State dependence in youth labor market experiences and the evaluation of policy interventions

Denise Doiron* Tue Gørgens†

October 2005

Abstract: The finding of strong duration dependence in explaining the length of unemployment spells has influenced the design of many labor market policy reforms. However very little work has been done on more complex effects of labor market experiences and in particular on the causal effects of past outcomes involving other labor force states. In this paper we use longitudinal data to investigate the extent of state dependence in labor market outcomes for young Australians. The econometric model estimates the effects of past outcomes in three labor force states, employment, unemployment and out of the labor force, on current transitions between any two states allowing for observed and unobserved heterogeneity. Our findings suggest strong state dependence in all three states and we use the estimates to simulate various policy experiments.

Keywords: Transition data, event history analysis, state dependence, unobserved heterogeneity, labor force states, policy effectiveness.

J.E.L. Classification Numbers: C33, C41, J64, J68.

Acknowledgment: We wish to thank seminar participants at the University of Melbourne, the University of Copenhagen, and the University of Aarhus. Tue Gørgens gratefully acknowledges the financial support of the Department of Family and Community Services. The views expressed in this paper reflect those of the authors and do not represent the opinions of the Department.

*Address: School of Economics, University of New South Wales, Sydney NSW 2052, Australia. E-mail: D.Doiron@unsw.edu.au.

†Address: SPEAR Centre RSSS, Australian National University, Canberra ACT 0200, Australia. E-mail: Tue.Gorgens@anu.edu.au.

Executive summary

- In this paper, we extend the literature on youth labor market outcomes (employment, unemployment and being out of the labor force) by modeling the effects of labor market experiences in a general and flexible manner. The model is estimated on longitudinal data for young Australians.

- Our estimates suggest that the effects from one's past experiences on the current and future labor market outcomes are large. Consequently periods of employment (unemployment) have long-term effects on the future probability of employment (unemployment) and the length of future employment (unemployment) spells. These effects are over and above the impact of many other personal characteristics and the state of the labor market.

- From the perspective of society, the benefits of early intervention may therefore be substantial. If bad labor market outcomes increase the probability of future bad outcomes, a government program which is successful in placing young people in employment early would benefit the affected individuals in the immediate future and would have persistent effects in the longer-term as well.

- Our findings have implications for the policy evaluation. The usual methods of policy evaluation which compare labor market outcomes before and shortly after a policy intervention provide an incomplete and possibly misleading estimate of the impacts of programs since they do not include the medium to long term consequences of the policy changes.

- Simulations of three policy interventions in providing employment and training to medium-term unemployed youths show that the effects of these programs are substantially larger when the state dependence is included. For example, consider the effect of providing a short (30 days) job to a young person with little education. The number of days employed in the four year period following the program intervention are increased by a factor of four when state dependence is taken into account.

1 Introduction

Youth employment and unemployment have received much attention among researchers as well as in public debate. Joblessness occurs more frequently among young people than in the rest of the labor force. The higher unemployment rates are partly explained by the learning processes faced by both sides of the labor market. New entrants to the labor market need to discover their own skills and preferences as well as the opportunities available to them, and employers need to assess the potential productivity of new entrants. This results in "job-shopping" (e.g. Topel and Ward, 1992) and higher mobility among young people. Moreover, temporary jobs and spells of unemployment often accompany investments in education or training (e.g. Wolpin, 1987).

Recently trends in youth unemployment have been the cause of renewed concern. Youth employment is believed to be particularly sensitive to the state of the economy; yet, youth unemployment has remained at twice or more the adult rate of unemployment in most OECD countries despite the continued period of expansion (e.g. OECD, 2002). Increased levels of education and the aging of the workforce have also failed to solve the youth unemployment problems.

To combat youth unemployment, many countries have implemented a wide range of policies targeted at unemployed and disadvantaged youth. The effectiveness of these programs is unclear in many cases. There is now a substantial and growing literature which estimates the effects of employment policies and training programs on the subsequent employment experience of the participants. Key papers include, for example, Ridder (1986), Gritz (1993), Ham and LaLonde (1996), and Bonnal, Fougère, and Sérandon (1997). The findings in this literature are diverse; however, the failure of many of the large-scale programs (e.g. Blanchflower and Freeman (2000) and other articles in the same volume) can be seen as evidence that the workings of the youth labor markets and the impact of policies in this area are still not well understood.

In this paper we address an important issue which until now has not received much attention in the program evaluation literature: the role of state dependence in youth labor market outcomes and the implications of state dependence for public policy. State dependence refers to a causal link between previous outcomes and current outcomes. For example, having experienced unemployment in the past may affect the probability of experiencing unemployment in the future through "scarring", irrespective of personal characteristics such as education and motivation and external environmental factors such as the business cycle and seasonality. The extent of state dependence has serious implications for the effectiveness of labor market programs. If personal characteristics are the main determinants of future labor force states, then policy should target these characteristics. The timing of the intervention may not matter much. On the other hand, if state dependence is significant, policy should aim at preventing unfavorable outcomes from occurring early in a person's career. Disentangling the effect of personal characteristics and the environment from the effect of the previous labor market outcomes is therefore critical for designing effective labor market policies.

Early papers on the estimation of state dependence include for example Heckman and Borjas (1980) and Ellwood (1982); for recent contributions see for example Arulampalam, Booth, and Taylor (2000) and Gregg (2001). Most studies, with Heckman and Borjas (1980) as an notable exception, have approached the problem using autoregressive models for panel data. That is, they have compared either labor force status at distinct points in time or the proportion of time within given periods spent in each state. State dependence is represented by lagged dependent variables in this framework.

The evaluation literature has often taken a different approach and applied event history methods (e.g. previous references). These studies are based on models of the timing of transitions between distinct states such as program participation, employment, and unemployment. The event history approach is particularly well suited for this kind of research, given the availability of high-quality longitudinal data and the delicate econometric issues involved, such as the endogeneity of programs participation, missing data (left- and right-censoring), and the influence of unobserved heterogeneity. All of these issues have received great attention in this literature; as mentioned, less attention has been paid to state dependence.

