B^E(t)\right) = \ln\left(h_A^E(t)\right), \tag{4.6}$$

$$\ln\left(h_B^U(t)\right) = \ln\left(h_A^U(t)\right), \tag{4.7}$$

$$\ln\left(h_B^M(t)\right) = \ln\left(h_A^M(t)\right) + m_8\mathbf{1}\{E(t)\}\ln\left(h_B^E(t)\right) + m_9\mathbf{1}\left(1 - \{E(t)\}\right)\ln\left(h_B^U(t)\right), \tag{4.8}$$

$$\ln\left(h_B^D(t)\right) = \ln\left(h_A^D(t)\right) + d_8\mathbf{1}\{E(t)\}\ln\left(h_B^E(t)\right) + d_9\mathbf{1}\left(1 - \{E(t)\}\right)\ln\left(h_B^U(t)\right), \tag{4.9}$$

$$\begin{aligned}\ln\left(h_B^C(t)\right) = &\ln\left(h_A^C(t)\right) + c_8\mathbf{1}\{E(t)\}\ln\left(h_B^E(t)\right) + c_9\mathbf{1}\left(1 - \mathbf{1}\{E(t)\}\right)\ln\left(h_B^U(t)\right) \\ &+ c_{10}\mathbf{1}\{M(t)\}\ln\left(h_B^M(t)\right) + c_{11}\left(1 - \mathbf{1}\{M(t)\}\right)\ln\left(h_B^D(t)\right)\end{aligned} \tag{4.10}$$

where $\ln(h_A^s)$ are the log hazards from Model A for $s = E, U, M, D, C$. For example, m_8 captures the influence of the hazard of becoming nonemployed on the hazard of entering a union. More precisely, an increase by 1% of the hazard becoming nonemployed, results in an increase of the hazard of entering a union by $m_8\%$. The coefficient reflects whether and to what extent individuals with stable jobs are more attractive for possible partners on the marriage market. Obviously, one could also assume that the risk of becoming pregnant has an effect on employment or union dissolution. However, this study particularly focuses on the effects employment risks have on union formation, union dissolution and conception. For pregnancy, I only include a pregnancy indicator. The hazard of becoming employed or nonemployed are likely to be well represented by the other observed covariates (age, education, etc.) and the correlated structure of unobserved heterogeneity. Other effects, like the effect the union dissolution hazard would have on employment outcomes are of minor interest and can be neglected. These choices result in a triangular form of the system of hazards which makes identification more easy and estimation more tractable.

4.5.1 Likelihood Function

Let $\psi(t)$ denote the history of outcomes, $\phi^s(t) = \{T^s(t), A^s(t), \ldots\}$ the path of observed components relevant for each state $s = E, U, M, D, C$ and v^s be the value of the unobserved heterogeneity component. Further, let $T = \bar{t}_i$ be the censoring point for individual i. Then conditional on $\Phi^s(t) = \phi^s(t)$, and $V^s = v^s$, the contribution to the likelihood function of person i's history can be expressed as the product of the contribution of each spell in each state,

$$\mathscr{L}\left(\psi(t_{i,n_i}), \bar{t}_i | v_i\right) = \prod_s \left\{ \mathscr{L}^s\left(\bar{t}_i | \phi^s(t_{i,n_i}), v_i^s\right) \times \left(\prod_{j=1}^{n_i} \mathscr{L}^s\left(t_{i,j} | \phi^s(t_{i,j-1}), v_i^s\right) \right) \right\}^{\mathbf{1}\{S(t)=s\}}, \tag{4.11}$$

where $\mathbf{1}\{S(t) = s\}$ is a binary indicator for the current state.
The second term in equation (4.11) refers to all completed spells. Conditional on $\Phi^s(t) = \phi^s(t)$, and $V^s = v^s$, the contribution to the likelihood of the event of individual i moving from one state to another for $s = E, U, M, D$ or restarting the process $s = C$ (i.e. restarting the conception process) at time $t_{i,j}$ is

$$\mathscr{L}^s\left(t_{i,j} | \phi^s(t_{i,j-1}), v_i^s\right) = h^s\left(t_{i,j} | \phi^s(t_{i,j-1}), v_i^s\right) \times \exp\left(- \int_{t_{i,j-1}}^{t_{i,j}} h^s\left(u | \phi^s(u), v_i^s\right) \mathrm{d}u \right), \tag{4.12}$$

where for $j = 1$, $t_{i,0}$ is the individual date of labor market entry. In equation (4.12) the right-hand side has the familiar "hazard function times survivor function"-expression, where the first term provides the hazard, i.e. the intensity of moving from one state to another and the second term is the probability of no events taking place between time $t_{i,j-1}$ and $t_{i,j}$. Because $t_{i,0} \geq \tilde{t}_{i,0}$, where $\tilde{t}_{i,0}$ is the start date of the current (union formation, union dissolution, or conception) spell before entering the labor market, equation (4.12) automatically corrects for left-truncation by conditioning on the probability of no events taking place between time $\tilde{t}_{i,0}$ and $t_{i,0}$ (see for example D'Addio and Rosholm, 2002b). Under the assumption that $\bar{t}_i$ is independent of the transition processes and observed and unobserved heterogeneity, $\bar{t}_i$ is uninformative about the parameters of interest and the distribution of $\bar{t}_i$ can be ignored in the likelihood function. Therefore, the contribution to the likelihood of the last right-censored spell, i.e. the first term in equation (4.11), is

$$\mathscr{L}^s\left(\bar{t}_i|\phi^s(t_{i,n_i}), v_i^s\right) = \exp\left(-\int_{\bar{t}_i}^{t_{i,n_i}} h^s\left(u|\phi^s(u), v_i^s\right)\,\mathrm{d}u\right). \tag{4.13}$$

Equation (4.13) is simply the probability of no events taking place between t_{i,n_i} and $\bar{t}_i$.

4.5.2 Initial conditions and unobserved heterogeneity

As already mentioned, individuals may form unions or have children before entering the labor market. These outcomes may be influenced by unobserved characteristics, such as a strong preference for having children. In addition, the first employment state may be influenced by unobserved characteristics, such as a strong motivation to work. In general, such unobserved characteristics may bias results of other covariates. For example, a strong desire for children may result in having children while being in education and thereby affect the educational level, which in turn has an effect on the entry date and later on on other employment outcomes. It is therefore necessary to take account of these so-called initial conditions. Following Wooldridge (2005), I condition each of the processes of an individual i on a set of covariates $\mathbf{Z}^s(t_{i,0})$, where $\mathbf{Z}^s(t_{i,0})$ accounts for the age at entry, whether the individual is employed after entering the labor market, whether she was in a union, had children, and of an interaction term accounting for whether she went to university and had children prior to entering the labor market. Conditioning on $\mathbf{Z}^s(t_{i,0})$ requires to specify the probability function of V_i conditional on $\mathbf{Z}^s(t_{i,0})$ in order to integrate out the unobserved effect V_i. Wooldridge (2005) suggests the use of a parsimonious function for specifying the probability function of V_i^s conditional on $\mathbf{Z}^s(t_{i,0})$. I assume V_i^s to be a linear function of $\mathbf{Z}^s(t_{i,0})$ and a residual random effect W_i^s, whose distribution is independent of everything else, i.e. $V_i^s = \gamma^s \mathbf{Z}^s(t_{i,0}) + w_i$. By doing so, integrating out V_i^s conditional on $\mathbf{Z}^s(t_{i,0})$ results in integrating over the unconditional distribution of the random effect W_i^s and estimating some additional coefficients that refer to $\mathbf{Z}^s(t_{i,0})$, i.e. to the "initial conditions". The resulting likelihood contribution of individual i is then given by

$$\mathscr{L}_i = \int_{-\infty}^{\infty} \mathscr{L}\left(\psi(t_{i,n_i}), \bar{t}_i | \mathbf{z}(t_{i,0}), w_i\right) \, \mathrm{d}A^*\left(w\right), \tag{4.14}$$

where A^* is the time-invariant marginal distribution of w_i and integration is done using a Stieltjes integral.

In contrast to what is common in the literature, I do not assume W_i to be multivariate normal distributed. I follow Heckman and Singer (1984) and assume W_i to take on only a small number of different values. Steele et al. (2005) show how a discrete frailty may also be used for simultaneous hazard models. Let the discrete support of W_i^s be $w_1^s, \ldots, w_M^s$ and let $\pi_m = \mathrm{P}(W_i = w_m)$ be the joint probability for the m^{th} point of support for $s = E, U, M, D, C$. Equation (4.14) then becomes

$$\mathscr{L}_i = \sum_{m=1}^{M} \mathscr{L}\left(\psi(t_{i,n_i}), \bar{t}_i | \mathbf{z}(t_{i,0})\right) \pi_m. \tag{4.15}$$

It is common practice to think of the points of support as different types of persons. Using a larger number of types results in a more flexible distribution of unobserved heterogeneity. In practice however, most studies only use a small number of types. Following Gaure et al. (2005) I use the Akaike Information Criterion in order to select an appropriate number of $M = 3$ points of support for Models A and $M = 4$ for Model B.

4.5.3 Identification

The identification scheme for Model A is similar to the ones proposed by Aassve et al. (2006), Steele et al. (2005), or Upchurch et al. (2002). Model A uses the information on repeated events for each individual, i.e. multiple transitions from employment to nonemployment and vice versa, multiple union formation and dissolution, and multiple conceptions. There are also overlaps of all varieties in the events across the five processes. Identification is then ensured, as unobserved heterogeneity is assumed to be time-constant for each individual. The potentially endogenous variables enter the other processes as lagged transitions or as stocks of outcomes. This ensures identification of the parameters without further exclusion restrictions (see Maddala, 1983).

