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Duration dependence, lagged duration dependence, and Occurrence dependence in individual employment histories: Evidence from German register data [1]

Markus Niedergesäss (University of Tübingen)

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Abstract. This paper analyzes the extent and type of state dependence in labor market outcomes using a sample of German males aged 30 to 50, which was extracted from the German Integrated Biographies Sample (IEBS). I differentiate between three labor market states: employment, unemployment, and out of labor force. The three labor market states have to be identified using the information in the data set, which, due to its administrative nature, requires some case-by-case analysis. Event-history methods are used, which allow for observed and unobserved heterogeneity. The empirical results indicate that all forms of state dependence, i.e. duration dependence, occurrence dependence and lagged duration dependence, can be found for the six transitions. The existence of many short unemployment and employment spells significantly increases the risk of entering the state of unemployment when employed, but also to find employment, when unemployed. By contrast, long unemployment spells in the past increase the risk to become unemployed, but also to remain unemployed. I discuss the implications of my results for labor market policy.

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Correspondence:

Markus Niedergesäss, Department of Economics, University of Tübingen, Mohlstr. 36, 72074 Tübingen, Germany, Phone: +49-7071-2977662, markus.niedergesaess@uni-tuebingen.de

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1 Introduction

It is a well-established finding that individuals who currently experience a period of unemployment are more likely to experience periods of unemployment in the future. Or as Arulampalam et al. (2001) state, "unemployment tends to bring future unemployment". On the one hand, such a relationship can be due to observed characteristics such as low endowments of human capital or unobserved characteristics such as low motivation to work or lack of abilities. Given that these characteristics persist over time, they may create a spurious relationship between current and future unemployment. On the other hand, a true causal relationship may exist between current and future unemployment, which is called state dependence. Most studies relate this true state dependence to so-called scarring effects (see for example Arulampalam et al. (2001), Gregg (2001)), i.e. to lower wage offers by the potential employers due to a decay in human capital. Also stigmatization effects (Blanchard and Diamond (1994) or Biewen and Steffes (2010) for the case of Germany) are named as a reason, i.e. employers use unemployment histories as a signal for low productivity. Nonetheless, state dependence is not only due to past unemployment experiences. By contrast, past employment experiences may help unemployed to find a new employment due to network effects or on-the-job human capital acquisition. However, only recently there have been advances to account for state dependence across states (see for example Doiron and Gorgens (2008), Magnac (2000) or Cockx and Picchio (2010)).

The distinction between spurious and true state dependence within and across states is of great interest for the design and timing of active labor market policies (ALMP). For example, if short-term employments build a bridge to find a long-term employment, then measures should focus on bringing unemployed back into employment by means of (short-term) government-sponsored jobs. Recently, there is a large and growing literature on the effectiveness of labor market policies and training measures (see for example the comprehensive overviews by Heckman et al. (1999), Martin (2000), Martin and Grubb (2001), Kluve (2006) and Kluve and Schmidt (2002)). For the case of Germany, this increase in the literature came hand in hand with the introduction of large administrative data sets that allow for broad analysis of these measures. In contrast to earlier findings for Germany during the 1990's (see Lechner et al. (2005), Fitzenberger et al. (2006), and Fitzenberger and Völter (2007)), newer results by Biewen et al. (2007) imply that (short-term) practically oriented training may have advantages over (long-term) classroom training.

The forms of state dependence can be various. In this paper, I follow Heckman and Borjas (1980) who distinguish between three types of state dependence: dependence on the current duration, and dependence on past occurrence and past duration. From an econometric point of view, vast parts of the literature investigate state dependence using autoregressive panel data models, which only limitedly allow for a distinction between the three types, because one either has to use labor market outcomes at certain points in time or the proportions of time within given periods spent in each state. In order to account for those problems and to allow for a precise timing of the transitions between the certain states, I apply event history methods (see for example Heckman et al. (1999)). Given the large administrative data set used in this study, namely the Integrated Employment Biography Sample (IEBS), with its precise start and ends, event history methods are well suited for this kind of analysis.

The aim of the paper is to disentangle the extent and type of state dependence for German men aged 30-50. I allow for the three labor market states employment, unemployment and out of the labor force as also the companion paper by Doiron and Gorgens (2008) does. The paper adds to the literature by accounting for state dependence within and across labor market states for the group of prime aged men. Until now literature has primarily focused on labor market outcomes of youth individuals (see for example Doiron and Gorgens (2008), Magnac (2000), and D'Addio and Rosholm (2000a, 2000b)). However, men aged 30-50 are of special interest, because they still compose the largest group of employed and unemployed. Furthermore, this group is the most likely to become unemployed in recession times, because the proportion of men working in sectors that are affected by economic downturns is a lot higher than that of women[2].

Econometrically, the transitions between two states are modeled by mixed proportional hazard models, which allow for observed and unobserved heterogeneity and implicitly for duration dependence. State dependence due to past occurrence is accounted for by including the type of the most recent spell and the cumulative number of previous spells as regressors. Lagged duration dependence is modeled in several forms, i) the cumulative duration in a certain labor market state is used, ii) the proportion a certain state takes on of the time observed is used, and iii) in addition to i) the duration of the most recent spell is used.

Results for duration dependence imply that for unemployed finding a new employment becomes less likely, the longer they are unemployed. For employed individuals, however, the risk to become unemployed seems to be unaffected by the time employed, suggesting that no positive work experience effects are at work. A further finding indicates that a long job search does not induce unemployed to leave the labor force, i.e. no discouragement effects seem to exist. Results for

[2]See Bundesagentur für Arbeit (2009)

occurrence dependence imply that leaving the vicious circle that consists of alternating short-term employment and unemployment, becomes less likely with an increasing number of employment and unemployment spells. Results regarding lagged duration dependence show that in addition to an effect that is related to the time an individual is observed, long unemployment durations in the past increase the probability of movements into unemployment and also to remain in unemployment.

The remainder of the paper is structured as follows. Section 2 provides an overview about theoretical and empirical findings for state dependence within labor market states, while in Section 3 the data set and the precise definition of the labor market states, as well as the sampling scheme are described. Section 4 presents the econometric method used, while in Section 5 estimation results are discussed. Finally, Section 6 concludes.

2 Implications from theory and empiricism

Heckman and Borjas (1980) were the first to precisely define the concept of state dependence based on the theory of survival analysis. They also proposed some test procedures to disentangle the different types of state dependence. Heckman and Borjas (1980) allow for three types of state dependence. First, duration dependence accounts for the fact that the probability of leaving the current labor market state is dependent on the time spent in this state. Secondly, occurrence dependence takes into account that the experiences of certain labor market states affect the probability of leaving the current labor market state. Thirdly, lagged duration dependence is assumed to affect the probability of leaving the current labor market state by the duration of previous spells. In the following, I will present some of the implications of labor market theory for the three types of the state dependence, as well as some stylized facts.

Duration dependence Most studies automatically account for duration dependence by specifying the baseline hazard using proportional hazard models. In general, literature provides ample evidence that the transition from unemployment into employment exhibits negative duration dependence, i.e. that finding a new job becomes less probable with time spent in unemployment. The reasons for negative duration dependence are various. On the one hand individuals are thought to lose skills and work experience when they are unemployed for a long time, as for example Pissarides (1992) suggests. On the other hand, employers generally have imperfect information about the unemployed's skills or motivation to work. Therefore, as Vishwanath (1989) points out, employers use time spent in unemployment as a proxy for the unobserved productivity. Similarly, Blanchard and Diamond (1994) suggest that employers hire unemployed according to their unemployment duration. For the design of active labor market policies (ALMP) this means, that measures should be preferred that try to bring back unemployed into employment as early as possible. Otherwise, future employment becomes less probable due to stigmatization effects. Furthermore, a long job search probably leads to a discouragement of the unemployed and therefore raises the probability of leaving the labor force (Schweitzer and Smith (1974)). Besides, opportunity costs of dropping out of the labor force decrease with time, because unemployment compensation vanishes or at least is reduced after a certain point in time[3].

Less evidence can be found for transitions from employment into unemployment. They are generally thought to depend negatively on duration, because costs of dismissal increase with time. Firstly, because firm-specific human capital increases with the time employed and therefore raises opportunity costs, and secondly, because severance payments also increase with the time employed. In an empirical study for Belgian long-term unemployed school leavers, Cockx and Picchio (2010) find that dismissals mostly occur during the first year of employment, which implies negative duration dependence.

For other transitions, the literature hardly any provides any theoretical or empirical results. Spending time out of the labor force is a form of nonemployment but without job search, and certainly, leads to a loss of work experience the longer the individual is not employed. However, for employers the information asymmetry with respect to the skills and motivation of the individual out of the labor force is even higher. On the one hand, not searching for a job may imply less motivation to work. On the other hand, the individual may have used the time out of the labor force to gain further professional qualifications. In general, transitions from and into out of labor force can be assumed to behave similar to transitions from and into unemployment, although the impact probably differs.