In this paper, we estimate the extent of state dependence in transitions between labor force states for young Australians and investigate some of the implications of state dependence for public policy. Our main data source is the Australian Youth Survey 1989–1994, and we study the respondents' weekly histories of labor force status after they have left secondary school. We distinguish between three labor force states, namely, employment, unemployment and out-of-the-labor force. In his review of the literature on the school-to-work transition, Ryan (2001) points out the lack of evidence on the structure of dependence across labor force states other than the (current) duration dependence in unemployment. Our study also contributes to the literature in estimating these cross-state effects. In addition to the personal past history of transitions, we consider a large set of explanatory variables representing personal demographic characteristics as well as external environmental factors such the business cycle and seasonal variation. Finally our model includes random effects to reduce the effect of unobserved heterogeneity.

Parameterizing state dependence is a challenge in these models, because of the need to summarize the past history and the limited guidance available in the literature on how to achieve this. The parameterization used in this paper is inspired by Heckman and Borjas' (1980) distinction between duration dependence, occurrence dependence and lagged duration dependence. Specifically, we include variables representing both the number of transitions and the time spent in each state prior to the start of the current spell, in addition to elapsed time in the current spell.

Our estimates show a large amount of state dependence in labor force status despite the inclusion of a large number of personal and external characteristics and the modeling of unobserved heterogeneity. We investigate the importance of this state dependence for labor market programs by simulating the medium-term impacts of three stylized policies: successful employment search, a short-term subsidized job and a training program. The model estimates also show the importance of educational attainment in determining future employment probabilities and the sensitivity of youth unemployment to labor market conditions. Simulations are used to illustrate these findings as well.

The paper is organized as follows. Section 2 discusses the data as well as sample selection and censoring issues. This is followed by a presentation of the econometric model in section 3. Section 4 proceeds to discuss the estimation results and concludes by summarizing the fit of the model. Section 5 presents simulation results on the effect of education, the effect of the 1991 recession, and three policy experiments. Section 6 summarizes the findings and offers concluding comments.

2 Data

This section discusses the data set. A description of the institutional and policy environment in Australia at the time of the survey can be found in Doiron and Gørgens (2005). We mention here only the fact that no major policy changes were implemented during the time period under study, 1989–1994. Also, this period is particularly interesting, because the Australian economy went into a recession in 1991–1992, and the data period covers both the downturn and the subsequent recovery.

2.1 Australian Youth Survey

The main data source is the Australian Youth Survey 1989–1994 (AYS). The AYS was designed to be representative of the Australian population of young people, with the exception of those living in sparsely populated areas. The AYS consists of six cohorts. The initial cohort were between 16 and 19 years of age in September 1989. Additional cohorts of 16-year-olds were added to the sample in each of the years 1990–1994. Face-to-face interviews were carried out annually from 1989 to 1994.[1]

The AYS is a rich data set which contains detailed demographic and economic information about each respondent. Topics covered by the questionnaire include basic demographic characteristics, family background, secondary school and post-school education, as well as labor market experience and job information. In particular, at each interview the respondents were asked to provide detailed week-by-week information about jobs and job search. From the job and job search histories it is possible to determine the labor force

[1] No additions were made to the sample after 1994, but telephone interviews were conducted in 1995 and 1996 for those already selected. Our analysis is restricted to the years 1989–1994, because the information on labor force status collected in the 1995 and 1996 interviews is less detailed.

status of each person in each week, starting in January of the year of the first interview and ending in the week of the last interview. These weekly labor force status histories form the core data for the analysis in this paper.

To simplify the analysis we assume that at any point in time a person can be in one and only one of three labor force states: out of the labor force (O), unemployed (U), or employed (E). We classify a person as employed if he or she reported to have a job, no matter how short the hours and how low the salary. This is similar to the standard definition. We classify a person as unemployed if he or she is not employed and is looking for work.[2] Finally, persons not employed and not unemployed are classified as being out of the labor force.

We assume that a person's history begins when he or she leaves secondary school, and we treat the event of leaving secondary school as exogenous. We exclude secondary school students on the grounds that their labor market experiences in most cases are completely determined by schooling and the type of work performed by school students is likely to be different from other work. Our analysis also ignores the effect of work experience acquired prior to leaving school. We expect this assumption to be an acceptable approximation. We do, however, include persons enrolled in post-secondary studies. Even in the early 1990s, the combination of work and study was widespread among Australian youths. It is therefore interesting and important to analyze the interaction between work and study and to analyze the consequence of combining work and study on later labor market activities.

In the AYS data, histories are left-censored if the person left secondary school before the year of the first interview. In addition, all histories are naturally right-censored at the time of the last interview.[3] A few histories have censored periods in the middle. This happens when a person misses a scheduled interview, but is participating in the survey again in a following year. The results presented in this paper are based on analysis which exclude all left-censored histories and which right-censor histories at the time of

[2]This is less stringent than the standard definition used in official Australian Bureau of Statistics figures, which requires a certain minimum active search effort and, additionally, that the person is available to start work within a short period of time. Consequently, we expect the unemployment rates in our analysis to be slightly higher than official estimates.

[3]Left-censoring means that states and transitions are not observed during the beginning of the history. Similarly, right-censoring means that states and transitions are unknown after some point in time.

any gap (i.e. we use only the first part of a history with a gap in the middle). This follows the standard approach in the literature.[4] However, excluding left-censored histories may cause a sample selection bias as older persons with little education are more likely to have left-censored histories than others.

In addition to endogenous variables representing previous labor market experience (discussed in section 3.3), we consider a large set of exogenous explanatory variables which represent personal demographic characteristics as well as external environmental factors. While some of our exogenous variables are time-invariant, such as sex and language background, most are time-varying. Age, student status, and educational achievements are measured on a monthly scale, and we assume that any changes occur between successive calendar months. Information about the place of residence and marital status is collected for the time of each interview. For these variables, we assume that any changes occur on the day following the previous interview.