Such exclusion restrictions, however, are required for identification of the preferred Model B. In this model, the (contemporaneous) hazards of employment and nonemployment enter the processes of union formation and dissolution, while the (contemporaneous) hazards of employment, nonemployment, union formation, and dissolution enter the process of conception. As Lillard (1993) points out, dependence on the contemporaneous hazards requires exclusion restrictions, i.e. variables are required to have an effect on, for example, the process of employment but must not enter the processes of union formation and dissolution, and the process of conception. As one can only be employed or nonemployed at a time, the same set of variables could enter the processes of employment and nonemployment. The same holds true for union formation and dissolution. Identification of Model B is more involved, because the employment and nonemployment hazards enter the conception hazard a second time via the union formation and dissolution hazards. This requires that the union formation and dissolution hazards include variables that neither enter the conception hazard nor the employment and nonemployment hazards. As mentioned, the process starts at different times and there are all forms of overlaps. Further, time enters the processes in a nonlinear way. Therefore, the variables accounting for duration dependence should suffice as exclusion restrictions. Nonetheless, it is always better to have more exclusion restrictions. Therefore, for each process an additional set of exclusion restrictions is used. By taking advantage of the

variation over time in the maternity leave durations, I construct a binary indicator for whether an individual is currently taking or could potentially take maternity leave. This indicator is then used as an exclusion restriction for the hazards of becoming employed and nonemployed. However, this exclusion restriction is only meaningful for women. Further exclusion restrictions are, for example, macroeconomic variables like the regional unemployment rate, the regional growth rate or the regional birth rate. A full list of all exclusion restrictions for each process is given in Table B2.1 in the appendix.
The effects the endogenous variables have on the respective simultaneous hazards, can also be considered as treatment effects. For example, the treatment of moving from employment to nonemployment may change the probability of conceiving, while the treatment of conception may change the search behavior of nonemployed individuals. Identification of such treatment effects, however, requires that the treatment date can not be anticipated (see Abbring and van den Berg, 2003a and 2004). If the exact date of treatment was known, individuals would act on this information and parameter estimates could not be identified. This does not mean that individuals do not know about the process itself and do not act on this information. However, it is necessary that transition dates are defined as dates when information about an event emerges. In sum this means that identification is still given, although individuals may act on the conception process, for example by stopping the usage of contraceptives, because the point of conception is still random. Nonetheless, one has to be cautious about women's transitions from employment to nonemployment, as these may to some extent be planned events in order to become pregnant.

4.6 Results

Following Gauré et al. (2007) the Akaike Information Criterion (AIC) is used to choose the appropriate number of points of support for the unobserved heterogeneity. For both genders the AIC selects three mass points for Model A and four mass points for Model B. The results for the Akaike Information Criteria are given in Table 4.2.

	1 MP	2 MP	3 MP	4 MP
Women				
AIC_A	76681.495	76514.196	76465.107*	
AIC_B	76413.057	76246.225	76210.656	76154.036*
Men				
AIC_A	64014.617	63737.815	63699.166*	
AIC_B	63894.321	63614.514	63582.083	63558.382*

Table 4.2: Model selection. The table presents the Akaike Information Criteria for the Models A and B for women and men. The chosen Model is indicated by *

The results for both genders are presented in the Tables 4.3 - 4.7. Coefficients are given as average partial effects and standard errors are calculated using the Delta method. If there are no major differences between Model A and B, only results for the preferred Model B are discussed.

4.6.1 The effects of employment on union formation, dissolution and conception

In contrast to Aassve et al. (2006), my results for Model A suggest that the employment state has no effect on finding a partner for women but a slightly positive effect for men, as can be seen in the first and third column of Table 4.5. However, this positive effect vanishes for Model B, a point that can be seen in the second and fourth column of Table 4.5, and results suggest that men with a high hazard of losing a job are less likely to start a union. This means that for men the stability of a job is important and less the job itself. My results are therefore in line with Ahn and Mira (2001) who show that Spanish men delay marriage decisions due to bad employment prospects. Results for Model B further indicate that women with a high hazard of finding a job are more likely to find a partner. One reason may be that women with better labor market perspectives are more confident and therefore considered as more attractive or partners want to benefit from better labor market perspectives.

With regard to union dissolution, as shown in columns one and three of Table 4.6, results for Model A indicate that unions of employed men tend to be more stable, while no such effect can be found for women. However, the effect for men is no longer significant, if the hazards of finding and losing employment are included as regressors (see column four of Table 4.6). Nonetheless, results still indicate that male employment plays a positive role for union stability. These results are supported by Eliason (2012) who shows that for Swedish men a job loss increases the excess divorce rate by 13%. Since men still contribute a larger part to the household income, a job loss often results in a severe loss of household income. This in turn may yield a loss of self-confidence as unemployed men can not manage their role as breadwinners what may destabilize a union. For women the effects are ambiguous. While for couples in which women contribute a large part to the household income a wife's job loss may destabilize a union, the effect might be reverse for women becoming housewives. Therefore, it is not surprising that no effect can be found for women.

With regard to conception, results for Model A indicate that being employed has no effect on childbearing for men and a negative effect for women (see columns one and three of Table 4.7). For men the absence of a positive employment effect is surprising, because most nonemployed men are unemployed and it is plausible that unemployed men are less likely to have children than employed men due to income restrictions. The results are also in contrast to what Aassve et al. (2006) have found. For women the negative employment effect vanishes for Model B (see column two of Table 4.7) and is now captured by the hazard of losing a job which indicates that for women a high hazard of losing a job decreases the hazard of having children. This is similar to what Del Bono (2001) finds for British women. Women working in an unstable employment in general depend heavily on the income from these employments. This is particularly true for single-mothers and women living in households depending strongly on wife's income.

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Duration dependence				
Elapsed duration (base: <6 months)				
Elapsed 6-12 months	0.1289	0.1255	0.2971	0.3162*
	(0.1379)	(0.1344)	(0.1877)	(0.1867)
Elapsed 12-24 months	-0.1772	-0.2231**	-0.1861	-0.1554
	(0.1119)	(0.1105)	(0.1245)	(0.1245)
Elapsed 24-60 months	-0.2384**	-0.3022***	-0.4650***	-0.4132***
	(0.1080)	(0.1065)	(0.1215)	(0.1225)
Elapsed 60-120 months	-0.5070***	-0.6018***	-1.0057***	-0.9603***
	(0.1266)	(0.1242)	(0.1530)	(0.1556)
Elapsed >120 months	-0.7768***	-0.8593***	-1.1826***	-1.0883***
	(0.1761)	(0.1751)	(0.2260)	(0.2376)
Age				
Age structure (base: <20 years)				
20-24 years	-0.0640	-0.0409	-0.3151**	-0.3279**
	(0.1568)	(0.1560)	(0.1323)	(0.1330)
25-29 years	0.1501	0.1594	-0.6779***	-0.6997***
	(0.1735)	(0.1718)	(0.1706)	(0.1723)
30-34 years	0.1489	0.1650	-0.8061***	-0.8228***
	(0.2105)	(0.2094)	(0.2301)	(0.2335)
35-39 years	0.2183	0.2523	-0.8631***	-0.8858***
	(0.2459)	(0.2443)	(0.2887)	(0.2917)
>40 years	0.2465	0.2920	-0.9033***	-0.9230***
	(0.2896)	(0.2898)	(0.3339)	(0.3356)
Education				
Highest degree achieved (base: no degree)				
Voc. Train.	-0.0833	-0.0663	-0.3004**	-0.3088**
	(0.0903)	(0.0827)	(0.1502)	(0.1296)
HS degree	-0.1028	-0.0827	-0.0977	-0.1114
	(0.2003)	(0.2005)	(0.2295)	(0.2242)
HS + VT	-0.1445	-0.1089	-0.4953***	-0.5286***
	(0.1185)	(0.1208)	(0.1904)	(0.1730)
Tech. College	-0.0819	0.0108	-0.8998***	-0.9135***
	(0.1618)	(0.1607)	(0.2197)	(0.2073)
Uni. degree	-0.2246	-0.1538	-0.8154***	-0.8411***
	(0.1661)	(0.1678)	(0.2197)	(0.2063)

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Table 4.3: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Children				
Number of children (base: no child)				
1 child	-0.3562***	-0.3204***	-0.1352	-0.1534
	(0.1029)	(0.1021)	(0.1407)	(0.1412)
2 children	-0.5653***	-0.5341***	-0.3113*	-0.3549**
	(0.1302)	(0.1309)	(0.1702)	(0.1717)
3 or more children	-0.7666***	-0.7503***	-0.3669	-0.5016*
	(0.2032)	(0.2134)	(0.2798)	(0.2790)
children <3y	-0.1481	-0.1347	-0.0718	-0.0781
	(0.1490)	(0.1442)	(0.1977)	(0.2045)
children 3y-6y	0.2327	0.2349**	0.0597	0.0573
	(0.0969)	(0.0950)	(0.1183)	(0.1191)
Pregnant	3.0415***	3.0765***	-0.0729	-0.0989
	(0.0604)	(0.0633)	(0.1687)	(0.1740)
Union				
Currently in a union	0.3701***	0.3255***	-0.2998*	-0.2961*
	(0.1082)	(0.1050)	(0.1550)	(0.1753)
Partner has VT (+HS) degree	-0.0204	0.0287	0.0297	0.0137
	(0.0793)	(0.0833)	(0.1539)	(0.1575)
Partner has TC or UD degree	-0.0594*	-0.0353	0.1999	0.1675
	(0.0800)	(0.0806)	(0.1860)	(0.1848)
Other covariates				
East	0.1385	0.0499	0.6086	0.6477
	(0.3829)	(0.3984)	(0.4298)	(0.4328)
Public employee	-0.3537***	-0.3042***	-0.6278***	-0.6482****
	(0.0606)	(0.0617)	(0.0976)	(0.0997)
Civil servant	-0.4554***	-0.4722***	-0.3159*	-0.3602***
	(0.1591)	(0.1507)	(0.1653)	(0.1826)
Fixed-term contract	1.0667***	1.0259***	0.9034***	0.9369***
	(0.0966)	(0.0949)	(0.0953)	(0.0989)
Self-employed	-0.3252**	-0.3077**	-0.9783***	-0.9981***
	(0.1435)	(0.1428)	(0.1793)	(0.1941)
Regional U-rate	0.0169*	0.0178*	-0.0009	-0.0044
	(0.0097)	(0.0094)	(0.0129)	(0.0133)
Regional growth rate	0.0018	0.0033	-0.0371**	-0.0365**
	(0.0126)	(0.0471)	(0.0154)	(0.0156)

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Table 4.3: (continued)

	Women		**Men**	
	Model A	*Model B*	*Model A*	*Model B*
Maternity protection	-0.6511***	-0.6526***	0.0954	0.0945
	(0.1629)	(0.1529)	(0.2004)	(0.2060)
State dependence				
Cum. # of employments	0.1335***	0.1392***	0.0823***	0.0843***
	(0.0513)	(0.0471)	(0.0209)	(0.0199)
Cum. dur. in employment	-0.0001	-0.0006	0.0011	0.0011
	(0.0012)	(0.0012)	(0.0015)	(0.0016)
Cum. dur. in nonemployment	0.0006	0.0009	0.0008	0.0006
	(0.0011)	(0.0011)	(0.0015)	(0.0016)
Initial conditions				
Situation at labor market entry				
Age at entry	-0.0226	-0.0287*	0.0268	0.0305
	(0.0170)	(0.0169)	(0.0205)	(0.0204)
Employed at entry	0.0339	0.0469	0.0948	0.1004
	(0.1120)	(0.1085)	(0.1509)	(0.1520)
In union before entry	-0.0267	-0.0437	-0.0119	-0.0144
	(0.0645)	(0.0640)	(0.1179)	(0.1204)
Children before entry	0.1884	0.1452	-0.4150	-0.3790
	(0.2053)	(0.2072)	(0.4665)	(0.4431)
Children while at college	-0.1173	-0.1839	0.5258	0.5139
	(0.4136)	(0.4418)	(0.5213)	(0.5058)
Unobserved heterogeneity				
Points of support				
$\ln \upsilon_1^E$	-5.2899***	-5.1292***	-4.2692***	-4.2846***
	(0.3464)	(0.3528)	(0.4022)	(0.4120)
$\ln \upsilon_2^E$	-5.2620***	-5.1559***	-3.7348***	-4.0681***
	(0.3534)	(0.3471)	(0.4283)	(0.4342)
$\ln \upsilon_3^E$	-4.6196***	-5.0829***	-4.2678***	-4.4563***
	(0.3780)	(0.3676)	(0.4248)	(0.4439)
$\ln \upsilon_4^E$		-4.5965***		-3.4209***
		(0.3799)		(0.4917)