Occurrence and lagged duration dependence Workers are generally assumed to be scarred by previous unemployment experiences, decreasing the probability to find a new job (see for example Arulampalam et al. (2001) or Gregg (2001)). Gibbons and Katz (1991) show that scarring effects and the unemployed's own perception of his loss of valuable work experience increase

[3] In Germany an unemployed drops from the higher level of unemployment benefits to the lower level of unemployment assistance after the entitlement ends.

the pressure to accept bad job matches. This again increases the probability of a dismissal. The effects mentioned are assumed to become even stronger for longer unemployment durations. In a study using a data set on Austrian unemployed, Winter-Ebmer and Zweimüller (1992) find evidence that both lagged duration and occurrence of previous unemployment spells significantly increase the probability to become unemployed again. By contrast Cockx and Picchio (2010) find that it is occurrence of previous unemployment spells that seems to induce scarring effects and not lagged duration. Moreover, lagged unemployment duration even lowers the probability of dismissals. Their finding is in line with Ehrenberg and Oaxaca (1976), who argue that a longer job search, and therefore a longer previous unemployment duration, may improve the quality of the job match and hence dismissals become less probable.

Past employment experience, even though it is only short spells, are assumed to increase the probability of finding a new job. On the one hand, it signals the employer a higher productivity or at least a higher motivation of the unemployed. On the other hand, past employment could have been used to build informal networks, which facilitate job search (see for example Ioannides and Loury (2004)). Again Cockx and Picchio (2010) find empirical evidence that even very short employment spells help to find an unlimited employment. Their finding supports measures of ALMP that help long-term unemployed to find an unlimited employment via government-sponsored short-term employments.

However, Ljungqvist and Sargent (1998) point out that if the now unemployed was employed by just one employer, there exists a gap between the gain in human capital, which is firm-specific and not necessarily relevant for the new employer, and the gain in tenure. This results in a reservation wage, which is too high and a therefore decreasing probability of finding a new job.

Although, the gain in human capital may be firm-specific, it is generally assumed that past employment experiences results in better job matches. Hence, the probability of becoming unemployed again decreases (see for example Haan (2010)).

3 Data and Institutional Framework

In this section I present the institutional and policy environment in the period under investigation (2000 - 2003). I also describe the data set and how the sample used for estimation was extracted. Finally, I discuss identification of the labor market spells, which requires some case-by-case analysis due to the administrative nature of the data set.

3.1 Institutional Framework

For the period under consideration 2000 - 2003 the German unemployment compensation system consisted of two components, unemployment benefits ("Arbeitslosengeld") and unemployment assistance ("Arbeitslosenhilfe").

Unemployment benefits are insurance benefits and as such limited in time. To become eligible the claimant must first 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 must have been 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 exclusive 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 requirements of time being employed subject to social security contributions. Unemployment assistance is tax-funded and requires the unemployed to pass a means-test. It is further unlimited in time and with 57% and 53% replacement ratios are lower as in the case of unemployment benefits. Summing up, individuals receiving unemployment assistance are mostly long-term unemployed and, therefore, the suitability criteria what job the unemployed has to accept, are somewhat stricter than in the case of unemployment benefits. Unemployment benefits and unemployment assistance both allow the unemployed to work for less than 15 hours a week. The level of the entitlement is then adjusted for, depending on the income from the additional employment.

In distinction to unemployment benefits and assistance, the social assistance ("Sozialhilfe") provides a basic income protection for all individuals residing in Germany independent of their current labor market status. It is also paid as an additional income support if the level of unemployment assistance is below some critical value. Hence, one can 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 did not change during the period under consideration, thus one can ignore that the data set used here does not provide information on

transfers due to social assistance.
As already mentioned, individuals, that are registered as unemployed and receive unemployment benefits or unemployment assistance, are required to be available on short notice for any type of measures of Active Labor Market Policies. The set of measures during the period 2000 - 2003 has comprised of job-creation measures ("Arbeitsbeschaffungsmaßnahme"), settling-in allowances ("Eingliederungszuschuss"), support for founders of new businesses ("Existenzgründerzuschuss"), training measures that range from activation measures or German language courses to vocational trainings. Individuals, that are registered as unemployed, have the possibility to receive income maintenance during training ("Unterhaltsgeld") while participating in a public sponsored training measure.

3.2 German Integrated Employment Biographies Sample

The 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 2.2% random sample from a merged data file that ingrates data from four different administrative registers.
The first register contains data on individual employment histories ("Beschäftigten-Historie", BeH). Any employment spell that is subject to social contributions additional to some personal information on the individual is registered by the public pension funds and then used to construct the individual's employment histories. Exclusion of employment spells that are not subject to social contributions means that employment histories of self-employed individuals or life-time civil servants are not included in the data set. In total, the BeH provides information on employment spells for the period 1992 - 2003, and in addition information that is relevant for the employment, such as the type of employment, income or an identifying number for the employer.
The second register provides data on individual's histories of receipt of transfers of unemployment compensation ("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 is available for the period 1992 - 2004 as well as further information like the level of unemployment benefits or assistance.
The third register offers data on the histories of registered unemployment ("Arbeitsuchenden und Bewerbungsangebotsdaten", BewA). As mentioned individuals have to be registered as unemployed in order to receive unemployment compensation, but are required to actively search for a

job. Data on registered unemployment therefore helps to differentiate between the labor market states of unemployment and out of labor force. Nevertheless, full availability on data on registered unemployment is only given for the period 2000 - 2004.

Finally, the fourth register contains data on individual's histories of participation in public sponsored measures of Active Labor Market Policies ("Maßnahme-Teilnehmer-Gesamtdatenbank", MTG). Data on these histories is again only available for the period 2000 - 2004.

All four registers are then merged and result in a data set that provides individual labor market histories for the period 1992 - 2004 with start and end dates measured on daily basis. Because data on employment spells is only available until 2003, I use data from the period 2000 - 2003. Figure (1) shows a typical history of an individual in the IEBS. At the beginning of the observation period, spells are left-censored, i.e. the start date is not observed, while spells at the end of the observation period are right-censored, i.e. the end date is not observed. As one can see, there may also exist periods, for which no information is available for the individual. Further, parallel and overlapping spells from one or more registers exist. Many of them occur naturally, for example, an individual should be registered as unemployed, if he or she receives unemployment benefits. However, some types of overlapping spells are inadmissible as for example the receipt of unemployment benefits with a parallel full-time employment. In order to properly account for those inadmissibilities, I adopt data cleansing methods suggested by Bernhard et al. (2006) and Jaenichen et al. (2005).

— Figure 1 about here —

3.3 Definition Labor Market States

Labor market states have to be constructed from the labor market histories given by the data set. As mentioned, I use the three disjunct labor market states employment, unemployment and out of labor force. In general, the information from the different registers clearly identifies the current labor market state. However, there are some ambiguous cases, for which a precise description, on how the labor market state is defined, has to be given.

Unemployment: Spells that come from the LeH or BewA are generally assumed to be unemployment spells. The same holds true for all spells from the MTG, except for spells that are due to job-creation measures, settling-in allowances or support for founders of new businesses. In general, founding a new business results in self-employment. I drop all individuals that become self-employed from the sample, because of comparison problems. Self-employed individuals typically have different characteristics than employed individuals, and are no subject of this study. Decisions about periods with no information from any of the four registers are mainly about whether the period has to be considered as unemployment or out of labor force. In order to account for this problem I use the approach "unemployment between jobs" by Fitzenberger and Wilke (2010). This approach originally was suggested for the IAB Employment Sample (IABS), which is a subset of the IEBS. I slightly adjust Fitzenberger and Wilkes approach so that it fits the IEBS. This results in the decision rule, that for the time between 1992 and 1999, a period between two employment spells is considered as unemployed, if the individual at least has experienced one unemployment spell within, although there may exist periods without any information. However, these interruptions are allowed to be at most 30 days for periods between two unemployment periods and between the previous employment spell and the first period of unemployment. For a period with missing information, which lies between the last period of unemployment and the next employment spell, the maximum length of interruption is set to 45 days. Because data is fully available from all four registers, I reduce the maximum length of interruptions to at most seven days for the period 2000 - 2003.

Employment: In principle, all spells that come from the BeH are assumed to be employment spells, unless there is a parallel unemployment spell. However, if individuals are temporarily or marginally employed and have a parallel unemployment spell, they are considered as unemployed, because unemployed are allowed to work for at most 15 hours per week. Individuals that are undergoing a vocational training, which lasts less than 90 days and which have a parallel unemployment information, are also assumed to be unemployed. If the vocational training lasts longer than 90 days, those spells are considered as employment spells. Constraining vocational training spells with parallel unemployment spells to last for more than three months seems to be appropriate to circumvent them from spells, which are inconsistently declared as vocational training. In addition, spells that are due to job-creating measures or settling-in allowances are considered as employment if no parallel unemployment information is available. Finally, periods with missing information on what the individual does are considered as employment, if they lie between two periods of employment and do not last for more than seven days. Otherwise the periods are considered as out of labor force.