To capture differences in the external environment, we include local unemployment rates, dummies for calendar year and month, state/territory dummies, and the dummies for degree of urbanization. The AYS does not contain information about local labor markets, but as mentioned it does have detailed information about the respondents' residence at the time of the interview (census collector's districts or postcodes). This allows us to merge local unemployment rates published by the Australian Bureau of Statistics (ABS) with the AYS data. The ABS figures are available monthly by sex, age group and statistical region.[5] We assign a local unemployment rate to each person in each month.

2.2 Data overview

There are altogether 11431 persons in the AYS. Table 1 shows that 5439 have left school at the time of the last interview and have non-missing values for all explanatory variables used in the analysis presented later. The average history length is 878 days (29.3 months, or 2.4 years). Of the time under observation, 169 days are spent out of the labor force (5.6 months), 139 unemployed (4.6 months) and 570 days employed (19.0 months). The

[4] D'Addio and Rosholm (2002b) examine the effects of the exclusion of left-censored spells.

[5] We use the ABS unemployment rates for 15–24-year-olds.

longest observed history is 2111 days (70.4 months, or 5.8 years).

The table also shows summary statistics for the spells. In total there are 22925 spells, of which 28.1% are not in the labor force, 30.8% are unemployment and 41.1% are employment. The fact that unemployment accounts for only 15.8% of total history time but 30.8% of the spells, while employment accounts for 41.1% of the spells but 64.9% of the total history time simply reflects the fact that spells of unemployment tend to be much shorter than spells of employment.

The table shows that the majority of the AYS respondents were employed at the time of their last interview. The next three rows of the table shows the transition matrix from one spell to the next. There are slightly more transitions from being out of the labor force into unemployment than into employment (3038 versus 2650). From unemployment, substantially more spells end with transition into employment than to out of the labor force. The transition from employment are of very similar magnitudes (2735 and 2843).

The bottom panel of table 1 shows quantiles of the distribution of spells. For example, the first entry shows that 10% of spells out of the labor force are shorter than 6 days and that 90% are longer than 6 days. The median length of a period spent out of the labor force is 69 days, or just over two months. The median length of unemployment and employment spells are 61 days and 272 days. While the medians are roughly similar for being out of the labor force and for being unemployed, the higher quantiles show that unemployment spells tend not to be as long as periods out of the labor force. Employment spells tend to be the longest, with 10% of the spells longer than 2048 days, or 5.6 years.

3 Econometric framework

3.1 Outcome and explanatory variables

The outcome (or dependent) variable for person i is his or her history; that is, the transition times and destination states. Let $T_{i,0}$ and $S_{i,0}$ denote the point in time when the history begins and the initial state. In our application, $T_{i,0}$ is the (calendar) time when person i leaves secondary school and $S_{i,0}$ indicates whether he or she is out of the labor force (O), unemployed (U) or employed (E) immediately after leaving school. Let $T_{i,j}$ and $S_{i,j}$ for $j = 1, 2, \dots$ denote subsequent transition times and destination states (with $T_{i,j-1} < T_{i,j}$ and $S_{i,j-1} \neq S_{i,j}$). Person i's history is observed over the period $(T_{i,0}, C_i]$, where C_i is a random variable representing the time of the last interview. Let N_i denote the number of transitions during $(T_{i,0}, C_i]$.

It is necessary to distinguish between exogenous and endogenous explanatory variables in the notation. Let $X_i(t)$ denote a vector of exogenous explanatory variables at time t for person i, and let $\mathbf{X}_i(t)$ denote the path of the explanatory variables from the beginning of time until time t.[6] Let $\mathbf{Y}_i(t, s)$ denote the history of outcomes from the beginning of time until time t; that is, $\mathbf{Y}_i(t, s) = \{T_{i,j}, S_{i,j}\}_{j=0}^{n(t)}$, where $s = S_{i,n(t)}$ and $n(t)$ is the maximal integer such that $T_{i,n(t)} \leq t$.[7]

A main aim of this paper is to disentangle the effect of previous labor market outcomes (state dependence) from other factors such as personal characteristics and the external environment (heterogeneity). Since any heterogeneity not accounted for is likely to induce spurious state dependence, it is important to minimize the effect of unobserved heterogeneity. To this end, we follow the literature and include random effects in the model. Let V_i be a vector representing unobserved personal and environmental characteristics. We assume that V_i is person-specific, time-invariant, and independent of observed personal characteristics and environmental factors, apart from the past history of outcomes.

3.2 Transition intensities and likelihood function

Assuming continuous measurement of time, let $h(t, s|\mathbf{y}(\tilde{t}, \tilde{s}), \mathbf{x}(t), v)$ denote the conditional transition intensity to state s at time t given the current spell in state $\tilde{s}$ began at time $\tilde{t}$, and given the history, $\mathbf{y}(\tilde{t}, \tilde{s})$, the path of exogenous variables, $\mathbf{x}(t)$, and value of unobserved characteristics, v.

Conditional on $\mathbf{X}_i(C_i) = \mathbf{x}_i(c_i)$ and $V_i = v_i$, the contribution to the likelihood function

[6] To simplify the exposition, we assume that the exogenous explanatory variables are external, as defined by Kalbfleisch and Prentice (1980, p123).