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Table 4.3: (continued)

	Women		**Men**	
	Model A	*Model B*	*Model A*	*Model B*
Probabilities				
π_1	0.4606***	0.1745***	0.7145***	0.6423***
	(0.0757)	(0.0320)	(0.0672)	(0.1445)
π_2	0.4044***	0.5761***	0.1172***	0.0925***
	(0.0782)	(0.0795)	(0.0174)	(0.0226)
π_3	0.1351**	0.1069**	0.1682**	0.2191
	(0.0622)	(0.0489)	(0.0659)	(0.1487)
π_4		0.1425**		0.0461*
		(0.0747)		(0.0250)

Table 4.3: Model results (Employment to Nonemployment). The table presents the results for the transition from employment to nonemployment. Results for the Models A and B for both women and men are given as average partial effects. Heteroskedasticity-robust standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Duration dependence				
Elapsed duration (base: <6 months)				
Elapsed 6-12 months	-0.3097***	-0.2667***	-0.4217***	-0.4110***
	(0.1003)	(0.1009)	(0.0927)	(0.0934)
Elapsed 12-24 months	-0.3741***	-0.3014***	0.6213***	0.6263***
	(0.1011)	(0.1063)	(0.0918)	(0.0985)
Elapsed 24-60 months	-0.2505**	-0.1132	0.2470*	0.2786*
	(0.1005)	(0.1148)	(0.1399)	(0.1506)
Elapsed 60-120 months	-0.5123***	-0.3942**	0.1068	0.0984
	(0.1441)	(0.1671)	(0.1697)	(0.1742)
Elapsed >120 months	-0.6979***	-0.5560**	-0.0283	-0.0473
	(0.2060)	(0.2290)	(0.2378)	(0.2384)
Age				
Age structure (base: <20 years)				
20-24 years	-0.0398	0.1062	0.6278***	0.6539***
	(0.1847)	(0.1904)	(0.1531)	(0.2384)
25-29 years	-0.3613	-0.0884	0.4115*	0.5126**
	(0.2335)	(0.2465)	(0.2141)	(0.2329)
30-34 years	-0.2188	0.1846	0.2737	0.4142
	(0.2843)	(0.2932)	(0.2568)	(0.2852)
35-39 years	-0.5845*	-0.0820	0.0611	0.2561
	(0.3417)	(0.3588)	(0.3207)	(0.3539)
>40 years	-0.6612	-0.1735	-0.4205	-0.1835
	(0.3965)	(0.4060)	(0.4247)	(0.4687)
Education				
Highest degree achieved (base: no degree)				
Voc. Train.	0.8794***	0.4586***	0.2751**	0.3904***
	(0.1637)	(0.1561)	(0.1236)	(0.1215)
HS degree	0.2668	0.1551	-0.2433	-0.2279
	(0.2639)	(0.2014)	(0.2030)	(0.2152)
HS + VT	0.9153***	0.4796**	0.2370	0.3837**
	(0.2195)	(0.1917)	(0.1634)	(0.1694)
Tech. College	1.1764***	0.6571**	0.5697**	0.6274***
	(0.4078)	(0.2699)	(0.2252)	(0.2132)
Uni. degree	1.4576***	1.0024***	0.3015	0.3561*
	(0.3241)	(0.2828)	(0.2107)	(0.2158)

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Table 4.4: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Children				
Number of children (base: no child)				
1 child	-0.5045***	-0.6474***	0.0379	-0.1173
	(0.1396)	(0.1938)	(0.1840)	(0.1877)
2 children	-0.7162***	-1.1472***	-0.0377	-0.1431
	(0.1724)	(0.2562)	(0.2098)	(0.2468)
3 or more children	-0.8842***	-1.4333***	0.1788	0.2054
	(0.2339)	(0.3169)	(0.3527)	(0.4423)
children <3y	-1.0334***	-1.0443***	0.1166	0.3253*
	(0.1180)	(0.1299)	(0.2106)	(0.1949)
children 3y-6y	-0.1505*	-0.0584	0.2257	0.2081
	(0.0847)	(0.0888)	(0.1662)	(0.1935)
Pregnant	-1.6885***	-1.8701***	-0.0201	0.0222
	(0.1905)	(0.2171)	(0.1625)	(0.1617)
Union				
Currently in a union	-0.2758*	-0.4291***	0.3562**	0.3987*
	(0.1481)	(0.1566)	(0.1800)	(0.2125)
Partner has VT (+HS) degree	0.2226	0.1003	-0.2466	-0.2920*
	(0.1555)	(0.1635)	(0.1631)	(0.1771)
Partner has TC or UD degree	0.0554	-0.0334	-0.1482	-0.2435
	(0.1517)	(0.1702)	(0.2301)	(0.2339)
Other covariates				
East	-0.5014	-0.2257	-1.2903***	-1.3291***
	(0.3360)	(0.4410)	(0.3973)	(0.3892)
In education	-0.4173***	-0.4503***	-0.5788***	-0.5620***
	(0.1537)	(0.1678)	(0.1306)	(0.1227)
Unemployed	0.9285***	0.8814***	1.3651***	1.4234***
	(0.0927)	(0.0979)	(0.1173)	(0.1187)
Regional U-rate	-0.0115	-0.0241	-0.0312**	-0.0280**
	(0.0148)	(0.0152)	(0.0144)	(0.0139)
Regional growth rate	0.0393***	0.0437**	0.0259	0.0308
	(0.0149)	(0.0152)	(0.0166)	(0.0178)
Maternity protection	-0.2137	-0.3168**	-0.0238	-0.1534
	(0.1314)	(0.1427)	(0.2175)	(0.2106)

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Table 4.4: (continued)

	Women		**Men**	
	Model A	*Model B*	*Model A*	*Model B*
State dependence				
Cum. # of employments	-0.0485	-0.1255	0.1127***	0.0871***
	(0.0666)	(0.0780)	(0.0154)	(0.0268)
Cum. dur. in employment	-0.0000	-0.0006	-0.0011	-0.0012
	(0.0015)	(0.0015)	(0.0016)	(0.0017)
Cum. dur. in nonemployment	0.0015	0.0036*	-0.0009	-0.0018
	(0.0017)	(0.0019)	(0.0014)	(0.0016)
Initial conditions				
Situation at labor market entry				
Age at entry	-0.0157	-0.0298	-0.0157	-0.0215
	(0.0260)	(0.0267)	(0.0227)	(0.0230)
Employed at entry	-0.2254	-0.0016	0.0829	0.0277
	(0.1528)	(0.0174)	(0.1365)	(0.1443)
In union before entry	0.1927*	0.2022*	0.1358	0.1341
	(0.1070)	(0.1183)	(0.1543)	(0.1815)
Children before entry	0.3450	0.5329**	-0.1846	-0.2346
	(0.2585)	(0.2304)	(0.2432)	(0.2945)
Children while at college	-0.1537	-0.3591	-0.4107	-0.3496
	(0.6075)	(0.4436)	(0.6357)	(0.6460)
Unobserved heterogeneity				
Points of support				
$\ln \upsilon_1^U$	-1.7572***	-0.2822	-3.1150***	-3.1833***
	(0.4885)	(0.5313)	(0.4400)	(0.4417)
$\ln \upsilon_2^U$	-3.4207***	-1.9667***	-5.0168***	-5.3581***
	(0.4717)	(0.5181)	(0.4580)	(0.4638)
$\ln \upsilon_3^U$	-3.0926***	-3.8093***	-2.9143***	-2.7273***
	(0.4880)	(0.5553)	(0.5106)	(0.6832)
$\ln \upsilon_4^U$		-2.6801***		-4.2803***
		(0.5936)		(0.4636)
Probabilities				
π_1	0.4606***	0.1745***	0.7145***	0.6423***
	(0.0757)	(0.0320)	(0.0672)	(0.1445)
π_2	0.4044***	0.5761***	0.1172***	0.0925***
	(0.0782)	(0.0795)	(0.0174)	(0.0226)

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Table 4.4: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
π_3	0.1351**	0.1069**	0.1682**	0.2191
	(0.0622)	(0.0489)	(0.0659)	(0.1487)
π_4		0.1425**		0.0461*
		(0.0747)		(0.0250)

Table 4.4: Model results (Nonemployment to Employment). The table presents the results for the transition from nonemployment to employment. Results for the Models A and B for both women and men are given as average partial effects. Heteroskedasticity-robust standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Duration dependence				
Elapsed duration (base: <6 months)				
Elapsed 12-24 months	0.2148	0.1998	0.2125	0.2080
	(0.1933)	(0.1968)	(0.1784)	(0.1914)
Elapsed 24-60 months	0.2849*	0.2840*	0.0540	0.0841
	(0.1728)	(0.1721)	(0.1692)	(0.1800)
Elapsed 60-120 months	0.2713	0.2557	0.0511	0.0782
	(0.2021)	(0.1974)	(0.1976)	(0.2260)
Elapsed >120 months	-0.0594	-0.0128	0.1282	0.2011
	(0.2635)	(0.2429)	(0.2231)	(0.2784)
Age				
Age structure (base: <20 years)				
20-24 years	0.5209***	0.5768***	0.5679**	0.5628**
	(0.1990)	(0.2100)	(0.2615)	(0.2668)
25-29 years	0.6589***	0.7295***	0.9414***	0.9344***
	(0.2246)	(0.2370)	(0.2822)	(0.3067)
30-34 years	0.2173	0.3536	0.7617***	0.7862**
	(0.2444)	(0.2827)	(0.2916)	(0.3245)
35-39 years	-0.4992*	-0.3211	0.3423	0.3872
	(0.2777)	(0.3285)	(0.3177)	(0.3632)
>40 years	-1.3850***	-1.199***	0.0212	0.0835
	(0.3307)	(0.3793)	(0.3381)	(0.3917)
Education				
Highest degree achieved (base: no degree)				
Voc. Train.	0.0594	0.0865	0.2062	0.2260
	(0.1538)	(0.1670)	(0.1915)	(0.1951)
HS degree	-0.0198	0.0487	0.3137	0.3152
	(0.2789)	(0.2949)	(0.2459)	(0.2857)
HS + VT	0.1195	0.1491	0.3368	0.3499
	(0.1907)	(0.2111)	(0.2225)	(0.2296)
Tech. College	0.1076	0.0486	0.4782*	0.4464
	(0.2393)	(0.2635)	(0.2624)	(0.2891)
Uni. degree	0.2557	0.2569	0.5228**	0.5403*
	(0.2474)	(0.2725)	(0.2611)	(0.2858)