Out of Labor Force: Finally, any remaining periods with no information on the labor market state, that lie between to spells, for whom the state is known, are assumed to be out of labor force. In addition, it is possible that no information on the labor market state is available between January 1, 1992 and the first employment or unemployment spell or between the last employment or unemployment spell and December 31, 2003. For those periods it is difficult to determine the proper labor market state. Especially determining the date of entry into the labor market seems difficult without any further information. For those individuals with no information on the labor market state at the beginning of their history, I, therefore, let the date of entry become a function of the educational level. The entry is then assumed to be the first spell with information on the labor market state or to be January 1 of the year the individual becomes 32 years old if the individual has a degree from technical college and 35 if the individual has a university degree. For the latter case the period until the first employment or unemployment spell is assumed to be out of labor force.

— Figure 2 about here —

Entry times for individuals with an educational level lower than technical college were all before the beginning of the observation period. Spells at the end of the analysis period that have no information on the labor market state are also considered to be out of labor force.
Figure (2) provides an example on how the labor market states are assigned to the example presented in Figure (1).

3.4 Sampling scheme

In the following, I will describe which individuals enter the sample and the implications for possible selection biases.
My overall sample consists of males, who were born between 1950 and 1970, i.e. who became at least 30 and at most 50 years old in 2000. In general, an individual's history begins when it is observed for the first time by one of the four registers, which at the earliest can happen on January 1, 1992. For estimation only those spells of the individual's labor market history are used, which begin after January 1, 2000. This means that individuals, who do not possess a spell that begins within the period 2000 - 2003 are excluded from the estimation sample. Figure (3) depicts which spells are used for estimation for the example labor market history above.

The sampling scheme used, is similar to the concept of flow sampling for univariate survival models. Normally, individuals are sampled from the stock of their current labor market state, as for example D'Addio and Rosholm (2000a) and Doiron and Gorgens (2008) do. However, these studies focus on the labor market outcomes of young individuals, whose entry in the labor market can be observed. This means they do not have to deal with problems concerning left-censoring or measurement errors in the information of past labor market outcomes. Solutions to left-censoring are rarely discussed in the literature[4] and require strong assumptions. With flow sampling, the problem of left-censoring does not arise, because only entire spells are used, as the spells used for estimation are fully observed. Sampling only spells beginning between 2000 and 2003 comes with a further advantage: the information from the period 1992 until the first spell after January 1, 2000 can be used to construct the individual's labor market history. This is the best proxy one can obtain for information on past labor market outcomes.
Nonetheless, as mentioned, flow sampling comes with the drawback that individuals, which do not possess spells beginning during the period 2000 - 2003 are excluded from the estimation sample. In particular, individuals being employed over the entire observation period are affected by this. However, especially the results for the subsample of individuals, who transit between the three states are relevant for the design of ALMP.

— Figure 3 about here —

All histories are right-censored at the end of the observation period. However, individuals may also exit the sample before the end of the observation period. This may happen because an individual dies or becomes self-employed. While death is a natural end of an history, becoming self-employed is for sure a non-random process. I, therefore, drop the entire histories of all individuals becoming self-employed.

3.5 Covariates

For estimation a large set of exogenous explanatory variables, which represent personal characteristics like age, nationality or education and external factors such as labor market conditions and business cycles, is used. Most of those covariates are time-varying. Some of the variables have

[4] D'Addio and Rosholm (2002b) and Gritz (1993) provide exceptions

to be imputed, because they are missing for certain registers or information is not reliable. As mentioned, out of labor force spells have to be constructed from periods, for which information is missing on all covariates. Although start and end dates are found easily, information on covariates is still missing. Identification requires explanatory variables to be predictable processes, i.e. values of explanatory variables are only influenced by events that have occurred until the current point in time[5]. One, therefore, has to be careful with extrapolating values of explanatory variables to out of labor force spells from spells that occur later in time.

Age Age is measured on yearly basis and changes on January 1 of each year, because only the year of birth is known. For out of labor force spells, age can be easily adjusted, once the year of birth is known.

Education One of the most important determinants of labor market outcomes is education. As mentioned, education additionally determines the date of entry into the labor market for individuals with unknown entry date. However, the data set comes with the drawback that, first, the LeH does not provide information on the educational level and, second, information on the educational level from the BeH is not fully reliable. To account for those drawbacks, I follow Fitzenberger et al. (2005)[6] and adopt their approach "IP2B" to correct for the possible inconsistencies in the education variable of the BeH and for missing values in the LeH. The general idea is that the value of the educational level is considered to be inconsistent, if it indicates a lower educational level than the prior value and consistent values are imputed for inconsistent ones. The correction method was only designed for the IABS and has therefore be modified for the BewA and MTG. For those two registers, I impute missing values with the last value mentioned and extrapolate forward reliable values of the educational level, until the next reliable value is reached. A value of the educational level is considered as reliable, if it is stated three times in a row. Putting both sets of registers together, I consider values from the BewA or MTG as more reliable and impute this values to the BeH and LeH, if the emerged time series has not been consistent.

Labor market conditions To control for local labor market conditions, I use a set of dummy variables, that are built out of a categorical variable, which categorizes regional labor market

[5]See van den Berg (2001)

[6]I thank Aderonke Osikominu for generously providing their code.

conditions into five different groups[7]. 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. A more precise characterization is impossible with the Scientific Use File of the IEBS. Missing values are imputed by backwards-extrapolation.
In order to control for overall labor market conditions, I use German monthly unemployment rates, which were published by the Federal Employment Agency. Moreover, I use quarterly GDP growth rates published by the Federal Statistical Office to control for business cycles.

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[8] and construct six dummy-variable using only the first digit. Although occupation is time-varying, individuals only rarely change their occupation. Hence, I assume occupation to be time invariant, if nothing else is known and impute missing values by forward and backward extrapolation.

3.6 Descriptive Analysis of the Data Set

Altogether 69761 male individuals begin a spell during the period 2000 - 2003, i.e. they have one or more spells that are used for the construction of the estimation sample. Table 1 shows, that the individuals included in the estimation sample on average are observed for 960 days or two-and-a-half years after the beginning of their first spell after January 1, 2000. Of the time under observation, on average 524 days (54.61% of the total time) are spent in employment, 289 days (30.15%) unemployed, and 146 days (15.24%) out of labor force. The maximum length of time under observation is 1460 days, that is exactly four years or the entire period 2000 - 2003. Table 1 also provides summary statistics for spells. In total there are 241638 spells, of which 38.75% are employment spells, 35.55% are unemployment spells and 25.7% are out of labor force

[7]See Blien and Hirschenauer (2005)

[8]See Bundesanstalt für Arbeit (1988): Klassifizierung der Berufe. Systematisches und alphabetisches Verzeichnis der Berufsbenennungen. Nürnberg: Bundesanstalt für Arbeit.

spells. With regard to the length of the spells, those results reflect the fact that employment spells are much longer than spells of unemployment or out of labor force.

In 49.11% of the cases the last spell is spent in employment. Most of the transitions occur from unemployment into employment (46528 transitions or 27.13% of all transitions) or vice versa (38145 or 22.24%). Incidence rates display the number of exits per year and type of spell, that means for instance, that there are 0.59 exits from employment per year and employment spell. Results from incidence rates again indicate that employment spells tend to be longer than unemployment spells or out of labor force spells.

The bottom panel of Table 1 shows deciles of the distribution of all three types of spells. For instance, the 10%-decile shows that 10% of all employment spells are shorter than 32 days and 90% are longer. In general, for all deciles employment spells are longer than all unemployment spells . Further, for all deciles unemployment spells are longer than spells of out of labor force. The median length of employment spells is 324 days, while that of unemployment and out of labor force spells is 166 days and 85 days respectively.

— Table 1 about here —

Table 2 shows the average number of previous spells and the average duration of previous spells for the individual's first spell after January 1, 2000. The average individual has experienced 2.87 employment spells, 1.89 unemployment spells and 1.61 spells out of labor force. In total, an individual on average has passed 3625.81 days in the labor market. Of this time, 66.06% was spent employed and 14.78% unemployed. In comparison to the estimation period, individuals have passed a lot more time in employment than in unemployment.

— Table 2 about here —

Table 3 shows some personal characteristics of the individuals. The mean age for all individuals in the estimation sample is 41.54 years in 2000. The individual's occupation in almost 89% can be assigned to the sectors of manufacturing or service, while only a small number is employed or searches employment in the sectors of farming, mining, engineering or others. Information on individual's education shows that 20.1% of all individuals has not obtained any educational degree until the last observation. Most individuals have passed a vocational training (65.3%), while only few individuals have obtained higher educational degrees. The large number of individuals with no educational degree can be explained with the leaving out those individuals, who are continuously employed during the period 1992 - 2003. Of those individuals only very few have no educational degree.

— Table 3 about here —

4 Econometric Methods

The econometric framework is based on Doiron and Gorgens (2008), who present a model for event history frameworks that can be estimated by maximum likelihood. However, in order to be fully identified, the model has to be adjusted due to the different sampling scheme.