[7] The argument s in $\mathbf{Y}_i(t, s)$ is redundant, but we find it helps clarifying the discussion.

of person i's history can be expressed as the product of the contributions of each spell,

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

In this paper, we focus on the transitions and do not model the decision to leave school nor the first labor force state.[8] In terms of (1), this means that we omit the last two terms and effectively condition on $T_{i,0}$ and $S_{i,0}$.[9]

Conditional on entering state $s_{i,j-1}$ at time $t_{i,j-1}$, $\mathbf{Y}_i(t_{i,j-1}, s_{i,j-1}) = \mathbf{y}_i(t_{i,j-1}, s_{i,j-1})$, $\mathbf{X}_i(t_{i,j}) = \mathbf{x}_i(t_{i,j})$ and $V_i = v_i$, the contribution to the likelihood of the event that person i moved to state $s_{i,j}$ at time $t_{i,j}$ is

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

The right-hand side of (2) is similar to the "hazard function times survivor function"-expression familiar from the analysis of single-spell duration data. The first term is the intensity of moving to state $s_{i,j}$ at time $t_{i,j}$ and the second, exponential term is the probability of no events taking place between time $t_{i,j-1}$ and time $t_{i,j}$.

Assume that the end time, C_i, is independent of the transition process and of observed and unobserved heterogeneity.[10] Then C_i is uninformative about parameters of interest. Ignoring the distribution of C_i in the likelihood function, the contribution of the last

[8] This simplification is common in the literature, see for example Gritz (1993), Bonnal, Fougère, and Sérandon (1997), and D'Addio and Rosholm (2002a).

[9] The predictions presented later in the paper do not condition on $S_{i,0}$, they are based on the simplest possible model of the conditional distribution of $S_{i,0}$ given $T_{i,0}$, $\mathbf{X}_i(t_{i,0})$ and V_i, namely the unconditional distribution of $S_{i,0}$, estimated by the sample frequencies.

[10] This is a standard, and in most cases unproblematic assumption, since C_i is simply the time of the 1994 interview for most AYS respondents, and the time of the 1994 interview is exogenous. The assumption may be violated for respondents who are lost to the survey before 1994 to the extent that attrition from the panel is correlated with changing labor force status.

right-censored time period becomes

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

This is simply the probability that no events took place between t_{i,n_i} and c_i.

After integrating out the random effect, V_i, the contribution to the likelihood for person i is (using a Stieltjes integral[11])

$$L_i = \int_{-\infty}^{\infty} L\big(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i), v_i\big)\, dA^*(v), \tag{4}$$

where A^* is the marginal distribution of V_i at time $T_{i,0}$ in the population.

Following common practice in this literature, we assume that V_i takes only a small number of different values.[12] These values are often thought of as different "types" of persons. Let the discrete support of V_i be $\{\nu_1, \ldots, \nu_M\}$ and let the corresponding probability function be $\pi_m = \Pr(V_i = \nu_m)$. Then (4) becomes

$$L_i = \sum_{m=1}^{M} L\big(\mathbf{y}_i(t_{i,n_i}, s_{i,n_i}), c_i|\mathbf{y}_i(t_{i,0}, s_{i,0}), \mathbf{x}_i(c_i), \nu_m\big)\pi_m. \tag{5}$$

Allowing for more types yields a more flexible distribution of unobserved heterogeneity. In practice, researchers have usually estimated models with a small number of types (two or three). In the current version of the model we have four types.

3.3 Parameterization

In general, the transition intensities may depend on the entire path of the exogenous variables, $\mathbf{X}_i(\cdot)$. However, we assume that $X_i(\cdot)$ is sufficiently rich that only contemporaneous values affect the transition intensities. This assumption is standard in the literature and

[11] The Stieltjes integral allow for both discrete and continuous V_i. If V_i is continuous, the integral can be written in the more familiar form $\int(\cdots)a^*(v)\,dv$, where a^* is the density corresponding to A^*. The discrete case is given in (5).

[12] Our specification is considerably more general than the one- or two-factor loading models used by for example Gritz (1993), Bonnal, Fougère, and Sérandon (1997), and D'Addio and Rosholm (2002a).

can usually be satisfied by including appropriate state variables in $X_i(\cdot)$.

In practice, it is not possible to condition on every aspect of the past history, and we summarize the effects into four sets of variables: the number of previous spells in each labor force state (i.e. spells before the current spell), the type of the previous spell (i.e. the spell immediately before the current spell), duration of the previous spell by state, and the cumulative duration in each state since leaving secondary school. Of course, our model also includes elapsed time in the current spell to capture recent history.[13] Let $Y_i(t)$ denote the vector of endogenous state variables at time t for person i. Note that these variables are time-varying, but constant within each spell.

The vector of unobserved heterogeneity, V_i, is assumed have six components, one for each transition. Thus, each point in the distribution of V_i, that is, $\{\nu_1, \ldots, \nu_M\}$, is a six-dimensional vector. We make no prior assumptions about the location of the support points. In particular, the correlation between components representing different transitions is not restricted. In this paper, we assume $M = 4$, which results in 27 unknown parameters the distribution of V_i. Of these, 24 relate to the support and 3 to the probability function.

We model the transition intensities using a proportional hazards model with Weibull baseline intensities.[14] Specifically, the conditional transition intensity is

$$h(t, s|\mathbf{y}(\tilde{t}, \tilde{s}), \mathbf{x}(t), v) = \alpha_{\tilde{s},s}(t - \tilde{t})^{\alpha_{\tilde{s},s}-1} \exp\big(x(t)'\beta_{\tilde{s},s} + y(\tilde{t}, \tilde{s})'\delta_{\tilde{s},s} + z(v)'\nu_{\tilde{s},s}\big),$$
$$t \geq \tilde{t},\ s \neq \tilde{s}, \quad (6)$$

where $z(v) = \big(1(v = \nu_1), \ldots, 1(v = \nu_M)\big)'$ is an M-dimensional vector indicating the support point and $\nu_{\tilde{s},s} = (\nu_{1,\tilde{s},s}, \ldots, \nu_{M,\tilde{s},s})'$ where $\nu_{m,\tilde{s},s}$ denotes the component of ν_m which represents the transition from $\tilde{s}$ to s. We estimate the unknown parameters, $\alpha_{\tilde{s},s}$, $\beta_{\tilde{s},s}$, $'\delta_{\tilde{s},s}$, $\nu_{\tilde{s},s}$ and $\pi_1, \ldots, \pi_M$, by the method of maximum likelihood.