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Table 4.5: (continued)

	Women		**Men**	
	Model A	*Model B*	*Model A*	*Model B*
Children				
Number of children (base: no child)				
1 child	-0.0634	-0.1284	0.1735	0.1018
	(0.1783)	(0.1875)	(0.1786)	(0.1858)
2 children	0.1956	0.1141	0.4620**	0.3856
	(0.2070)	(0.2262)	(0.2301)	(0.3045)
3 or more children	0.4201	0.3424	0.3991	0.3010
	(0.3862)	(0.4498)	(0.5510)	(0.6120)
children <3y	-0.2818	-0.1855	0.2781	0.3195
	(0.2065)	(0.2241)	(0.2074)	(0.2175)
children 3y-6y	-0.0071	0.0222	-0.1661	-0.1645
	(0.1890)	(0.1877)	(0.1842)	(0.1863)
Pregnant	1.7911***	1.7330***	2.2745***	2.1780***
	(0.1250)	(0.4377)	(0.1596)	(0.1862)
Employment				
Currently employed	0.0467	-0.1077	0.2003*	0.2490
	(0.1467)	(0.7903)	(0.1045)	(0.7402)
Hazard of becoming NE		-0.0670		-0.1276*
		(0.0693)		(0.0727)
Hazard of becoming E		0.2268**		0.0395
		(0.0946)		(0.1208)
Other covariates				
East	-0.0120	0.0668	0.3857	0.4351
	(0.4781)	(0.4310)	(0.3752)	(0.4586)
Religion	-0.0360	-0.0887	0.0311	-0.0049
	(0.1156)	(0.1294)	(0.0838)	(0.0952)
Spring / summer	0.5811***	0.5823***	0.4213***	0.4227***
	(0.0648)	(0.0654)	(0.0627)	(0.0627)
State dependence				
Cum. # of unions	0.0263	-0.1302	0.4104***	0.3185*
	(0.1394)	(0.1557)	(0.1543)	(0.1763)
Initial conditions				
Situation at labor market entry				
Age at entry	0.0109	0.0017	-0.0175	-0.0192
	(0.0213)	(0.0245)	(0.0197)	(0.0233)

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Table 4.5: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Employed at entry	0.0810	0.0897	0.1446*	0.1353
	(0.0881)	(0.1002)	(0.0830)	(0.0853)
In union before entry	0.1685	0.2481	0.2989*	0.3354*
	(0.1536)	(0.1676)	(0.1737)	(0.1972)
Children before entry	-0.2985	-0.2559	0.4939	0.6163
	(0.3284)	(0.3474)	(0.5668)	(0.7101)
Children while at college	-0.5316	-0.5463	-1.0736	-1.1840
	(0.5016)	(0.7014)	(0.8240)	(0.9404)
Unobserved heterogeneity				
Points of support				
$\ln \upsilon_1^M$	-5.4430***	-4.7424***	-5.6292***	-5.3585***
	(0.4937)	(0.5857)	(0.4535)	(0.7387)
$\ln \upsilon_2^M$	-5.3878***	-4.3774***	-6.5917***	-6.3351***
	(0.5235)	(0.5733)	(0.4407)	(0.6711)
$\ln \upsilon_3^M$	-6.4926***	-4.5761***	-6.8274***	-6.6963***
	(0.5504)	(0.8952)	(0.4618)	(0.6832)
$\ln \upsilon_4^M$		-5.8240***		-6.6778***
		(0.7293)		(0.6904)
Probabilities				
π_1	0.4606***	0.1745***	0.7145***	0.6423***
	(0.0757)	(0.0320)	(0.0672)	(0.1445)
π_2	0.4044***	0.5761***	0.1172***	0.0925***
	(0.0782)	(0.0795)	(0.0174)	(0.0226)
π_3	0.1351**	0.1069**	0.1682**	0.2191
	(0.0622)	(0.0489)	(0.0659)	(0.1487)
π_4		0.1425**		0.0461*
		(0.0747)		(0.0250)

Table 4.5: Model results (Union formation). The table presents the results for the union formation transition. Results for the Models A and B for both women and men are given as average partial effects. Heteroskedasticity-robust standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Duration dependence				
Elapsed duration (base: <12 months)				
Elapsed 12-24 months	0.3327	0.2196 **	0.5965***	0.2365
	(0.2607)	(0.1044)	(0.2411)	
Elapsed 24-60 months	0.7388***	0.3378***	0.9949***	0.5558
	(0.2329)	(0.1237)	(0.2413)	(0.4186)
Elapsed 60-120 months	0.6342**	0.2274*	1.0168***	0.4142
	(0.2624)	(0.1244)	(0.2734)	(0.3962)
Elapsed >120 months	0.6961**	-0.1315	0.9321***	0.0283
	(0.3218)	(0.1500)	(0.3522)	(0.3252)
Age				
Age structure (base: <20 years)				
20-24 years	0.1744	-0.1109	0.3570	0.1916
	(0.4711)	(0.3052)	(1.0762)	(0.7639)
25-29 years	-0.2733	-0.3736	0.2103	0.3999
	(0.4890)	(0.3093)	(1.0694)	(0.7423)
30-34 years	-0.3313	-0.3350	0.4246	0.5039
	(0.5137)	(0.3233)	(1.0837)	(0.7842)
35-39 years	-0.3286	-0.2346	0.3225	0.4873
	(0.5373)	(0.3495)	(1.1039)	(0.7870)
>40 years	-0.4644	-0.3886	0.1740	0.3303
	(0.5656)	(0.3813)	(1.1135)	(0.8227)
Education				
Highest degree achieved (base: no degree)				
Voc. Train.	-0.1158	0.1970	-0.4013	-0.1844
	(0.2837)	(0.1656)	(0.3594)	(0.2677)
HS degree	-0.2488	0.2694	-0.6549	-0.2524
	(0.5376)	(0.2743)	(0.5362)	(0.4432)
HS + VT	-0.1402	0.2230	-0.8763**	-0.2934
	(0.3420)	(0.2098)	(0.4327)	(0.3545)
Tech. College	-0.1961	0.1511	-1.0637**	-0.5852
	(0.3905)	(0.2562)	(0.5001)	(0.3680)
Uni. degree	-0.9908	-0.0472	-1.3856***	-0.7822*
	(0.4608)	(0.2845)	(0.5311)	(0.4216)

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Table 4.6: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Children				
Number of children (base: no child)				
1 child	-0.5310**	-0.3208**	-0.7149***	-0.5598***
	(0.2101)	(0.1634)	(0.2269)	(0.2086)
2 children	-1.1930***	-0.8828***	-1.2335***	-1.0335***
	(0.2721)	(0.2145)	(0.2852)	(0.2747)
3 or more children	-1.2238***	-0.8210***	-1.6534***	-1.2756***
	(0.3680)	(0.2823)	(0.4523)	(0.4758)
children <3y	-0.4967**	-0.4423**	-0.9255***	-1.1025***
	(0.1939)	(0.1780)	(0.2352)	(0.2692)
children 3y-6y	0.1990	0.1299	-0.1753	-0.2784
	(0.1629)	(0.1424)	(0.1988)	(0.2015)
Pregnant	-1.0725***	-2.3032***	-1.7662***	-3.7691***
	(0.2848)	(0.4451)	(0.4196)	(2.0350)
Employment				
Currently employed	-0.0447	0.0394	-0.6080***	-0.5630
	(0.1668)	(0.2574)	(0.2070)	(0.6364)
Hazard of becoming NE		0.0735		-0.0201
		(0.1353)		(0.1239)
Hazard of becoming E		-0.1494		0.2741
		(0.0993)		(0.1866)
Other covariates				
East	1.2406**	0.9101**	0.0982	-0.1743
	(0.5515)	(0.4229)	(0.5035)	(0.4891)
Religion	-0.3809**	-0.3211***	-0.3609**	-0.2951**
	(0.1494)	(0.1216)	(0.1410)	(0.1230)
Age difference	-0.0045	-0.0130*	0.0596***	0.0072
	(0.0170)	(0.0073)	(0.0228)	(0.0235)
Partner has higher edu.	-0.0981	-0.0470	0.5484**	0.0504
	(0.1945)	(0.0693)	(0.2193)	(0.1932)
Partner has lower edu.	-0.4631***	-0.0226	-0.4765***	-0.1899
	(0.1392)	(0.0590)	(0.1783)	(0.2052)
No information on partner	1.8136***	0.1380	2.1354***	0.6348
	(0.2769)	(0.2211)	(0.2194)	(1.0647)
Children from other partner	0.5605***	0.2679**	0.1132	-0.0385
	(0.2041)	(0.1151)	(0.2408)	(0.1543)

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Table 4.6: (continued)

	Women		**Men**	
	Model A	*Model B*	*Model A*	*Model B*
2^{nd} half of year	0.2683***	0.1409***	0.2518**	0.1140
	(0.0997)	(0.0513)	(0.1008)	(0.1163)
State dependence				
Cum. # of unions	0.0011	0.0492	-0.1488	0.0242
	(0.1817)	(0.0726)	(0.1803)	(0.1228)
Initial conditions				
Situation at labor market entry				
Age at entry	0.0709	0.0362	0.0763**	0.0702***
	(0.0299)	(0.0228)	(0.0327)	(0.0262)
Employed at entry	-0.0376	-0.0653	-0.0946	-0.0767
	(0.1488)	(0.1009)	(0.1386)	(0.1148)
In union before entry	0.2607*	0.3313***	-0.2513	-0.1790
	(0.1465)	(0.1128)	(0.1984)	(0.1684)
Children before entry	0.3204	-0.0496	-0.0663	0.1363
	(0.2905)	(0.2914)	(0.6074)	(0.5751)
Children while at college	-0.5065	0.0691	-0.3542	-0.6571
	(0.8697)	(0.6606)	(0.8029)	(0.8925)
Unobserved heterogeneity				
Points of support				
$\ln \upsilon_1^D$	-7.0306***	-7.0919***	-7.7167***	-6.2701***
	(0.7428)	(0.6533)	(1.1797)	(1.1055)
$\ln \upsilon_2^D$	-8.1419***	-7.1241***	-6.7809***	-5.4058***
	(0.8076)	(0.6159)	(1.1931)	(1.1811)
$\ln \upsilon_3^D$	-6.0201***	-8.0288***	-5.5205***	-4.8587***
	(0.8076)	(0.8272)	(1.2139)	(1.1607)
$\ln \upsilon_4^D$		-6.6447***		-4.4697***
		(0.7377)		(1.0653)
Probabilities				
π_1	0.4606***	0.1745***	0.7145***	0.6423***
	(0.0757)	(0.0320)	(0.0672)	(0.1445)
π_2	0.4044***	0.5761***	0.1172***	0.0925***
	(0.0782)	(0.0795)	(0.0174)	(0.0226)