4.1 Outcome and explanatory variables

Individual's labor market history is used as the outcome or explanatory variable, that means individual's transition times and destination states. Let $T_{i,0}$ be the (calender) time of the start date of the first spell beginning within the period 2000 - 2003, and $S_{i,0}$ be the labor market state taken on, that means whether the individual was employed (E), unemployed (U) or out of labor force (O). Then, let $T_{i,j}$ and $S_{i,j}$ be the preceding and subsequent transition times and destination states, with $j^- = -N_i^-, \ldots, -1, 0$ indicating the preceding transition times and destination states, and $j^+ = 1, 2, \ldots, N_i^+$ indicating the subsequent transition times and destination states. Finally, it is required that $j = j^-, j^+$, $T_{i,j-1} < T_{i,j}$, and $S_{i,j-1} \neq S_{i,j}$. Further, N_i^- is the number of spells used to construct the labor market history for the spell beginning at $T_{i,0}$, and N_i^+ is the number of spells used for estimation. Individual i's history is observed for the period $(T_{i,-N_i^+}, C_i]$, where C_i is a random variable indicating the individual time of right-censoring and $N = N_i^- + N_i^+$ is the total number of spells observed for the period 1992 - 2003. For estimation only spells from the period $[T_{i,0}, C_i]$ of individual i's history are used.

To clarify the discussion, it is essential to differentiate between exogenous and endogenous explanatory variables in the notation. Let $X_i(t)$ be a vector of explanatory variables for person i at time t, and $\mathbf{X}_i(t)$ be the path of explanatory variables from the beginning of observation $T_{i,-N_i^-}$ until the point in time t. Further, define $\mathbf{Y}_i(t,s)$ to be the path of outcome variables, again from $T_{i,-N_i^-}$ until t, i.e. $\mathbf{Y}_i(t,s) = \{T_{i,j}, S_{i,j}\}_{j=-N_i^-}^{J_i(t)}$, where $s = S_{i,J_i(t)}$ and $J_i(t)$ is the maximal integer such that $T_{i,J_i(t)} \leq t$.

This paper primarily focuses on disentangling effects that emerge due to state dependence from effects due to other factors, such as personal or external characteristics. Because any unobserved heterogeneity is likely to induce spurious effects of state dependence, it is essential to minimize its effects. Therefore, I follow the literature and include random effects in my model. In the following, let V_i be a random vector that represents unobserved personal and external characteristics, and assume that V_i is independently and identically distributed, person-specific and time-invariant.

4.2 Transition intensities and construction of the likelihood function

Because of the daily-based information on transitions in the data set, it is possible to assume a continuous measurement of time. Now, let $h(t, s|\mathbf{y}(\tilde{t}, \tilde{s}), \mathbf{x}(t), v)$ be the intensity to transit to state s at time t, given that the current spell began at time $\tilde{t}$ in state $\tilde{s}$ and conditional on individual i's labor market history, $\mathbf{y}_i(\tilde{t}, \tilde{s})$, its path of explanatory variables $\mathbf{x}(t)$ and its value of unobserved heterogeneity, v.

Let $\mathbf{Y}_i(t_{i,0}, s_{i,0}) = \mathbf{y}_i(t_{i,0}, s_{i,0})$ be individual i's labor market history at the beginning of its first spell after January 1, 2000, $\mathbf{X}(C_i) = \mathbf{x}(c_i)$ its path of explanatory variables at the censoring point, and $V_i = v_i$ its value of unobserved heterogeneity. Then the contribution to the likelihood function of person i's labor market history can be formulated as the product of the likelihood contribution of each labor market spell,

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

As mentioned, I adopt a sampling scheme that is similar to flow-sampling in the analysis of single-spell duration data. Hence, I do not have to account for initial conditions and left-censoring.

Conditional on its realizations $\mathbf{Y}_i(t_{i,j-1}, s_{i,j-1}) = \mathbf{y}_i(t_{i,j-1}, s_{i,j-1})$, $\mathbf{X}_i(t_{i,j}) = \mathbf{x}_i(t_{i,j})$, and $V_i = v_i$ at $t_{i,j-1}$ and $t_{i,j}$ the likelihood contribution of individual i's transition to state $s_{i,j}$ at time $t_{i,j}$ is

$$\begin{aligned}\mathscr{L}\left(t_{i,j}, s_{i,j}|\mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(t_i), v_i\right) &= h\left(t_{i,j}, s_{i,j}|\mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(t_{i,j}), v_i\right) \\ &\quad \times \exp\left(-\sum_{\substack{k=E,U,O \\ k\neq s_{i,j-1}}} \int_{t_{i,j-1}}^{t_{i,j}} h(u, k|\mathbf{y}_i(t_{i,j-1}, s_{i,j-1}), \mathbf{x}_i(u), v_i)\,\mathrm{d}u\right). \end{aligned} \tag{2}$$

The first term on the right-hand side expresses the intensity of moving to state $s_{i,j}$ at time $t_{i,j}$, while the second term displays the probability of no transitions taking place between $t_{i,j-1}$ and $t_{i,j}$, i.e. the "survivor function" of individual i. More precisely, the right-hand side of equation (2) displays a competing risks situation, because tan individual always has two alternative destination states.

I assume the point of right-censoring C_i to be independently distributed from the transition process, and both observed and unobserved heterogeneity[9]. Then C_i is uninformative about all parameters and the last right-censored spell evolves as

$$\mathscr{L}\left(c_i|\mathbf{y}_i(t_{i,n_i^+}, s_{i,n_i^+}), \mathbf{x}_i(c_i), v_i\right) = \exp\left(-\sum_{\substack{k=E,U,O \\ k\neq s_{i,n_i^+}}} \int_{t_{i,n_i^+}}^{c_i} h(u, k|\mathbf{y}_i(t_{i,n_i^+}, s_{i,n_i^+}), \mathbf{x}_i(u), v_i)\,\mathrm{d}u\right). \tag{3}$$

The right-hand side of equation (3) is simply the probability of no transitions taking place between the beginning of the last spell t_{i,n_i^+} and the point of censoring c_i, i.e. the probability that the survival time of individual i in state s_{i,n_i^+} lasts at least until the point of censoring c_i.

Maximum likelihood estimation requires integrating out the random effect V_i. Thus the likelihood contribution of individual i evolves as

$$\mathscr{L}_i = \int_{-\infty}^{\infty} \mathscr{L}\left(\mathbf{y}_i(t_{i,n_i^+}, s_{i,n_i^+}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0})\mathbf{x}_i(c_i), v_i\right)\,\mathrm{d}A^*(v), \tag{4}$$

where A^* is the time-invariant marginal distribution of V_i and a Stieltjes integral[10] is used for integration. Following the literature, I assume V_i to take on only a small number of values. Then the realizations of V_i display a set of different types of persons. Each of these types has different characteristics with regard to the six transitions. Let the discrete support of V_i be $\{v_1, \ldots, v_M\}$ and $\mathrm{p}_m = \mathrm{P}(V_i = v_M)$ be the probability of V_i taking on the value v_m, then equation (4) evolves as

$$\mathscr{L}_i = \sum_{m=1}^{M} \mathscr{L}\left(\mathbf{y}_i(t_{i,n_i^+}, s_{i,n_i^+}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0})\mathbf{x}_i(c_i), v_i\right)\mathrm{p}_m. \tag{5}$$

Allowing for more types of persons, i.e. increase M, results in a more flexible form of the likelihood function but is computationally more demanding. I again follow the literature and assume M=3 to be a sufficient number.

[9]The assumption of independence of C_i might be too strong given the current sampling scheme. I will adjust for this dependence in further research

[10]The Stieltjes integral allows for both continuous and discrete random effects V_i

4.3 Parametrization and estimation

The transition intensities depend on the paths of $\mathbf{X}_i(t)$ and $\mathbf{Y}_i(t,s)$ at time t. However, estimation becomes impossible, if the entire paths would be included. Therefore, I assume that the random vector $X_i(t)$ is sufficiently rich to capture the effects of the path $\mathbf{X}_i(t)$, i.e. that only contemporaneous values of personal and external characteristics affect the transition intensities. Clearly, $X_i(t)$ may include variables that represent current information on previous values, such as lagged unemployment rates. I further assume that $\mathbf{Y}_i(t,s)$ affects the transition intensity only by a finite-dimensional random vector $Y_i(t)$, which summarizes the information on the path $\mathbf{Y}_i(t,s)$. $Y_i(t)$ does not depend on the current state s, because the effect is captured by variation in parameters.

The vector $Y_i(t)$ includes several variables to account for state dependence. The presence and type of the most recent spell, as well as the number of previous spells in each labor market state are used in order to control for occurrence dependence. To control for lagged duration dependence the cumulative duration in each previous labor market state is used. Those variables are time-varying but constant within each spell. I also control for duration dependence by including parameters to measure the effect of elapsed duration in the current state. A more precise description is given later.