[13] Heckman and Borjas (1980) distinguishes between duration dependence, lagged duration dependence and occurrence dependence.

[14] See e.g. Kalbfleisch and Prentice (1980, chapter 7).

4 Estimation results and fit of the model

4.1 Estimated transition intensities

The number of estimated parameters is large (423) since we include a large number of explanatory variables and each variable affects six transition intensities. The main estimation results are shown in table 2, which spans several pages.[15] In this section we discuss the estimated effects of the explanatory variables on the six transition intensities. We assess the implications of the estimates for time spent in each labor force state in section 5.

Consider first the effect of elapsed time in the current spell or duration dependence. This is measured by $\ln \alpha$ which has a benchmark value of zero. For transition out of employment the estimates of $\ln \alpha$ are negative and large, which means that employment spells become less likely to end as time goes by. This is not unexpected as long-term employment relationships indicate good matches between employees and employers; hence the longer the job tenure the smaller the probability of the job ending. Our estimates are closer to zero for the transitions from being out of the labor force and for transitions from unemployment. Still the effects are significantly different from zero. Transitions into employment are more likely the longer the person remains unemployed. This is contrary to what is usually found for the general population, however it is consistent with the findings for youth in other countries (e.g. D'Addio and Rosholm, 2002a).[16] Also it is interesting that the intensity declines with time spent out of the labor force. The finding of opposite signs in duration dependence implies that unemployment and out of the labor force are different states and should be modeled separately.[17] Finally, our estimates show that transitions between unemployment and out of the labor force increase with the duration

[15]In addition to the variables listed in the table, the model also includes dummies for state, calendar month, month in which a qualification was obtained and each of the two adjacent months, rural/urban areas (three dummies), two variables capturing breaks in the unemployment series in certain regions prior to 1992, and 27 unknown parameters the distribution of the random effects. These parameters are not shown to save on space.

[16]As mentioned by D'Addio and Rosholm, this could be evidence of a declining reservation wage among the young cohorts.

[17]There is an ongoing debate about the distinct nature of these two states given the sometimes frequent transitions between them amongst young people. It is common to combine unemployment and out-of-labor-force into spells of nonemployment. See Ryan (2001) for a discussion.

in the origin state. This suggests interesting dynamics in search behavior; Doiron and Gørgens (2005) looked at this issue in more detail.

The remaining estimates represent approximate proportional effects of each explanatory variable on the transition intensities. We begin with the effects of previous labor market outcomes.[18] It is important to keep the interrelation between the variables in mind when interpreting the results. The estimates for the cumulative previous number of spells indicate the effect of having had an additional spell in the past, holding the total time in each state constant. Essentially these variables are capturing the difference between having had many short spells as opposed to a few long spells. The estimates for cumulative previous duration indicate the effect of an additional month spent in a particular state in the distant past, holding the number of spells in each state constant. That is, the effect of a spell of a given type being one month longer. The variables for type of previous spell capture the influence of recent history, over and above the effects captured by the cumulative variables. These effects must be added to the cumulative effects to obtain the total impact of a previous spell.

There is a large amount of state dependence present in these processes, especially from previous experiences in the current state. This is evident from the movements in and out of employment. The hazard out of employment is reduced by around 20% with each previous spell in employment. The beneficial effects of employment are also found in the transitions involving the other states. Person with previous employment spells are more likely than those without to transit from unemployment and out of the labor force into employment. In addition, previous employment spells reduce the transition from unemployment to out of the labor force. This further increases the likelihood of future employment, since transitions from unemployment to employment are more likely than transition from begin out of the labor force to employment. In brief, the more frequently a person experiences employment spells, the more likely that person is to become employed again, the less likely that person is to move out of employment and the less likely he/she is to not search when not employed. It is worth noting that since our model includes

[18] Analysis time is measured in days, and previous durations are measured in months.

random effects, these findings cannot be interpreted simply as coming from unobserved heterogeneity, but rather we must look to interpretations which are based on the effects of experience. For example, a possible explanation for the lower transition intensities out of employment is that people learn from past employment experiences and become better at generating offers from suitable employers, possibly through a more extensive network of contacts.

There are notable differences between the effects of previous employment versus those of the non-employment states. Whereas employment spells in the recent past (the previous spell) increase the transition intensity into employment the same is not true of the other states. Exits into unemployment from out of the labor force are less likely if the person was unemployed before dropping out of the labor force. This could indicate discouraged workers who are unlikely to resume search unless exogenous factors change or other shocks occur. There is also further evidence to support the separate treatment of unemployment and out of the labor force. For example, previous spells of unemployment increase the transition intensity out of employment and into unemployment, but do not have any effect on transitions from employment out of the labor force.

Most of the state dependence we find in these results stem from the number of past spells, rather than the time spent in each state. This could be due to the presence of many short spells in the histories of these young people. Experience in each labor force state takes the form of more spells rather than longer spells. Although the effects are small, there is evidence of positive lagged duration dependence in unemployment in that longer cumulative previous duration in unemployment increases the transitions out of current unemployment. The same is true for spells out of the labor force and employment.

We now turn to the effects of the labor market variables. We consider two sets of variables: the unemployment rate and the year dummies. The transition intensities are generally higher in 1989 and 1990 than in 1991 and the following years, reflecting the effect of the recession which developed in 1991. Interestingly, the transition intensity from unemployment to out of the labor force is relatively low in 1992 and 1993. This suggest that jobless persons are more likely to search for work in recessions, a result also found by Doiron and Gørgens (2005). It is also interesting to note that the employed are less likely to leave their jobs during the recessionary periods. Perhaps the increased layoffs are dominated by the reduction in quits by workers who are worried about finding another job in the slack labor market.[19]

Local unemployment rates have expected and statistically significant effects. The transition intensities into employment from both unemployment and from being out of the labor force are lower the higher the unemployment rates, and the transition intensity from employment to unemployment is higher. Interestingly, the transition intensity from employment out of the labor force is lower the higher the local unemployment rates. The combined effect on the transition out of employment is nil.