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Table 4.6: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
π_3	0.1351**	0.1069**	0.1682**	0.2191
	(0.0622)	(0.0489)	(0.0659)	(0.1487)
π_4		0.1425**		0.0461*
		(0.0747)		(0.0250)

Table 4.6: Model results (Union dissolution). The table presents the results for the union dissolution transition. Results for the Models A and B for both women and men are given as average partial effects. Heteroskedasticity-robust standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Duration dependence				
Elapsed duration (base: <24 months)				
Elapsed 24-60 months	1.4642***	0.9969***	1.3961***	0.9419***
	(0.0752)	(0.0811)	(0.0935)	(0.1149)
Elapsed 60-120 months	1.1669***	0.4172***	0.8781***	0.1502
	(0.1030)	(0.1423)	(0.1348)	(0.1959)
Elapsed 120-180 months	1.2254***	0.1929	0.9687***	-0.1287
	(0.1046)	(0.1718)	(0.1153)	(0.2732)
Elapsed >180 months	1.2286***	0.1227	1.1182***	-0.1460
	(0.1259)	(0.1962)	(0.1329)	(0.3212)
Age				
Age structure (base: <20 years)				
20-24 years	0.6098***	0.6081*	0.5022	1.1257***
	(0.2149)	(0.3149)	(0.3808)	(0.5758)
25-29 years	0.7600***	1.2776***	0.7637**	1.7012***
	(0.2100)	(0.3193)	(0.3721)	(0.6280)
30-34 years	0.5319**	1.1755***	0.7561**	1.7768***
	(0.2178)	(0.3308)	(0.3691)	(0.6912)
35-39 years	-0.2781	0.2633	0.3749	1.4260***
	(0.2418)	(0.3717)	(0.3764)	(0.6968)
>40 years	-1.9670***	-0.5683	-0.4500	0.5554
	(0.3557)	(0.5033)	(0.4061)	(0.6538)
Education				
Highest degree achieved (base: no degree)				
Voc. Train.	-0.0507	-0.0930	0.1106	-0.0094
	(0.1062)	(0.1853)	(0.1669)	(0.2230)
HS degree	-0.0668	-0.2269	-0.0061	-0.1054
	(0.1738)	(0.3236)	(0.2335)	(0.3410)
HS + VT	-0.0504	-0.2290	0.1404	-0.0996
	(0.1287)	(0.2365)	(0.1870)	(0.3052)
Tech. College	0.0315	-0.2159	0.3487*	0.2299
	(0.1706)	(0.2959)	(0.2054)	(0.2948)
Uni. degree	0.2484	0.9970***	0.5199**	0.8013**
	(0.1615)	(0.3135)	(0.2105)	(0.3709)

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Table 4.7: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Children				
Number of children (base: no child)				
1 child	-0.2869**	-0.5768***	-0.3005**	-0.6475***
	(0.1115)	(0.2067)	(0.1344)	(0.2310)
2 children	-2.0050***	-2.1904***	-1.9403***	-2.1548***
	(0.1785)	(0.2704)	(0.1944)	(0.3155)
3 or more children	-2.2807***	-2.5029***	-2.1638***	-2.3957***
	(0.2669)	(0.3875)	(0.2809)	(0.3924)
children <3y	0.7869***	0.4766**	0.9589***	0.8050***
	(0.0956)	(0.2206)	(0.1133)	(0.1919)
children 3y-6y	0.2699***	0.1429	0.3540***	0.2589
	(0.0252)	(0.1793)	(0.1047)	(0.1710)
Union				
Currently in a union	1.6424***	1.0579***	2.2721***	1.6441***
	(0.0903)	(0.2317)	(0.1211)	(0.4356)
Hazard of finding partner		-0.0048		-0.1156
		(0.2042)		(0.3689)
Hazard of losing partner		1.1493***		0.7066
		(0.2863)		(0.5563)
Employment				
Currently employed	-0.3368***	0.2523	-0.0286	-0.2980
	(0.0572)	(0.5705)	(0.1108)	(0.3946)
Hazard of becoming NE		-0.2765*		0.0362
		(0.1465)		(0.0582)
Hazard of becoming E		0.0166		-0.1780*
		(0.0909)		(0.0983)
Other covariates				
East	0.4238	-0.5185	0.4725**	0.5783
	(0.2744)	(0.5695)	(0.2315)	(0.4558)
Religion	0.4273***	0.8940***	0.2850***	0.5261***
	(0.0796)	(0.1869)	(0.0682)	(0.1486)
Regional birth rate	0.1428***	0.1465***	0.1347***	0.1375***
	(0.0322)	(0.0334)	(0.0374)	(0.0390)
Potential child allowance	0.0413	0.0532**	-0.0160	-0.0064
	(0.0252)	(0.0266)	(0.0286)	(0.0251)

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Table 4.7: (continued)

	Women		Men	
	Model A	*Model B*	*Model A*	*Model B*
Initial conditions				
Situation at labor market entry				
Age at entry	0.0168	-0.0864***	0.0136	-0.0803
	(0.0133)	(0.0298)	(0.0139)	(0.0839)
Employed at entry	0.0329	0.0814	0.0190	0.0988
	(0.0571)	(0.1151)	(0.0623)	(0.0975)
In union before entry	-0.1003*	-0.3820**	-0.0471	0.1789
	(0.0607)	(0.1616)	(0.0782)	(0.1778)
Children before entry	0.0886	0.4780	-0.0859	-0.0864
	(0.2023)	(0.3982)	(0.3059)	(0.4108)
Children while at college	0.2893	0.0226	-0.2074	0.0169
	(0.4122)	(0.8019)	(0.3645)	(0.6733)
Unobserved heterogeneity				
Points of support				
$\ln \upsilon_1^C$	-9.7828	-7.6898***	-10.5124***	-10.7079***
	(0.4942)	(1.2271)	(0.6102)	(1.9128)
$\ln \upsilon_2^C$	-9.9413	-8.0124***	-10.6366***	-11.7387***
	(0.4957)	(1.1264)	(0.6108)	(2.3126)
$\ln \upsilon_3^C$	-9.1856	-7.5739***	-9.9820***	-11.1340***
	(0.4942)	(1.2844)	(0.5982)	(2.5602)
$\ln \upsilon_4^C$		-7.7363***		-10.8840***
		(1.4244)		(2.4976)
Probabilities				
π_1	0.4606***	0.1745***	0.7145***	0.6423***
	(0.0757)	(0.0320)	(0.0672)	(0.1445)
π_2	0.4044***	0.5761***	0.1172***	0.0925***
	(0.0782)	(0.0795)	(0.0174)	(0.0226)
π_3	0.1351**	0.1069**	0.1682**	0.2191
	(0.0622)	(0.0489)	(0.0659)	(0.1487)
π_4		0.1425**		0.0461*
		(0.0747)		(0.0250)

Table 4.7: Model results (Conception). The table presents the results for the conception transition. Results for the Models A and B for both women and men are given as average partial effects. Heteroskedasticity-robust standard errors are given in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

It is therefore not surprising that women with a high risk of becoming nonemployed are less likely to have children. For men, results from Model B suggest that a low hazard of finding a job increases the hazard of having children (see column four of Table 4.7).
Men with low job market perspectives might spend more time in other activities than searching for a job, which may include having children and they might also care less about contraceptives. Nonetheless, the absence of any positive effect of being employed for men is surprising.

4.6.2 The effects of partnership on employment, nonemployment and conception

For women having a partner increases the likelihood of becoming nonemployed and decreases the likelihood of finding a job (see columns one and two of Tables 4.3 and 4.4). Although the effects are small, they are significant and point in the same direction as supposed by Aassve et al. (2006). For men the effects point in the opposite direction (see columns three and four of Tables 4.3 and 4.4). My results therefore suggest a classical division of labor between women and men, with men as breadwinners and women as housewives. Surprisingly, the educational level of the partner does not seem to play a role, as the coefficients are very small and mostly insignificant.
Obviously, having a partner strongly increases the conception hazard (see columns one to four of Table 4.7). One can see that the effects are stronger for Model A than for Model B, since the hazards of starting and ending a union capture these effects in parts. Surprisingly, a high hazard of losing a partner results in an increase of the hazard of having children (see column two of Table 4.7) for women. An 1% increase in the union dissolution hazard increases the hazard of having a child by 1.15% for women. The effect is also large for men but not significant. These findings are in contrast to large parts of the economic theory (see for example Becker et al., 1976) which predicts that couples with a high risk of splitting up are less likely to invest in partnership-specific capital and therefore tend to have fewer children. The result is also in contrast to Lillard (1993) who finds that an 1% increase in the hazard of union dissolution results in a decrease

of the conception hazard by -1.62%. Note that the presented results here are based on cohabiting couples who are not necessarily married. It is important to note that Becker et al. (1976) and Lillard (1993) base their results on data of cohorts which had explicitly higher separation costs[16]. Over the years however, separation costs have considerably fallen. Today, many women work and therefore do not depend exclusively on husbands alimonies. Furthermore, normative issues seem to be less important, which is reflected in an increasing number of single-mothers and step families. A further aspect that has to be taken into consideration is that most forms of investment into partner-specific capital, e.g. marriage, have become less valuable with lower separation costs. The only investment that may be considered as an exception is having children. Therefore, for couples with a high risk of dissolving, having children may present the best form of investment, if they want to maintain their relationship, i.e. children are used in order to rescue the relationship. This may to some extent explain why couples with a high risk of dissolving are more likely to have children.

The results found here also shed some light on the increase in single-mothers and the high proportion of mothers among separated and divorced women. If couples that are likely to split up had fewer children, the proportion of mothers should be lower among separated and divorced women. However, Pötzsch (2012) shows that for the cohort 1959-1968 the proportion of mothers is the same for married and divorced women in Germany[17]. As some of the couples with a high risk of dissolving maintain their relationship due to the investment in children and therefore increase the proportion of mothers among married women, these results support the findings here. Also Kohler et al. (2006) show that from a European perspective the result seems to hold. They find that the cross-sectional correlation coefficient between the total fertility rate and the divorce rate of several European countries has switched from negative to positive between 1975 and 2002.

[16] Lillard (1993) uses data of US-American marriages for the period from 1955 until 1985 and accounts only for married couples and children born within a marriage.