The points of support of the distribution of the random effect V_i can be displayed as a $M \times 6$ random matrix

$$\begin{bmatrix} v_1^{s_E,s_U} & \cdots & v_M^{s_E,s_U} \\ \vdots & \ddots & \vdots \\ v_1^{s_O,s_U} & \cdots & v_M^{s_O,s_U} \end{bmatrix}, \tag{6}$$

with s_k indicating the states $k = E, U, O$. The rows of this matrix can be considered as row vectors that represent the points of support for the respective transition, while the columns can be seen as column vectors that represent the M types of persons and their personal "transition behavior". No assumptions are made on the location of the points of support. In particular, the correlation between transitions is unconstrained. In this study, I set $M = 3$, which results in $3 \times 6 = 18$ points of support that have to be estimated in addition to two points of the probability function.

Now, let $v^{\tilde{s},s}$ denote the M-dimensional row vector representing the M points of support for the transition $\tilde{s}$ to s. Further, let $z(\nu) = (\mathbb{1}(\nu = v_1), \ldots, \mathbb{1}(\nu = v_M))'$ be an M-dimensional vector function indicating the support points, with $\mathbb{1}(\cdot)$ representing the indicator function. Then $z(\nu)' v^{\tilde{s},s}$ is the component of the support of V_i that corresponds to the transition of type ν from state $\tilde{s}$ to state s.

Each transition is specified 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 covariates and a function of the unobserved heterogeneity. The transition intensity from $\tilde{s}$ to s then evolves as

$$h(t, s|\mathbf{y}(\tilde{t}, \tilde{s}), \mathbf{x}(t), v) = \lambda_{\tilde{s},s}(t - \tilde{t}; \alpha_{\tilde{s},s}) \exp\left(x(t)'\beta_{\tilde{s},s} + y(\tilde{t})'\gamma_{\tilde{s},s} + z(\nu)'v_{\tilde{s},s}\right), \tag{7}$$

$$t \geq \tilde{s}, s \neq \tilde{s}, \text{and} \quad \nu \in \{v_1, \ldots, v_M\}$$

where $\lambda_{\tilde{s},s}(t - \tilde{t}; \alpha_{\tilde{s},s})$ is the baseline transition intensity from state $\tilde{s}$ to state s and $\alpha_{\tilde{s},s}$, $\beta_{\tilde{s},s}$, and $\gamma_{\tilde{s},s}$ are additional parameters. The baseline transition intensity is parameterized as a Weibull function,

$$\lambda_{\tilde{s},s}(t - \tilde{t}; \alpha_{\tilde{s},s}) = \alpha_{\tilde{s},s}(t - \tilde{t})^{\alpha_{\tilde{s},s}-1}. \tag{8}$$

Finally, the unknown parameters $\alpha_{\tilde{s},s}$, $\beta_{\tilde{s},s}$, and $\gamma_{\tilde{s},s}$ are estimated by the method of Maximum Likelihood using analytical derivatives and the Newton-Raphson method as optimization method.

5 Results

In order to account for the different effects of state dependence I estimated several specifications of the model presented in the last section[11]. More precisely, only the covariates which indicate the distinct forms of state dependence change for the diverse specifications.

5.1 State dependence

Results for the base model including results for state dependence and further explanatory variables can be found in table (4).

— Table 4 about here —

Duration dependence As in all specifications, I modeled duration dependence by means of a Weibull functions. The hypothesis that all Weibull parameters are jointly equal to unity, i.e. that

[11]Estimations were conducted using a random subsample of 10.413 individuals, because of long-lasting convergence times. In further research, the full sample will be used.

there is no duration dependence, can be clearly rejected. The shapes of the baseline transition intensities, which are implied by the results are displayed in Figure (4).

— Figure 4 about here —

Of the respective transitions, those from employment into out of labor force, and from unemployment and out of labor force into employment exhibit negative duration dependence, i.e. transitions become less likely, the longer the individual remains in that state. Thereby, does the result for the transition from unemployment into employment clearly support the theoretical results by Pissarides (1992) or Blanchard and Diamond (1994) and is in line to what is usually found in the literature. The result suggests that also individuals being unemployed for a short period should be considered for policy measures.

No evidence of duration dependence can be found for the transition from employment into unemployment, since one can not reject the hypothesis that the Weibull coefficient is equal to unity for this transition. This result is surprising, because one would usually assume negative duration effects for this transition due to tenure or work experience effects. The transition from unemployment to out of labor force also does not exhibit any form of duration dependence. This finding contradicts the supposed discouragement effects, which assume that unemployed reduce their search efforts with the time spent in unemployment. Interestingly, the transition from out of labor force into employment is the only transition that displays positive duration dependence.

Occurrence dependence In order to measure the effects of occurrence dependence, I use a dummy variable indicating the type of the previous spell and the cumulative number of past spells. For an employed individual, a previous unemployment spell significantly increases the probability of becoming unemployed again, while it decreases the probability of leaving the labor force by almost the same amount. This finding indicates, that a previous unemployment spell strongly determines the destination state but less the transition time. A previous employment spell significantly increases the intensities of both transitions into employment. Furthermore, it lowers the probability that an unemployed stops searching, but also that someone out of the labor force starts searching again. Once again, the previous spell is an indicator for the destination state.

Interestingly, the cumulative number of previous employment and unemployment spells are significant and have the same sign for the transitions from employment into unemployment and

vice versa. On first sight, this might be surprising. However, one has to be aware of the fact that an employed individual can only have a past employment spell if he or she was unemployed or out of the labor force between. Although, the magnitude is small the results indicate that those individuals who have been transiting frequently between employment and unemployment in the past, are likely to do so in the future. Hence, there is no evidence that many short-term employments help to find a long-term employment as in Cockx and Picchio (2010). With respect to the design of policy measures, this result should be taken into account, because it suggests that (government-sponsored) short-term employments do not provide help to find long-term employments. Past out of labor force spells significantly increase the intensity of leaving the labor force in the future for employed and unemployed individuals. Further, the reentry into the labor force is clearly promoted by the occurrence of past employment and unemployment spells.
In addition to the finding that the previous spells are good indicators for the transition state, the magnitude of the parameters for the previous spells are still large compared to the cumulative number of past spells. This finding indicates that the spells occurred recently tend to have a higher impact on the current transition intensity.

Lagged duration dependence Lagged duration is accounted for by adding the cumulative durations of previous spells. The results display the surprising finding that for every respective transition except from out of the labor force into unemployment, the sign of the parameter estimate for the cumulative employment duration equals that for the cumulative unemployment and out of labor force duration. Although I control for individuals' age the results seem to be triggered by the cumulative duration of all three states at the beginning of a spell, i.e. by the time observed at the beginning of a spell. To account for this surprising finding, I include the time observed at the beginning of a spell as a regressor and account for lagged duration by using the shares of unemployment and out of labor force duration of the time observed. Results can be found in table (5). While the estimates for duration and occurrence dependence differ only very slightly, I find evidence that the time observed has a clear impact on the transition times of all transitions, except that from unemployment into out of labor force. The sign for the time observed equals the sign for the cumulative duration of the three states from the first specification. It seems that employment spells tend to be shorter for individuals, which have been observed for a long time, while unemployment and out of labor force spells tend to be longer. The results also imply that an increase in the share of unemployment and out of labor force duration significantly increase the intensities for the transitions out of employment, i.e. that individuals, which have not worked for a long time have a higher propensity to leave employment again. Hence, the results support the ideas that long unemployment durations decrease human capital and motivation to work. Furthermore, for an unemployed, a higher share of unemployment duration implies a lower propensity to find a job and to leave the labor force. The first finding points to scarring effects or a lower motivation to work. However, the second finding seems to contradict the idea that long job search induces a discouragement effect for the unemployed.

— Table 5 about here —

In a further model specification, I additionally accounted for the duration of the previous spell. Therefore, I include the duration of the previous spell independent of the type and an interaction effect, which is the absolute duration multiplied by an indicator for the type of the previous spell. The interaction effect points out, whether there are additional effects for the duration of certain states. As can be seen in table (6), the duration of the previous spell has a significant negative impact on the probability of exiting employment into unemployment, no matter if the previous spell was an unemployment or out of labor force spell.

— Table 6 about here —

Although, there is no significant additional effect for the interaction term, the result seems to support the hypothesis that a longer job search results in a better job match. For the reverted transition the probability of leaving unemployment decreases with the absolute duration. However, this effect is offset in the case of a previous employment spell. Interestingly, the absolute duration clearly drives the transition from out of the labor force into employment and even more if the last spell was an employment spell. The last effect may occur because individuals change jobs via some time out of the labor force.

5.2 Personal and environmental characteristics

In addition to the covariates that account for state dependence, I included several covariates to control for personal and environmental characteristics. The results, which can be found in the remainder of table (4), imply that age does not seem to have an effect on all transitions, because all coefficients concerning individual's age are insignificant. In contrast, nationality plays a role for the decision to leave employment. It seems that foreign employees less likely register as unemployed and more likely end out of the labor force than German employees. Employees working in the sectors of engineering and service are also less likely to leave employment, since both estimates exhibit a negative impact on the probabilities of those transitions. Interestingly, unemployed searching for employment in the service sector are also less likely to find a job. Surprisingly, results imply that the educational level does not play a role on the probability to find a job, when unemployed. Nonetheless, the fact that the probability of finding a new job does not seem to differ according to the educational level, says nothing about the quality of the following job match. Results rather imply that the educational level protects against unemployment. The risk of becoming unemployed for an employed individual even decreases with the educational level. In contrast to what theory suggests, these results suggest that measures with the goal to obtain a higher educational level do not seem to help in finding a new job. However, they clearly enhance the quality of future jobs, which results in longer employment durations. Finally, it seems that individuals with a high educational level have a much higher propensity to stay out of the labor force, once they left it.