The next part of table 2 concerns the effects of student status and highest qualification obtained. Part-time students are more likely than nonstudents to become employed if currently out of the labor force, and much less likely to leave employment if currently employed. In other words, part-time students are more likely to want a continued attachment to the workforce. Also as expected, full-time students are less likely to join the labor force if currently out, and more likely to drop out if currently in.[20] Apprentices and trainees are more likely to move into employment from either of the two alternatives. Also, once employed, they are more likely to stay employed. The transition from schooling to employment appears to be much smoother and faster for people in these training programs. This is consistent with results of cross-country comparisons, in particular evidence involving the US and Germany (e.g. Ryan, 2001). Additional results on the magnitude of these effects are presented in section 5.

Previous work on aggregate statistics shows a strong positive relationship between education and employment probabilities for Australia and other OECD countries (e.g. Blanchflower and Freeman, 2000). The effects of highest qualification obtained in this paper are complex, but generally support that finding. Persons who have not (yet) completed year 12 have lower transition intensities than those who have, except for the transition

[19]This is consistent with the theory proposed by Hall (2005) for the general population that during slack periods, unemployment rises mainly due to low hiring rates rather than increased separations.

[20]The results for people doing multiple studies are mostly similar to those for full-time students, but they are a very small group.

from employment to unemployment which is higher. A trade certificate significantly increases the transition from unemployment to employment. Other certificates have similar effects on the transition out of unemployment, and in addition increase both transitions from being out of the labor force to unemployment and to employment. Persons with diplomas and degrees have higher transition intensities from being out of the labor force, and generally higher transition intensities from unemployment to employment.

The estimated effects of sex and marital status are as expected. Unpartnered females out of the labor force are less likely to join than males. If employed, however, they are also less likely to exit, implying that females are more likely to remain employed the longer they have already been employed. Partnered females are even less likely than everyone else to join the labor force, if not in, and much more likely to leave the labor force, if currently in. Partnered males are less likely to move from employment to out of the labor force than unpartnered males, but there are no statistically significant effects of partnering on other intensities.

The estimates of the effects of age show that persons younger than 18 generally have higher transition intensities than 18-year-olds (the omitted group). Other significant effects of age are found in the transitions out of employment. Briefly, persons older than 18 have lower probabilities of leaving employment. These patterns are consistent with the notion that young people shop around for suitable employment and eventually settle down into stable employment. The estimated effect of language background shows, not surprisingly, that those with a language background other than English are less likely to join the labor force and less likely to move from unemployment to employment than persons from an English-speaking background. However, there seems to be little difference in transition intensities for those who are employed. In other words, we find evidence that language barriers exist when entering the labor market and in finding a job. Once people are employed, their transitions are indistinguishable regardless of their language group.

Finally, we mention that we have also estimated a model without random effects. As expected, the estimated state dependence is much stronger in this model. In particular, there is significant negative duration dependence in all six transition probabilities. The differences between the two models indicate that it is important to allow for unobserved heterogeneity when estimating the effects of previous labor market outcomes.

4.2 Model fit and simulation methods

Before proceeding, it is useful to check that the model fits the main characteristics of the data. There is no simple test available for this purpose, so instead we use an informal check based on simulation. We first describe the simulation exercise and then discuss the fit of the estimated model.

For a given set of exogenous variables, simulations are done dynamically over time. The first step is to draw a random value of the random effect from the estimated distribution of types and weights. The second step is to determine the labor force state immediately after leaving secondary school. This is done using the marginal distribution of first states. Then a transition time and a destination state are drawn in accordance with the time path of the exogenous variables, the random effect (now fixed), and the estimated model. After the transition takes place, the endogenous explanatory variables representing past history are updated to reflect the type and the duration of the first spell. Then the second transition time and destination state are drawn using updated values for the endogenous variables. This process is continued over the period of observation of the exogenous variables. The end result of this process is a random history which is statistically compatible with the given path of the exogenous explanatory variables. Most of the simulation results we present in this paper are averaged over the distribution of unobserved heterogeneity.

In order to assess how well the estimated model fits the data we simulate a single realization for each person in the analysis sample and compute summary statistics for the simulated outcomes. Since we are averaging over a large number of people, it suffices to draw a single history for each person — the randomness present for each person is averaged out over the entire sample.[21] A comparison of table 3 with table 1 shows that the model generally fits the data well, although the incidence of all transitions is slightly overpredicted.[22] Overall, we are satisfied that the model fits reasonably well.

[21] Averaging over two realizations for each person yields virtually identical results.

[22] We suspect that the assumption that distant and very distant histories have identical influence on

5 Predictions and policy simulations

The estimates discussed in the previous section exhibit strong effects of previous labor market experiences as well as significant effects of unobserved heterogeneity. This implies that the medium- to long-term effects of policy changes may differ markedly from the short-term effects. In this section we investigate the implications of our findings for three broad and hypothetical policy changes: a successful job search program, a training program and a subsidized employment program. However, before turning to these policy experiments, we present simulation results which confirm the importance of education and labor market conditions for youth employment and unemployment outcomes. These issues have been identified as crucial in understanding youth labor market outcomes in recent papers (e.g. Bonnal, Fougère, and Sérandon, 1997; Blanchflower and Freeman, 2000; Korenman and Neumark, 2000).

5.1 Effects of educational choice

In section 4, we discussed how the transition intensities depend on student status and qualifications. In this section, we investigate how time spent in the three labor force states is affected by educational choices. These quantities are computed using the simulation method described in the previous section. Expected outcomes are computed for representative persons who are unpartnered, from an English-speaking background and who turn 16 at the exact time they complete grade 10.[23] The external world is stationary with no variation in transition intensities across time and space. That is, local unemployment rates, yearly and monthly calendar effects, and the regional variables are fixed at their (time-weighted) mean values. The age, educational variables and the history of the each of the hypothetical persons are updated over time as appropriate.