[17] For both groups the rate of mothers is around 90% (see Pötzsch, 2012)

4.6.3 The effects of children and childbearing

In contrast to Aassve et al. (2006), I also include a dummy variable that displays current pregnancy. This variable leads to some changes with respect to variables that account for the number of children, in particular, for women. While the number of children accounts mostly for long-run decisions, current pregnancy accounts mostly for short-run decisions. With regard to the transition from employment to nonemployment, the results show that fathers are less likely to become nonemployed (see columns three and four of Table 4.3). Because children cause costs, there is an incentive to work for fathers who usually contribute a larger part to the household income. Fathers may therefore choose jobs that are more stable and put more emphasis on fulfilling their duties. Furthermore, for men virtually no effect can be found for the transition from nonemployment to employment (see columns three and four of Table 4.4). So far the literature has neglected that children may also have positive effects on job stability of women. By including a binary indicator for current pregnancy, I am able to show that it is only pregnancy that drives women out of employment, while children strongly increase the attachment with the current job (see columns one and two of Table 4.3). As for men, a possible reason for this is an increase in household expenses due to children and therefore a higher motivation to work and to remain employed. The finding is also of particular interest, because it applies most notably to women that are strongly affected by increases in household expenses, like single-mothers or women from low-income households. For the hazard of becoming employed, my results show that for nonemployed women, children and being currently pregnant strongly hamper the return to employment (see columns one and two of Table 4.4). This is in line with the existing literature which deals with the interrelation of fertility and female labor force participation (see for example Hyslop, 1999, or Michaud and Tatsiramos, 2011). However, most studies neglect that effects are different for women that are dependent on their job because of income reasons, e.g. single-mothers. The results in this chapter show that for these women children strongly increase the attachment to their jobs.

With regard to the hazard of starting a union, the results in column one to four of Table

4.5 show that a current pregnancy more than quadruplicates this hazard for women and more than septuples it for men[18]. This is consistent with economic theory, which predicts that cohabitations are more beneficial once partner-specific capital has been acquired. Moreover, normative aspects may force individuals to enter a union. Interestingly, the effect seems to be stronger for men. One reason for this may be that men tend to underreport children born outside a union more often than women. The number of children has no effect on forming a union for both women and men. This is surprising because children are generally considered to impede entering a (second) union. However, as already mentioned, the costs of entering a subsequent union have fallen.

Turning to the union dissolution hazard, one can see that the number and age of children play a strong role for the stability of a union (see columns one to four of Table 4.6). Economic theory often names children as a typical form of partner-specific capital increasing the cost of a dissolution. However, the effect seems to reduce somewhat with the age of children. This is in line with other empirical findings (see for example Steele et al., 2005, or Lillard and Waite, 1991). Normative forces may explain to a large extent the strong effect a current pregnancy has on the union dissolution hazard (reduces the hazard by 90% for women and 98% for men).

The results in columns two and four of Table 4.7 show that the first child reduces the hazard of conception by around 44% for women and 48% men compared to having no children. However, the effects are offset, if the child is younger than three years, whereas three years is the typical time span within a second child is born. A second child then reduces the hazard by around 88% for women and men, while the effect for three or more children is even stronger. These findings support the classical role model of families having two children born within a short time interval.

[18] Percentage values for the respective effects of a binary indicator can be calculated by $\exp(\beta_i) - 1$, where $\beta_i = e_i, u_i, m_i, d_i, c_i$

4.6.4 The effects of education

Note that education is measured by the highest degree obtained. For men, a higher educational level goes along with a higher job stability (see columns three and four of Table 4.3). This is not the case for women, for whom the hazard for a transition to nonemployment seems to be unaffected by the educational level (see columns one and two of Table 4.3). Furthermore, better educated women and men are more likely to find employment when nonemployed (see columns one to four of Table 4.4). Interestingly, the results for women are stronger than for men. This might indicate that highly educated women also return to employment more quickly after a voluntary nonemployment period (e.g. a parental leave).

The results in columns one to four of Table 4.5 suggest that for women education does not seem to have an effect on the hazard of union formation, while men with a university degree are more likely to find a cohabiting partner. Because higher education is also linked to more prestigious jobs and higher wages, this result supports the idea of a Jane Austen's world, where women prefer successful partners (Coles and Francesconi, 2011). Furthermore, the results in columns one and two of Table 4.6 show that a women's education plays no role for the decision to end a union, while results in columns three and four indicate that unions of better educated men are more stable. However, these effects are smaller for Model B, i.e. the variables accounting for education in Model A seem to capture in parts the effects of the hazards of finding and losing employment.

With regard to conception, results from Model B indicate that women and men having obtained a university degree are more likely to have children (see columns two and four of Table 4.7). On first sight, this result is surprising as academics are usually considered to have a low birth rate. However, two aspects may play a role here. First, university graduates are on average older when entering the labor market. This means that they are faced with a higher biological pressure to have children and therefore have children more rapidly. Furthermore, education accounts in parts for the current income level and also expectations about future income. Therefore, results for education suggest that the income level and income stability play a role for the decision on having children.

4.6.5 The effects of age

Concerning age effects, the results for men are as expected. Older men are less likely to become nonemployed, but also less likely to find a job (see columns three and four of Table 4.3). For women these results do not hold (see columns one and two of Table 4.3). Interestingly, both transitions from and to employment do not seem to depend on the current age of a woman. By contrast, Steele (2005) finds that for Australian women job stability increases with age.

The results for the union formation process (see columns one to four of Table 4.5) exhibit an inverse U-shape with respect to age for women and men with a peak for the group aged 25 to 30, indicating that within this age interval most unions are formed. Although many individuals find their partner at an earlier stage, cohabitations typically start when individuals have entered the labor market. Nonetheless, finding a cohabiting partner becomes less and less likely the older an individual gets. In particular, women aged 40 or older have poor chances of finding a cohabiting partner. These women are even less likely to start a union than women aged 20 or younger, i.e. women who are mostly still in school and live with their parents. The results with regard to age are in line with the literature, although Brien et al. (1999) find that American women and men enter unions at an earlier stage. However, the authors use data from the National Longitudinal Study of the High School Class of 1972, i.e. of a much older cohort. The union dissolution hazard seems to be independent of age (see columns one to four of Table 4.6). Even though one could assume that older partners have more stable unions, results show that this is not the case. The results for duration dependence show that the duration of a union and not the individuals age increases the stability of a union.

The results from Model B indicate that the hazard of conception also exhibits a typical inverse U-shape for both women and men (see columns two and four of Table 4.7). Women most likely become pregnant between 25 and 30, while men most likely become fathers between 30 and 35. Not surprisingly, men aged 40 or older are still more likely to become fathers than men aged 20 or younger, while the hazard of becoming pregnant drops sharply for women aged 40 or older due to biological reasons.

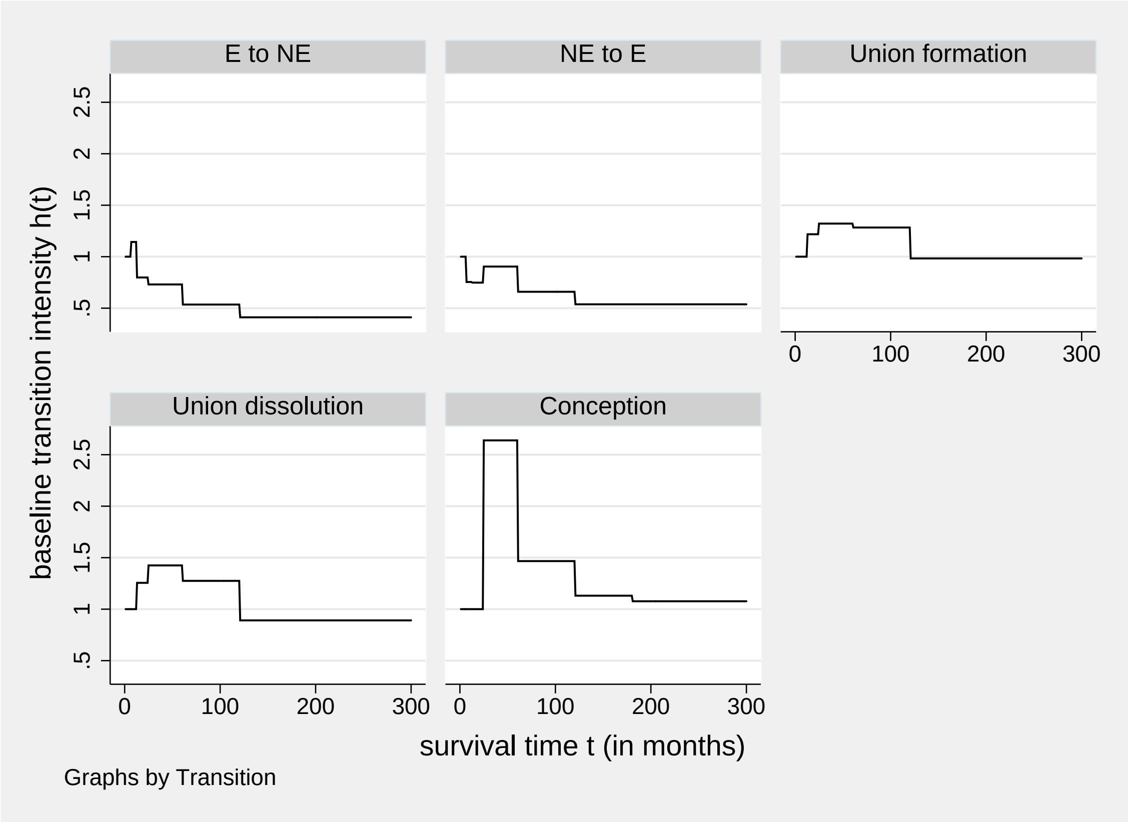

Figure 4.2: Estimated baseline transition intensities (women). The figure presents the estimated baseline transition intensities for the five transitions for women. The duration is measured in months. E: Employment, NE: Nonemployment.