During the period 2000 - 2003 Germany suffered a period of low GDP growth and high unemployment rates. Results show that GDP growth and the unemployment rate are slightly negatively correlated. Although not significant the level of the unemployment rate seems to lower the intensity for the transition from employment into unemployment, while it also seems to decrease the probability to find a job when unemployed. This is in line to what theory says. Hall (2005) proposes that during slack periods the unemployment rate rises because less unemployed are hired and not because of an increase in the rate of dismissals. The result for the transition from out of labor force into employment also supports this finding.

Furthermore, results for local labor market conditions suggest that individuals living in regions in Eastern Germany and regions in Western Germany with bad labor market conditions are more likely to become unemployed and less likely to find a new job. Interestingly, individuals living in those two regions are also less likely to leave the labor force, when unemployed.

5.3 Unobserved heterogeneity

Having a look on the parameter estimates of the unobserved heterogeneity reveals that the first type seems to be very erratic, because it is always the first to exit a state. In particular, the individual changes more frequently between employment and unemployment, if it is of the first type. Compared with the first type, the second type is equally likely to enter unemployment, but is less likely to leave it. Eventually, the third type seems to have a high propensity to be employed. This type exhibits the smallest probability to leave employment and is most likely to reenter employment when unemployed.

5.4 Model fit

In order to assess the model's fit, there is no simple test available. One rather has to assess the quality of the results by simulating individuals' histories. Simulations are done dynamically over time, taking into account a fixed set of time-varying exogenous variables. For the sample of individuals the entry time and type of the first state are given by the previous transition prior to the entry. In a first step, I draw a value from the probability distribution of unobserved heterogeneity. This value is then considered as fixed for the respective run of the simulation and indicates the value of random effects for the respective transitions. In a second step the transition times and destination states for the first transition are drawn. This is done in accordance to the exogenous variables, the random effect, and the parameter estimates. After a transition to a new state occurred, the labor market history is updated and again transition times and destination states are drawn. The process is conducted until the individual is observed for the last time, and the last spell is right-censored. In this way one obtains simulated histories for the individuals of the random sample that are statistically compatible to the original history. In total ten realization are simulated for the sample of individuals. Finally, summary statistics of the simulated histories are computed and compared to the raw data. Table (7) displays the results of the summary statistics for original and simulated histories.

— Table 7 about here —

While the model fits relatively well for durations of out of labor force spells, one can see that the model tends to overestimate the durations of employment spells and underestimate the durations of unemployment spells. Especially the predicted number of long unemployment spells is too low, while the number of long employment spells is too high. Figure (5) also displays these findings, plotting the survivor functions for original and simulated histories.

— Figure 5 about here —

6 Conclusion

This paper analyzes the extent and type of state dependence in labor market outcomes of German men during the period 2000 - 2003. Data from the Integrated Employment Biography Sample is used to construct the individual labor market histories. Labor market histories consist of the three states, employment, unemployment and out of labor force. Estimation is conducted using an event-history framework incorporating observed and unobserved heterogeneity together with a flexible specification for the state dependence. Following Heckman and Borjas (1980) state dependence is controlled for by including parameters that represent i) duration dependence (Weibull function), ii) occurrence dependence (type of recent spell and cumulative number of all past spells) and iii) lagged duration dependence (duration of recent spell and cumulative duration of all past spells).

I find support for all three forms of state dependence. Results imply that the probability to find an employment decreases with the time unemployed, while the for an employed individual the probability of becoming unemployed remains unaffected. Recent employment and unemployment spells have a huge impact on the destination, but also on transition times. Results for the cumulative number of spells show that individuals often transiting between employment and unemployment are likely to remain inside this vicious circle of short-time employment and unemployment. Further, individuals which were out of the labor force various times, are more likely to leave the labor force and also to remain outside the labor force. In addition to an effect that is related to the time an individual is observed, long unemployment durations in the past increase the probability of movements into unemployment and to remain unemployed.

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A Tables

Table 1 – Data overview

	Origin state			Total
	E	U	O	
Number of histories beginning after 01/01/2000				
Total				69761
Time under observation (days)				
Average per person	524.65	289.70	146.42	960.78
Per cent	54.61	30.15	15.24	100.00
Maximum history length				1460
Number of spells				
Total	93610	85690	61943	241243
Right-censored	34265	24112	11384	69761
Uncensored	59345	61578	50559	171482
Destination state				
E	0	46528	28615	
U	38145	0	21944	
O	21200	15050	0	
Incidence rate (exits per year)				
Total	0.59	1.11	1.80	
Destination state				
E	0	0.84	1.02	
U	0.38	0	0.78	
O	0.21	0.27	0	
Duration quantiles (days)				
10%	32	27	14	
20%	89	54	27	
30%	160	85	39	
40%	242	117	59	
50%	324	166	85	
60%	481	244	123	
70%	826	372	211	
80%		608	364	
90%		1216	774	

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.

Table 2 – Overview about previous labor market histories

Explanatory variables	E	U	O	Total
Previous spells				
Average number	2.87	1.89	1.61	6.37
Per cent	45.07	29.71	25.22	100.00
Previous duration				
Average duration	2395.40	535.77	694.64	3625.81
Per cent	66.06	14.78	19.16	100.00

Table 3 – Explanatory Variables

Explanatory Variable	***Date***	***Mean***	***Standard Deviation***
Age	January 1, 2000	41.54	4.61
	last spell	44.30	4.70
Occupation	last spell		
Farming		0.040	0.197
Mining		0.003	0.059
Manufacturing		0.457	0.498
Engineering		0.060	0.237
Service		0.429	0.495
Miscellaneous		0.010	0.099
Education	last spell		
No degree		0.201	0.401
Vocational Training		0.653	0.476
High School		0.011	0.103
High School + Vocational Training		0.036	0.186
Technical College		0.031	0.174
University Degree		0.067	0.251

Table 4 – Results from base model

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
State dependence						
Elapsed Duration						
Weibull $\alpha_{\tilde{s},s}$	0.978***	0.812***	0.935***	1.024***	1.063***	0.866***
	(0.016)	(0.013)	(0.014)	(0.022)	(0.024)	(0.020)
Wald-Test (all $\alpha_{\tilde{s},s} = 1$)						
p-value	0.168	0.000	0.000	0.285	0.008	0.000
Wald-Test (jointly $\alpha_{\tilde{s},s} = 1$)						
p-value = 0.000						
Previous spell (base: person with other type of spell)						
Previous E spell			0.280***	-0.530***	1.120***	-0.477***
			(0.058)	(0.055)	(0.082)	(0.063)
Previous U spell	1.021***	-0.625***				
	(0.049)	(0.057)				
Cumulative number of previous spells						
Previous cum. E spells	0.063***	-0.013	0.079***	-0.077***	0.097***	0.043***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.021)	(0.015)
Previous cum. U spells	0.060***	-0.014	0.047***	0.057***	-0.054**	0.082***
	(0.012)	(0.015)	(0.014)	(0.015)	(0.022)	(0.015)
Previous cum. O spells	-0.009	0.163***	-0.062***	0.144***	-0.042**	-0.046***
	(0.010)	(0.013)	(0.012)	(0.013)	(0.019)	(0.014)
Cumulative duration of previous spells (measured in days, results $\times 10^{-4}$)						
Previous cum. E duration	2.147***	2.033***	-3.401***	0.714	-4.651***	-5.607***
	(0.562)	(0.669)	(0.439)	(0.772)	(0.581)	(0.610)
Previous cum. U duration	4.908***	3.991***	-10.115***	-1.430	-7.787***	-3.437***
	(0.589)	(0.755)	(0.569)	(0.874)	(0.824)	(0.686)
Previous cum. O duration	3.502***	3.266***	-3.818***	1.494*	-4.983***	-4.712***
	(0.568)	(0.683)	(0.487)	(0.821)	(0.622)	(0.640)
Personal characteristics						
Age structure						
Age	-0.046	-0.043	-0.051	-0.093	0.028	0.117
	(0.061)	(0.830)	(0.064)	(0.099)	(0.084)	(0.101)
Age^2	0.001	0.000	0.000	0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nationality (base: German)						
Foreigner	-0.116**	0.186***	-0.002	-0.017	0.081	-0.025
	(0.052)	(0.056)	(0.057)	(0.069)	(0.068)	(0.072)