We consider nine educational choices. The predicted outcomes are summarized in tables 4 and 5, which show the expected number of days spent in each labor force state

present transition intensities may contribute to the overprediction of transitions and intend to investigate this issue in future work.

[23]The fraction of total time under observation accounted for by partnered persons is less than 2% for males and less than 6% for females. The fraction of time accounted for by persons with a language background other than English is less than 10%.

by age. Figures 1 and 2 show unemployment rates calculated as time unemployed divided by time unemployed or employed.

With few exceptions, the days spent in employment increase with age, for all educational paths and for both males and females. Ignoring for the moment the case of apprentices, figures 1 and 2 show the opposite trend in the unemployment rates. There is a large variation in annual days spent in employment within age groups and across educational groups. Consider for example persons age 24 (our representative persons have finished their human capital investments by this age). For males, annual days spent in employment vary between 339 and 344 per year for educational paths with post-secondary school qualifications. For those with only year 12 or lower, the number of employment days varies from 286 to 325 per year. The difference in outcomes between those with and without post-secondary qualifications is more marked for males than females, as women with secondary schooling only have higher employment rates than their male counterparts. The number of days spent in unemployment and out of the labor force show similar patterns, with the exception of full-time students who spend more time out of the labor force during their educational investments.

Apprentices have the highest employment rates among all nine education paths up to age 24. At 24, the time spent in employment by apprentices is similar to that of those with tertiary degrees. The apprentices seem to have an easier time securing employment throughout their youths.

5.2 Effects of labor market conditions

One of the advantages of the AYS is the fact that the survey period spans periods of tight labor markets (1989–1990), a recession (1991–1992) and recovery (1993–1994).[24] To illustrate the impact of the state of the economy on youth labor market outcomes, we simulate a counterfactual outcome for each person in the AYS sample under the assumption that the 1991 recession did not happen. That is, we assume that the yearly calendar effects are all identical to 1989, and we assume that the local unemployment

[24] See e.g. Doiron and Gørgens (2005) for statistics on aggregate vacancy and unemployment rates over the period.

rate is constant at the (time-weighted) average for 1989.[25] Sex, age, marital status, educational choices, geographical and regional effects etc. are all as observed in the AYS analysis sample.

The results are summarized in table 6 which shows that the AYS respondents spent about 16% of their combined time in unemployment. Had the recession not happened, these persons might only have spent 10% of the time unemployed. This is a reduction of almost 40%. As we have noted elsewhere, more young Australians seem to search during recessions. The model therefore predicts a slight increase in the proportion of time spent out of the labor force, if the recession had not occurred.

While tentative, this simulation exercise provides an estimate of the size of the impact one can expect from variations in labor market conditions. Given that the effects are large and that state dependence plays important role, the concern that young people who enter the market in times of high unemployment may be disadvantages and have difficulty catching up seems warranted.

5.3 Public policy experiments

The model estimated in this paper has been designed to provide detailed estimates of state dependence, and the controls for observed and unobserved heterogeneity are extensive. Although it has not been designed to estimate effects of any specific government program, it can be used to assess the magnitude of the effects of general policy experiments. In comparison with many program evaluation studies, an advantage of our model is the ability to predict over the medium to long term. For example, a government program which is successful in finding employment for the unemployed may not be cost effective if the newly employed people are not able to hold on to their jobs and re-enter the unemployment queue after a short period of time. Conversely, the value of the program may be underestimated if becoming employed reduces the chance of having additional future unemployment spells.

Tables 7 and 8 show outcomes of simulations illustrating the effects of three stylized

[25] For simplicity, we assume that the rate is the same in all regions.

policy interventions on durations in the three labor force states. The simulations are carried out for three of the representative persons described in section 5.1, namely, the persons with low (year 10), medium (year 12), and high education (year 12 plus a two-year diploma). The results are presented as the expected annual number of days spent in each state, averaged over the ages of 20 to 24. The tables also show the average participation rate (days unemployed plus days employed divided by 365) and the average unemployment rate (days unemployed divided by the number of days of participation). In each table, panel A presents results for the model described previously, while panel B shows results shows equivalent results based on a model without the history variables. (That is, the coefficients of the history variables are set to 0 and the model is re-estimated.) Comparing the two panels shows the role of state dependence.

The rows labeled "base" shows expected outcomes predicted by the models without introducing new policy interventions, and hence under the policies in effect during the sample period. In the first policy experiment, any unemployed person is given a job after 90 days of unemployment, and there is no limit on the number of times a person can participate in the program. The job is indistinguishable from other jobs in the sense that transition intensities out of employment are the same and accumulated employment is the same. This setup can be compared to a successful job search program for those who are medium-term unemployed.

The results are represented by the row labeled "Successful job search" and are shown in the form of differences from the base case. Focussing on panel A and the group with low education, the effects are large: days in employment increase by 50 to 60 per year, days spent unemployed fall by 40 to 50, and days out of the labor force also fall by 10. Note that these are expected effects, and in many realizations the representative person does not experience unemployment spells lasting 90 days. That is, the tables show "average treatment effects", not the "treatment effect on the treated". The effects on males are greater, because females at the bottom of the education distribution have higher employment rates than males and are less likely to benefit from this program. The net effect on the participation rate of increased employment and reduced unemployment is an increase of 3 percentage points. The unemployment rate falls by around 14 percentage points. For those with higher education levels, the effects are similar, but smaller in magnitude.