4.6.6 State dependence effects

The results for duration dependence are fully captured by the baseline hazards which are displayed in Figures 4.2 and 4.3. The transitions from employment to nonemployment exhibit strong negative duration dependence, i.e. transitions become less likely over time for both men and women. At least for men, this is a typical finding, often linked with higher opportunity costs for a dismissal and institutional issues, like Germany's strict Dismissal Protection Law (*Kündigungsschutzgesetz*). In addition, the likelihood of a transition for both women and men increases with the number of prior employment spells but not with their duration (see columns one to four of Table 4.3). The results therefore indicate stigmatization effects and no positive effect on human capital due to

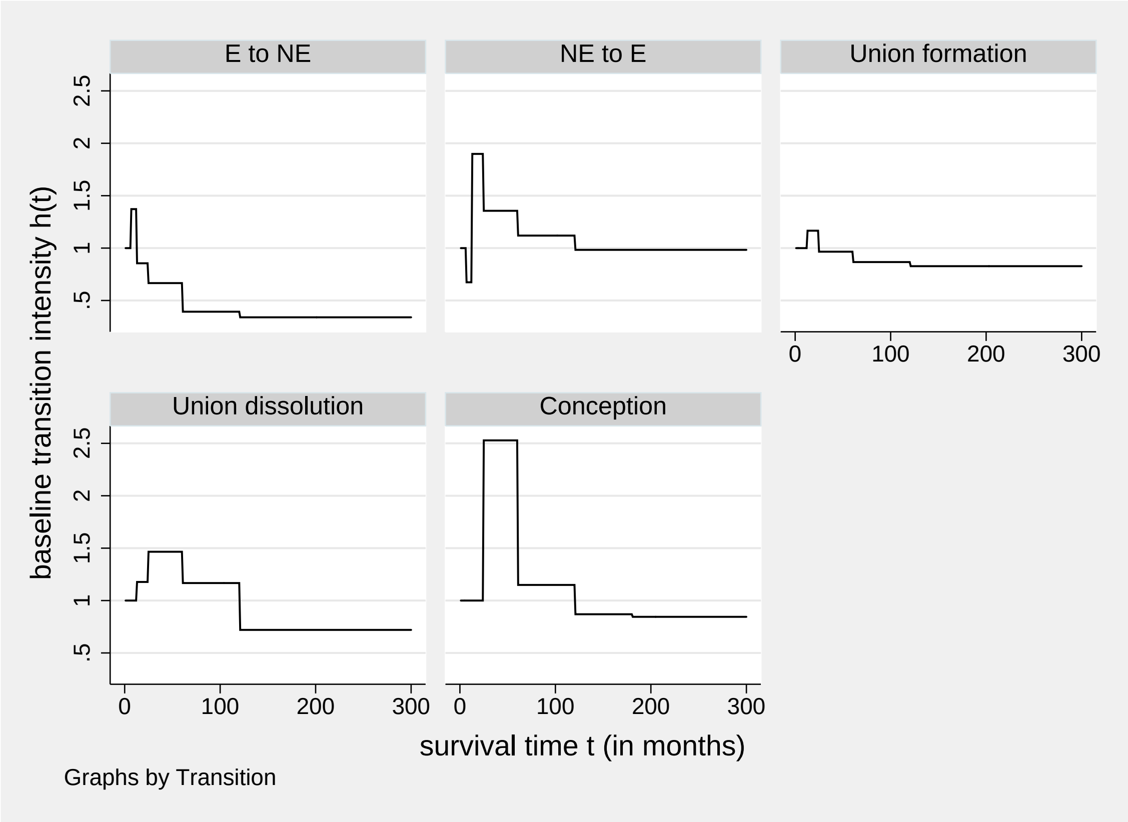

Figure 4.3: Estimated baseline transition intensities (men). The figure presents the estimated baseline transition intensities for the five transitions for women. The duration is measured in months. E: Employment, NE: Nonemployment.

longer lasting employment spells.[19]

With regard to the transition from nonemployment to employment, the results show a decaying baseline hazard for women and men. For men, however, the baseline hazard first increases strongly and then decreases to its base level, while for women, the baseline hazard decreases directly. In general, decaying baseline hazards are often found in the literature (see for example Cockx and Dejemeppe, 2005) and typically linked with decreases in human capital or stigmatization effects. Results for men also suggest that again no lagged duration dependence can be found and that the more often someone has been employed, the more likely he is to find employment (see columns three and

[19] Note that the number of nonemployment spells is directly linked to the number of employment spells.

four of Table 4.4). However, the jobs found seem to be of a poor quality, as results for occurrence dependence for the hazard of becoming nonemployed reveal. This means that for men, there might be a vicious circle of unstable employment and nonemployment and exiting this circle becomes less likely the more often someone has transited between employment and nonemployment.

The success of search for a partner seems to depend only on age, but not on the duration of the search process (see columns one to four of Table 4.5). By contrast, a reverse effect is found for the process of splitting up a partnership, when age does not play a role, but an inverse U-shaped pattern is found for the baseline hazard for women and men (see columns one to four of Table 4.6). Such an inverse U-shape is plausible, because the longer a relationship lasts, the higher are the costs of splitting up. Furthermore, the start of a cohabiting union is related to an investment, e.g. the partners have to move together, and therefore typically do not split up directly. For women, the number of prior partnerships does not play a role for both transitions, meaning that they neither learn from prior partnerships nor are stigmatized by having had many relationships before (see columns one and two of Table 4.6). However, for men, the union formation hazard increases with the number of prior partnerships.

Note that the process of conception is a recursive one. While effects for the first birth are mostly captured by age variables, variables concerning duration dependence mostly capture effects from subsequent births. Therefore, the strong peak for the period from two to five years after a birth, probably indicates that a subsequent birth typically occurs within a time span of two to five years. Separate estimation of hazard rates subject to the order of birth would certainly help to elaborate such effects in more detail.

4.6.7 The effects of environmental and other background variables

My results for the transitions from and to employment suggest that the region in Germany has no effect on becoming nonemployed (see columns one to four of Table 4.3) but that men living in East Germany are less likely to find employment (see columns three and four of Table 4.4). Similar to this finding, the results also show that an increase in the current unemployment rate does not play a role for the hazard of becoming nonemployed but decreases the hazard of finding a job for men. Furthermore, for men, a decay in the regional growth rate reduces the hazard of finding a job, while it has almost no effect on the transition from employment to nonemployment. For men, the findings with respect to regional unemployment and growth rate are therefore consistent with Hall (2005) who argues that during slack periods, unemployment rises mainly due to low hiring rates rather than increased separations. Nonetheless, the situation is reverse for women, for whom an increase in the regional unemployment rate increases the hazard of becoming nonemployed (see columns one and two of Table 4.3), while the regional growth rate has a positive effect on becoming employed (see columns one and two of Table 4.4). Furthermore, my results suggest for both genders that public employees, civil servants and self-employed individuals are less likely to become nonemployed, while employees with a temporary contract are more likely to become nonemployed. The results also point out that during maternity leave, women are less likely to become employed but also less likely to become nonemployed. For men, no such effect can be found[20]. The transition from nonemployment to employment also includes two binary indicators for whether an individual is unemployed or in education. They indicate that unemployed individuals return to employment more quickly than housewives or individuals in education. This is mostly due to the longer durations of the latter two occupations.

The only background variable having an effect on the union formation hazard is a dummy variable characterizing the months from March to September (see columns one to four of Table 4.5). Results show that during spring and summer months women and men more are more likely to start a cohabiting union. With regard to the union dissolution hazard, results show that women living in East Germany are more likely to end their relationship, while no effect can be found for men (see columns one to four of Table

[20] Following Paul (2011), maternity leave periods are modeled via a binary indicator that points out whether an individual is currently entitled to take maternity leave. As it is the wife who normally is entitled to take maternity leave, for men, the binary indicator is likely to act as a proxy for whether the wife is working or not.

4.6). Note that individuals in the sample were not raised in East Germany but moved to this region later. As the unemployment risk is considerably larger in East Germany, the dummy variable might act as a proxy for spouse's employment state. The results may therefore indicate that women tend to quit a relationship if the spouse is unemployed. Unions are also more stable, if one of the partners belongs to a religious denomination, probably, because conservative values and norms may be more important to them. With regard to information on the partner, the results depend strongly on the model choice (see columns one to four of Table 4.6). While most coefficients are significant for Model A, this is no longer the case for Model B. Finally, the results show that women are more likely to end their relationships during the second half of the year.

Turning to the conception hazard, my results suggest that the place of residence has no effect on the hazard of conception (see columns one, two and four of Table 4.7), although Model A indicates that for men, living in East Germany has a small and significant, positive effect on having children. Furthermore, belonging to a religious denomination increases the hazard of having children. Also a higher regional rate of births increases the likelihood for children. While this rate may proxy for the number of nurseries or kindergartens, it also displays regional preferences and attitudes towards children that may affect personal preferences. Finally, my results indicate that an increase in the potential amount of child allowance[21] tends to increase the hazard of having children for women.

4.6.8 The effects of initial conditions

With respect to the hazard of becoming nonemployed, one can see that none of the coefficients are significant except for the coefficient for women's age at entry of Model B, which has a small negative impact (columns one to four in Table 4.3). The results for the hazard of becoming employed show that for women being in a union and having

[21] Here the potential amount of child allowance is calculated as the amount an individual would potentially receive for his or her next child. The amount is divided by the current average gross income in order to make the amount of child allowance comparable across time.

children before entering the labor market have a positive effect on becoming employed (columns one and two in Table 4.4). This is not very surprising, because women who have already formed their family before entering the labor market may spend less time on raising children afterwards and are therefore more likely to become employed, if nonemployed.

The estimates for the union formation hazard suggest that men who have formed a union before entering the labor market are more likely to form subsequent unions afterwards (columns three and four in Table 4.5). The effect is in addition to the positive effect the cumulative number of unions has on the hazard of finding a partner. For the union dissolution hazard, results indicate that women who have formed a union prior to entering the labor market are more likely to quit this or any subsequent union (columns one and two in Table 4.6). For men, a dissolution becomes more likely, the older an individual is when entering the labor market. Note that the age at entry is on average higher, the higher the educational degree. My results further show that having obtained a university degree stabilizes unions of men. The result therefore holds particularly for men who are old when entering the labor market and have not obtained a university degree.

The results for the conception hazard show that women who formed a union before entering the labor market are less likely to have children (columns one and two in Table 4.7). Furthermore, results for Model B predict that women who are older at entry are less likely to have children. Again, note that the age at entry is, on average, higher, the higher the educational degree and that having obtained a university degree increases the hazard of having children for women. Therefore, the result holds particularly for women who are old when entering the labor market and have not obtained a university degree.

4.6.9 The effects of unobserved heterogeneity

The effects of unobserved heterogeneity are only considered for Model B, i.e. four points of support are used for women and men. It is common to assume the points of support as different types of individuals. The results then show that for women the second type is the most likely, while the other three types are almost equiprobable (e.g. column two

	EU	UE	UD	UF	C
EU	1	-0.348	0.897	-0.988	0.966
UE	-0.348	1	0.101	0.200	-0.093
UD	0.897	0.101	1	-0.955	0.981
UF	-0.988	0.200	-0.955	1	-0.994
C	0.966	-0.093	0.981	-0.994	1

Table 4.8: Correlations of unobserved heterogeneity in Model A (women). The Table presents the correlations of the unobserved heterogeneity in Model A for women. EU: Employment to Nonemployment, UE: Nonemployment to Employment, UD: Union dissolution, UF: Union formation, C: Conception.

in Table 4.3). With respect to the different transitions, the types of support differ only very slightly (column two in Tables 4.3 to 4.7). In particular, the variation is small for the hazard of childbearing. However, the volatility is relatively large with respect to the hazard of becoming employed. Of particular interest are the second and the fourth type. The second type is characterized by stable employments, short nonemployment periods, short periods of partner search and stable unions . The fourth type may be attributed to housewives, since this type is characterized by stable jobs, long nonemployment periods, short periods of search for a partner, stable unions and short periods until childbirth.