Table 4 – (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Occupation (base: manufacturing)						
Farming	0.049	-0.315**	-0.054	-0.194*	-0.205	-0.291**
	(0.056)	(0.122)	(0.074)	(0.117)	(0.131)	(0.118)
Mining	0.184	0.009	-0.003	-0.266	0.106	-0.126
	(0.325)	(0.392)	(0.295)	(0.364)	(0.340)	(0.302)
Engineering	-0.459***	-0.380***	-0.057	-0.075	-0.098	-0.244**
	(0.089)	(0.116)	(0.092)	(0.134)	(0.091)	(0.124)
Service	-0.227***	-0.084*	-0.140***	0.023	-0.064	-0.184***
	(0.035)	(0.045)	(0.035)	(0.050)	(0.047)	(0.050)
Miscellaneous	0.075	0.347*	0.128	-0.505**	-0.248	-0.380
	(0.119)	(0.193)	(0.182)	(0.245)	(0.184)	(0.237)
Education (base: no degree)						
Voc. Train.	-0.350***	-0.191***	0.071	0.059	-0.120**	-0.371***
	(0.041)	(0.051)	(0.046)	(0.055)	(0.061)	(0.060)
HS degree	-0.385**	-0.123	-0.456**	-0.230	-0.266	-0.728***
	(0.189)	(0.207)	(0.242)	(0.208)	(0.225)	(0.250)
HS + VT	-0.454***	-0.405**	-0.035	0.109	-0.201	-0.793***
	(0.096)	(0.164)	(0.108)	(0.143)	(0.128)	(0.154)
Tech. College	-0.498***	-0.733***	0.091	-0.123	-0.801***	-0.659***
	(0.138)	(0.136)	(0.145)	(0.198)	(0.143)	(0.172)
Uni. degree	-0.654***	-0.670***	0.046	0.062	-0.921***	-1.261***
	(0.095)	(0.110)	(0.098)	(0.129)	(0.127)	(0.142)
Environmental characteristics						
Business cycle						
GDP growth	0.109***	0.012	-0.052***	-0.050	0.076***	0.031
	(0.024)	(0.032)	(0.020)	(0.040)	(0.026)	(0.032)
Current labor market situation in Germany						
Unemployment rate	-0.022	-0.236***	-0.091***	-0.119***	-0.251***	-0.044
	(0.030)	(0.035)	(0.023)	(0.041)	(0.029)	(0.032)
Regional labor market segregation in Germany (base: West, hi. dyn. regions + good LM-cond.)						
E, shortcoming in employment	0.367***	-0.132*	-0.266***	-0.548***	-0.042	0.475***
	(0.046)	(0.070)	(0.049)	(0.077)	(0.072)	(0.078)
W, hi. urbanized + hi. U-rate	0.143**	0.009	-0.449***	-0.321***	0.053	0.220***
	(0.055)	(0.060)	(0.058)	(0.071)	(0.061)	(0.070)
W, more rural + avg. U-rate	0.050	-0.063	-0.177***	-0.299***	-0.017	0.122*
	(0.047)	(0.058)	(0.049)	(0.072)	(0.061)	(0.069)
W, hi. dyn. cent. + good LM-cond.	0.0189	0.096	-0.360***	-0.159**	-0.077	0.128
	(0.080)	(0.077)	(0.083)	(0.088)	(0.077)	(0.091)

Table 4 – (continued)

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Unobserved heterogeneity						
Type 1	-7.287***	-3.486*	-1.366	-3.626*	-2.512	-4.464**
	(1.352)	(1.806)	(1.394)	(2.161)	(1.811)	(2.192)
Type 2	-7.362***	-3.101*	-3.080**	-3.881*	-3.898**	-5.473**
	(1.334)	(1.796)	(1.393)	(2.154)	(1.803)	(2.159)
Type 3	-8.020***	-4.787***	-1.299	-3.704*	-4.461**	-6.298***
	(1.366)	(1.810)	(1.404)	(2.162)	(1.810)	(2.166)
Probability of type 1	0.376					
	(-)					
Probability of type 2	0.292***					
	(0.030)					
Probability of type 3	0.332***					
	(0.027)					

Standard deviation in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

Table 5 – Results accounting for the shares of time observed

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Elapsed Duration						
Weibull $\alpha_{\tilde{s},s}$	0.978***	0.811***	0.936***	1.023***	1.063***	0.867***
	(0.016)	(0.013)	(0.014)	(0.022)	(0.024)	(0.020)
Previous spell (base: person with other type of spell)						
Previous E spell			0.272***	-0.530***	1.120***	-0.464***
			(0.058)	(0.055)	(0.083)	(0.064)
Previous U spell	1.013***	-0.639***				
	(0.049)	(0.058)				
Cumulative number of previous spells						
Previous cum. E spells	0.062***	-0.008	0.078***	-0.077***	0.099***	0.044***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.020)	(0.015)
Previous cum. U spells	0.061***	-0.008	0.044***	0.056***	-0.058***	0.080***
	(0.012)	(0.014)	(0.014)	(0.015)	(0.021)	(0.015)
Previous cum. O spells	0.002	0.160***	-0.063***	0.144***	-0.045**	-0.046***
	(0.010)	(0.013)	(0.012)	(0.013)	(0.019)	(0.014)
Cumulative duration of previous spells (measured in days, results of total duration $\times 10^{-4}$)						
Previous total duration	3.009***	2.730***	-4.537***	-0.508	-4.923***	-4.826***
	(0.550)	(0.659)	(0.440)	(0.780)	(0.589)	(0.602)
Percentage of U duration	0.969***	0.790***	-2.326***	-0.749***	-1.026***	0.852***
	(0.010)	(0.151)	(0.133)	(0.145)	(0.207)	(0.151)
Percentage of O duration	0.456***	0.466***	-0.156*	0.270***	-0.095	0.311***
	(0.073)	(0.079)	(0.081)	(0.100)	(0.094)	(0.102)

Standard deviation in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

Table 6 – Results accounting for the duration of the most recent spell

	Transitions					
	E → U	E → O	U → E	U → O	O → E	O → U
Elapsed Duration						
Weibull $\alpha_{\tilde{s},s}$	0.975***	0.807***	0.946***	1.029***	1.076***	0.860***
	(0.016)	(0.013)	(0.015)	(0.023)	(0.023)	(0.020)
Previous spell (base: person with other type of spell)						
Previous E spell			0.217***	-0.512***	0.955***	-0.303***
			(0.082)	(0.065)	(0.104)	(0.073)
Previous U spell	1.008***	-0.635***				
	(0.059)	(0.068)				
Cumulative number of previous spells						
Previous cum. E spells	0.065***	-0.009	0.085***	-0.080***	0.117***	0.014
	(0.013)	(0.014)	(0.014)	(0.014)	(0.021)	(0.016)
Previous cum. U spells	0.049***	-0.012	0.041***	0.056***	-0.070***	0.091***
	(0.012)	(0.015)	(0.015)	(0.016)	(0.022)	(0.017)
Previous cum. O spells	-0.006	0.152***	-0.075***	0.146***	-0.053***	-0.041***
	(0.010)	(0.014)	(0.013)	(0.014)	(0.020)	(0.014)
Duration of previous spell (measured in days, results $\times 10^{-4}$)						
E spell × duration pre. spell			1.911***	-0.199	7.457***	-2.006**
			(0.503)	(0.566)	(2.086)	(0.855)
U spell × duration pre. spell	-0.273	0.056				
	(0.788)	(1.118)				
Duration pre. spell	-1.843***	1.697***	-1.962***	-0.233	6.889***	0.446
	(0.468)	(0.351)	(0.434)	(0.417)	(2.079)	(0.821)
Cumulative duration of previous spells (measured in days, results $\times 10^{-4}$)						
Previous cum. E duration	2.229***	2.022***	-3.512***	0.823	-5.002***	-4.768***
	(0.563)	(0.663)	(0.454)	(0.794)	(0.597)	(0.632)
Previous cum. U duration	5.681***	4.485***	-10.247***	-1.447	-6.860***	-3.324***
	(0.648)	(0.814)	(0.576)	(0.889)	(0.864)	(0.704)
Previous cum. O duration	3.885***	3.799***	-3.507***	1.539*	-4.895***	-4.598***
	(0.574)	(0.682)	(0.487)	(0.836)	(0.625)	(0.654)

Standard deviation in parentheses. Significance on 10%, 5% and 1%-level is indicated by *, ** and ***.

Table 7 – Model fit

	Origin state			Total
	E	U	O	
Raw data				
Time under observation (days)				
Average per person	524.65	289.70	146.42	960.78
Per cent	54.61	30.15	15.24	100.00
Incidence rate (exits per year)				
Total	0.59	1.11	1.80	
Destination state				
E	0	0.84	1.02	
U	0.38	0	0.78	
O	0.21	0.27	0	
Duration quantiles (days)				
10%	32	27	14	
20%	89	54	27	
30%	160	85	39	
40%	242	117	59	
50%	324	166	85	
60%	481	244	123	
70%	826	372	211	
80%		608	364	
90%		1216	774	
Model fit				
Time under observation (days)				
Average per person	599.82	218.64	144.81	963.26
Per cent	62.27	22.70	15.03	100.00
Incidence rate (exits per year)				
Total	0.46	1.51	1.51	
Destination state				
E	0	1.24	0.90	
U	0.32	0	0.61	
O	0.14	0.27	0	
Duration quantiles (days)				
10%	49	20	12	
20%	117	44	27	
30%	209	73	47	
40%	330	107	73	
50%	496	150	111	
60%	743	205	169	
70%	1135	282	268	
80%		397	445	
90%		622	807	

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.