For men the situation differs strongly. Here the first type is by far the most likely one. Together with the third type, they account for more than 86% of all men (e.g. column four in Table 4.3). One therefore should be cautious with the interpretation of types two and four. The first type is characterized by stable jobs, short job-search periods and short periods of search for a partner, stable unions and short periods until childbirth (column four in Tables 4.3 to 4.7). The third type is also characterized by stable jobs and short job-search periods, but longer periods of search for a partner and periods until childbirth, and also less stable unions.

I also calculated the correlations between the mass points for unobserved heterogeneity

	EU	UE	UD	UF	C
EU	1	-0.223	0.765	-0.940	-0.624
UE	-0.223	1	0.457	-0.123	-0.620
UD	0.765	0.457	1	-0.939	-0.980
UF	-0.940	-0.124	-0.939	1	0.853
C	-0.624	-0.620	-0.980	0.853	1

Table 4.9: Correlations of unobserved heterogeneity in Model B (women). The Table presents the correlations of the unobserved heterogeneity in Model B for women. EU: Employment to Nonemployment, UE: Nonemployment to Employment, UD: Union dissolution, UF: Union formation, C: Conception.

	EU	UE	UD	UF	C
EU	1	-0.961	0.005	-0.520	-0.295
UE	-0.961	1	0.272	0.263	0.548
UD	0.005	0.272	1	-0.857	0.954
UF	-0.520	0.263	-0.857	1	-0.663
C	-0.295	0.548	0.954	-0.663	1

Table 4.10: Correlations of unobserved heterogeneity in Model A (men). The Table presents the correlations of the unobserved heterogeneity in Model A for men. EU: Employment to Nonemployment, UE: Nonemployment to Employment, UD: Union dissolution, UF: Union formation, C: Conception.

in Model A and B (Tables 4.8 to 4.11). Although one has to be cautious with the interpretation, since for calculation of the correlations only three different values are used for Model A and four for Model B, comparing correlations for Model A and B provides some interesting insights. For both genders, Model A provides evidence for a strong positive correlation between union dissolution and conception and strong negative correlation between union formation and conception. These findings are similar to Aassve

	EU	UE	UD	UF	C
EU	1	-0.914	0.873	-0.730	-0.369
UE	-0.914	1	-0.600	0.390	-0.040
UD	0.873	-0.600	1	-0.971	-0.775
UF	-0.730	0.390	-0.971	1	0.904
C	-0.369	-0.040	-0.775	0.904	1

Table 4.11: Correlations of unobserved heterogeneity in Model B (men). The Table presents the correlations of the unobserved heterogeneity in Model B for men. EU: Employment to Nonemployment, UE: Nonemployment to Employment, UD: Union dissolution, UF: Union formation, C: Conception.

et al. (2006) who use data on British women and men. However, the situation is different for Model B. By including the union formation and dissolution hazards as regressors for the conception hazard, the coefficients switch signs. This means that to some extent the strong positive correlations in Model A are due to the strong positive effect the union dissolution hazards have on the conception hazards.

4.7 Conclusion

This study investigates the interrelated effects of employment, cohabitation and fertility. Using a simultaneous hazards approach due to Lillard (1993), I estimate a five-equation model. An important contribution of this chapter is to provide evidence how labor market risks influence union formation, dissolution as well as childbearing decisions. I do so by including the employment and nonemployment hazard rates as simultaneous regressors for the processes of union formation, union dissolution and conception. Furthermore, also the union dissolution and union formation hazard rates are used as regressors for the process of conception. The effects are analyzed using a sample of German women and men born between 1960 and 1969, which is drawn from the ALWA data set.

Results show that whether someone is employed generally has no effect on union formation, union dissolution and childbearing. This holds for both women and men, although for employed men, I find a significantly lower hazard of splitting up. Employed women with stable jobs and nonemployed men with poor chances to find a job are more likely to have children. The hazards of becoming employed and nonemployed are mostly influenced by the educational level and the duration of the current employment or nonemployment period. Another finding is that family events have significant effects on the transitions from and to employment. The results are of the expected direction. By adding a variable that indicates current pregnancy, I can show that for women children reduce the likelihood of becoming nonemployed. This is interesting also from a policy perspective, because many women who work and have (pre-school) children belong to disadvantaged groups (single-mothers or women from low-income households). For these women, children increase the dependence on earned income and therefore make transitions to nonemployment less likely. Results further indicate that children, in particular pre-school children, make unions more stable and do not present a burden for subsequent unions. Obviously, children are more likely to be born inside a union. However, my results show that unions that are likely to split up may use children as an investment in partner-specific capital in order to stabilize their relationship. This is in line with an increase in single-parents and step-families in Germany during the last forty years. Overall, the results support the view that the effects from employment on cohabitation and fertility are not as strong as the other way round. The interrelation between cohabitation and childbirth however exhibits strong influences for both directions.

Appendix B1: Definition of labor market entry

The labor market entry is defined as the start date of the first spell after the individual has left the educational institution, where she obtains or could possibly obtain her highest degree. However, there are some exemptions for whom the definition of the labor market entry does not fit very well. An example may be an individual, who after obtaining an high school and vocational training degree, works for ten years and then chooses to go to university. In order to account for such exemptions, age limits are set, until which a certain type of education at latest has to be started. The age levels are presented in table B1.1.

Schooling:	
School type	*Age level*
Lower secondary school	20
Intermediate school	21
Upper secondary school	23
Further Education:	
Type of further education	*Age level*
Vocational training	23
Master craftsmen's college	23
Technical college	25
University	26

Table B1.1: **Age limits.** The table presents the age limits until which a certain type of education at latest has to be started.

For schooling, the age levels for starting a certain type of school are arbitrarily set to four years after an individual typically finishes this form of schooling. For example, a typical individual leaves upper secondary school at nineteen. The age level to start this form of schooling is therefore set to 23. For further types of education the age levels are based on the required type of schooling and the age an individual typically has, when finishing this form of schooling. Although, for example, a relatively large fraction of individuals going to a master craftsmen's college does so at higher ages, these individuals typically have worked for a longer period after their last degree and therefore might have formed decisions with regard to their familiar situation.

Appendix B2: Exclusion restrictions

Hazard of becoming nonemployed
State dependence
Duration dependence
Cum. # of employments
Cum. dur. in employment
Cum. dur. in nonemployment
Additional exclusion restrictions
Regional Unemployment rate
Regional growth rate
Maternity protection
Hazard of becoming employed
State dependence
Duration dependence
Cum. # of employments
Cum. dur. in employment
Cum. dur. in nonemployment
Additional exclusion restrictions
Regional U-rate
Regional growth rate
Maternity protection
Union formation hazard
State dependence
Cum. # of unions
Additional exclusion restrictions
Duration dependence
Spring / summer
Union dissolution hazard
State dependence
Duration dependence
Cum. # of unions
Additional exclusion restrictions
Age difference
Partner has higher edu.
Partner has lower edu.
No information on partner
Children from other partner
2^{nd} half of year

—Continued on next page—

Table B2.1: (continued)

Conception hazard
State dependence
Duration dependence
Additional exclusion restrictions
Regional birth rate
Potential child allowance

Table B2.1: **Exclusion restrictions.** The table presents the exclusion restrictions for the five transitions.

Chapter 5

Conclusion

The last two decades have seen an exceptional rise in the use of Multivariate Mixed Proportional Hazard (MMPH) models in many different fields. MMPH models allow for estimation of multiple durations per individual. These durations may be successive and past durations may influence future durations, or they may appear simultaneously and influence each other at once. They also control for unobserved heterogeneity. In this thesis, I provide two applications of sophisticated MMPH models that use administrative spell data on employment histories and survey data on employment histories and other life course events.

As the dynamics of employment histories are of key interest for the design of labor market policies, I apply a MMPH with competing risks of exit in order to investigate state dependence effects for the three labor market states employment, unemployment and out of the labor force in chapter 3. Following Heckman and Borjas (1980), I distinguish between three forms of state dependence: duration dependence, lagged duration dependence and occurrence dependence. The investigation is conducted using German prime-aged men who were sampled from the Integrated Employment Biographies Sample. These prime-aged men come with the drawback that the early parts of their employment history are not observed. Based on Wooldridge's (2005) approach for panel data models, I suggest a solution in order to account for this initial conditions problem. The results from chapter 3 suggest that both employment and unemployment are highly persistent, because duration dependence is particularly strong for these two processes. The results for occurrence dependence indicate that past unemployment experience increase the probability of future unemployment experiences. Similarly, past employment experiences increase the probability of finding a job. However, past employment experiences do not help to remain employed. Conducting simulations that account for the long-run impacts of possible interventions in the labor market provide support for the findings that even short unemployment spells are scarring, while short employment spells help to find new employment.

An individual's employment history as considered in chapter 3 is typically interrelated with other processes. These interrelations are of particular interest to policy makers in the fields of labor market policy, welfare policy, and family policy. Chapter 4 provides the application of a MMPH model that accounts for the interrelations between employment, nonemployment, union formation, union dissolution, and childbearing. The model is estimated using a sample of the 1960-69 cohort of German women and men drawn from the from the "Working and Learning in a changing world" (ALWA) data set. A novelty of this chapter is to include the hazards of employment and nonemployment as regressors for the hazards of union formation, union dissolution, and childbearing, as well as the hazards of union formation, union dissolution as regressors for the hazard of childbearing. The chapter presents a multitude of findings. One of the key results is that for women and men the current employment state plays no role for starting and dissolving a union as well as for having children. It is rather the expectation about future the employment state, i.e. the probability of losing and finding a job, that has an impact. For example, employed women with a high hazard of becoming nonemployed and nonemployed men with a high hazard of finding a job both have a low hazard of having children. Children obviously reduce women's hazard of becoming employed. However, the inclusion of a variable that accounts for current pregnancy shows that the presence of (young) children also reduces the hazard of becoming nonemployed. Individuals living with a partner are more likely to have children and unions are more stable when (young) children are present. A surprising but reasonable result is that unions with a high hazard of splitting up are more likely to have children. In economic terms, this can be interpreted as an attempt to invest in partner-specific capital in order to reduce the likelihood of splitting up.

While the third chapter primarily focuses on how durations depend on past information, the fourth chapter mainly deals with dynamic treatment effects due to simultaneous durations. Following van den Berg (2001), the models in chapter 3 and 4 can therefore be classified into different categories of MMPH models, although they are similar in their basic structure. In summary, this thesis's results suggest that Germany's labor market exhibits strong dependencies in employment and nonemployment. Employment experiences, however, do not seem to help in finding stable jobs but rather interact with past nonemployment experiences, resulting in a vicious circle of employment and nonemployment. As to family outcomes, such a seesaw changing between finding and losing a job may have a negative impact on having children. To summarize, this thesis presents new results about the dynamics and interrelationship of employment and family outcomes that are much more informative than results based on the analysis of single or discrete durations.

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