B Figures

Figure 1 – A typical history

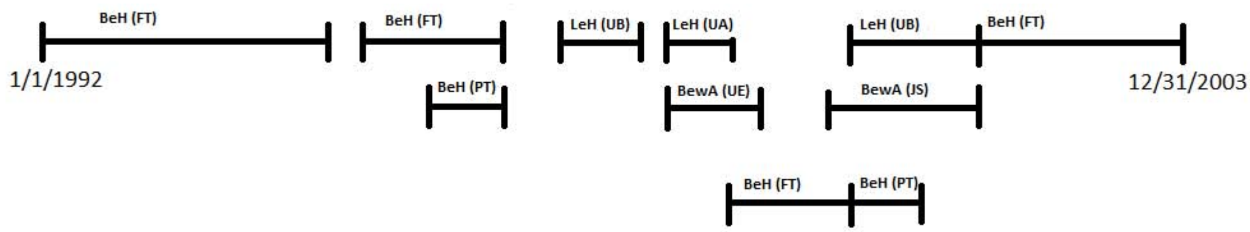

Figure 2 – Assignment of labor market states

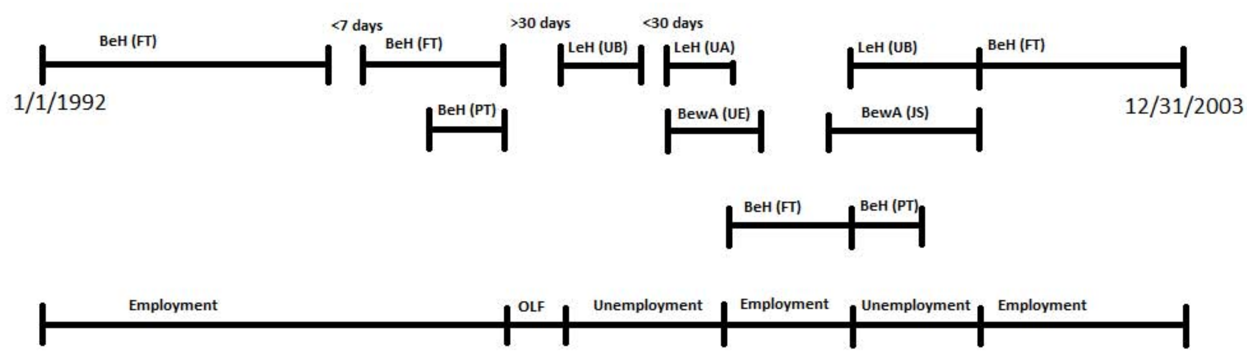

Figure 3 – Which spells are used for estimation?

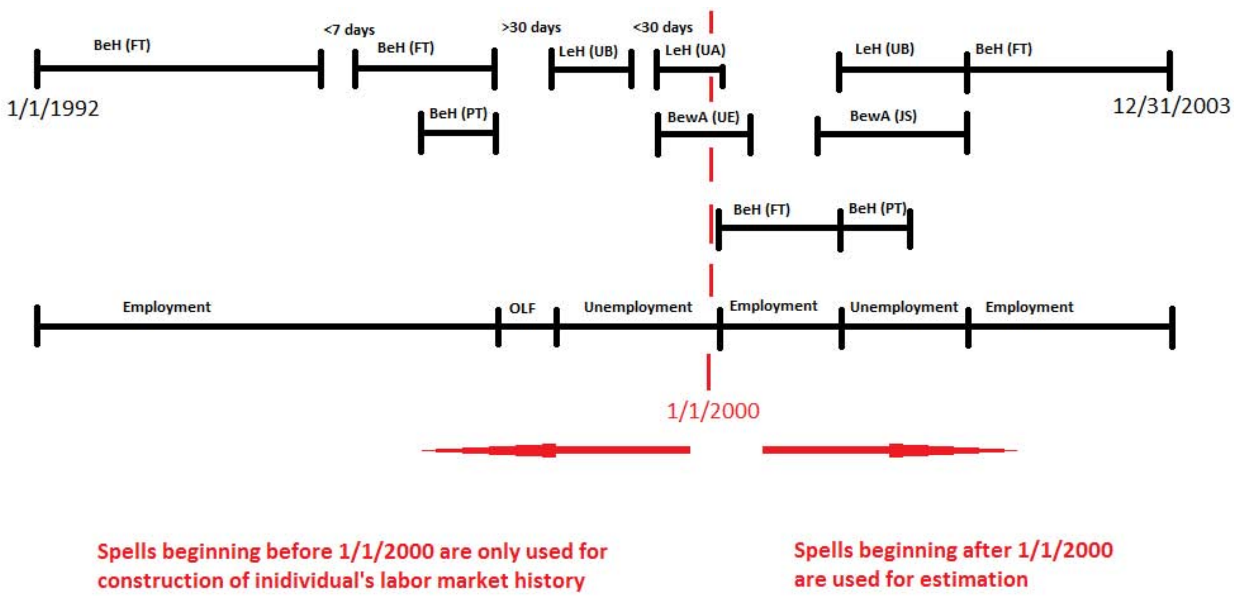

Figure 4 – Estimated baseline transition intensities

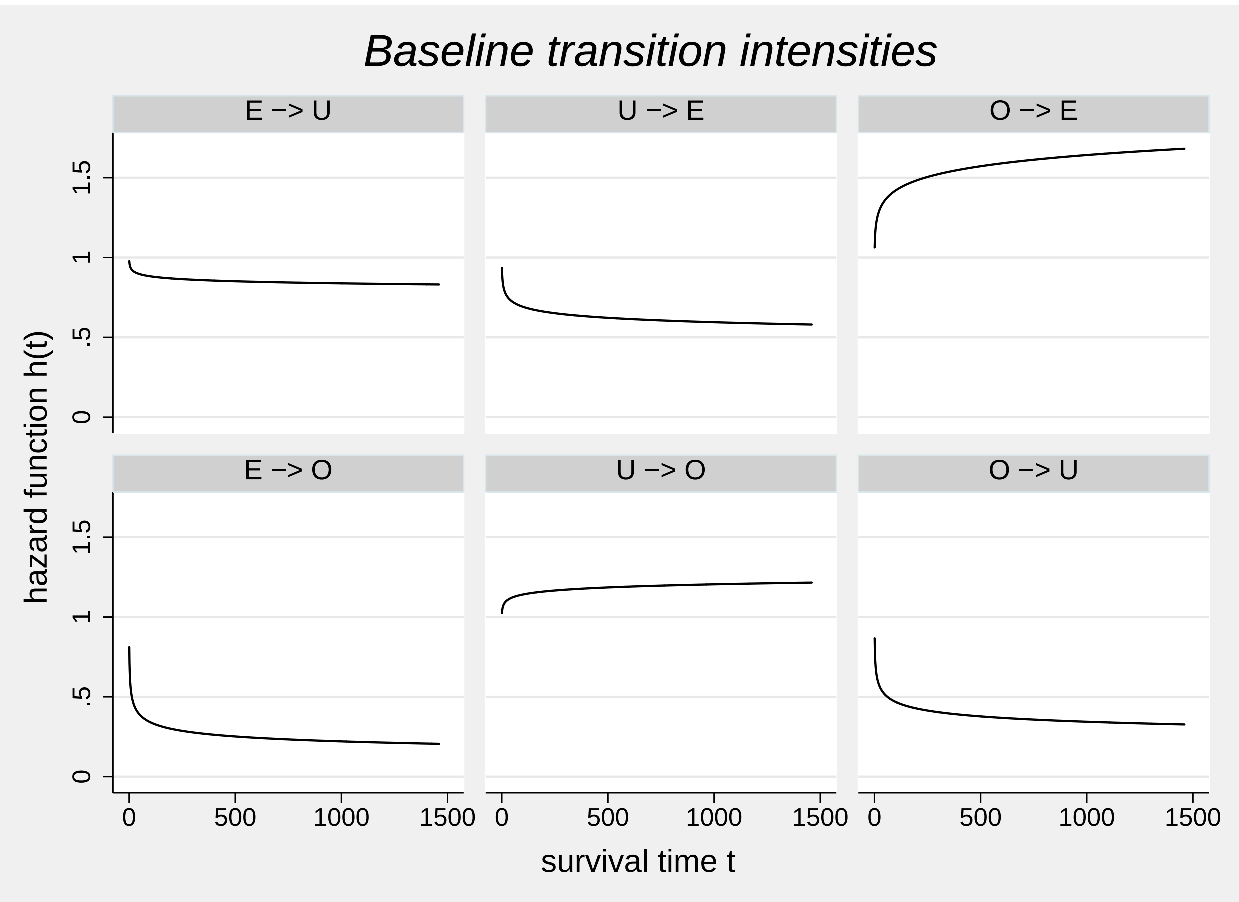

Figure 5 – Comparison of survivor functions from raw and simulated data