These effects represent the combination of the initial curtailment of the spell of unemployment (and the entry into a job) and the predicted future impact of having an additional employment spell. Panel B shows the predicted impacts from the model without state dependence. The effects on time spent in employment and out of the labor force are much smaller. For the lowest education group, the increase in the participation rate for males is now 1 percentage point compared to 3. Also the effect on unemployment is slightly larger for males. The effect of state dependence can be described as a substantial effect from the addition of a spell of employment and a smaller effect from the curtailed duration of unemployment. The former increases future durations of employment as well as transitions into employment. The latter causes a small increase in the duration of future unemployment spells for males.

The second policy experiment is more modest: as before all unemployed persons are given a job after 90 days of unemployment, but now this job ends after 30 days. When the job ends, the person rejoins the group of unemployed. After the person is moved back into unemployment, the job search clock is restarted and the person's history is updated to reflect an additional spell of employment experience of 30 days. During the 30-day employment period, transitions out of the labor force are governed by the estimated transition intensity from employment to out of the labor force, but transitions to unemployment are prohibited. This is allowing the person to quit the program before the full 30 days. Again there is no limit to how many times a person can participate in the program. This setup can be viewed as a subsidized employment program, where the subsidized job is short but it is considered as a typical job in providing employment experience. The experiment is labeled "Subsidized job (30 days)" in tables 7 and 8.

Consider panel A. While smaller than the effects of giving the unemployed a typical job, the changes in times spent in the three labor force states are still quite substantial. Each person in the low education group spends on average 25–30 days more in employment per year. The corresponding reduction in nonemployment is almost equally divided between time in unemployment and time out of the labor force. Again note that these are expected effects, averaged over all possible realizations of the random process, including those were the intervention never occurs. A comparison with panel B shows large differences in the results of the two models. This program works mainly through the addition of a short spell of employment and as seen above, the greatest effects are found in the experiences coming from the number of spells of employment in one's past.

The third policy experiment consists of a 30-day training program into which persons are enrolled after 90 days of unemployment. Here we adopt a worse-case scenario: trainees are still unemployed when finishing the training program, there is no effect on future employment probabilities directly coming from the program, and the 30 days of training are viewed as unemployment. Accordingly, after finishing the program the unemployment clock is not reset and the time spent in the program is subsequently treated as time spent unemployed. Thus, persons participating in the program are nominally worse off, because they are prevented from accepting a job during the training period. This experiment is labeled "30 days training (pessimistic)" in tables 7 and 8.

The effects of this last program are generally opposite in sign to the previous two experiments. This is not surprising, since the main effect is now to prevent some individuals from finding employment during the training. Time in employment is reduced and time in unemployment and out of the labor force is increased. When comparing the two panels of tables 7 and 8, we find that allowing for state dependence can provide greater or smaller effects. The main effect from the history variables is now in the form of increased time in unemployment. This tends to reduce future spells of unemployment but it can also reduce transitions into employment from out of the labor force. These effects are complex, and not large.

6 Concluding remarks

In this paper, we extend the literature on youth labor market experiences by modeling the effects of previous labor market experience in a general and flexible manner. The model uses transition data for young Australians and incorporates observed and unobserved heterogeneity along with state dependence. Furthermore, we consider three distinct labor force states (employment, unemployment, and out of the labor force), rather than the customary two states (employment and nonemployment).

We find substantial state dependence in all three states, mostly in the form of positive dependence from previous spells in the same state. More specifically, a larger number of past spells in a particular state increases the probability of entry and reduces exits out of that state. This is especially important for employment. It is interesting that state dependence for young persons takes the form of dependence from the number of spells rather than the time spent in each state. This seems to support a model of job shopping (e.g. Topel and Ward, 1992). It also suggests that positive effects from greater stability in early labor market experiences through later wage gains (e.g. Neumark, 2002) could be counteracted by worse matches (shorter jobs) from less "job shopping".

The state of the labor market varied substantially over the period of study (1989–1994) and local unemployment rates are included in the analysis. Simulations are used to show the very large impact of labor market conditions on youth unemployment rates. Simulations are also used to illustrate the importance of educational attainments over and above the labor market experiences of youth. These results are not unexpected, and it is reassuring to see that education and the business cycle continue to be important in a dynamic model with state dependence.

The presence of substantial state dependence also has important implications for the evaluation of labor market policies. The usual short-term evaluations (i.e. before-and-after comparisons) are likely to underestimate the total impact of policy intervention. We address this issue by using the estimated model to simulate the effects on time spent in employment and unemployment over a four-year period following the implementation of three stylized labor market policies: a successful job search program, a short-term subsidized employment spell, and an ineffective training program. In each case, the program affects a person who has been unemployed for 90 days. In order to assess the contribution of state dependence we compare the simulation results with similar results obtained from a model without state dependence. The comparison shows that the effects of state dependence are large, especially under the program which adds short spells of employment to the history of those who tend to have long spells of unemployment. In practice, the effects are sufficiently large, especially for young people with poor education, that programs which have been found to be ineffective in the short term may be considerably beneficial in the medium term.

References

Arulampalam, W., A. L. Booth, and M. P. Taylor (2000). Unemployment persistence. *Oxford Economic Papers 52*(1), 24–50.

Blanchflower, David, G. and R. B. Freeman (2000). The declining economic status of young workers in OECD countries. In G. Blanchflower, David and R. B. Freeman (Eds.), *Youth Employment and Joblessness in Advanced Countries*, NBER Comparative Labor Markets Series, pp. 19–56. Chicago: University of Chicago Press.

Bonnal, L., D. Fougère, and A. Sérandon (1997). Evaluating the impact of French employment policies on individual labour market histories. *Review of Economic Studies 64*, 683–713.

D'Addio, A. C. and M. Rosholm (2002a). Labour market transitions of french youth. mimeo, University of Aarhus. revised 2002.

D'Addio, A. C. and M. Rosholm (2002b). Left-censoring in duration data: Theory and applications. Working paper 2002-5, Department of Economics, University of Aarhus, Denmark.

Doiron, D. and T. Gørgens (2005). Search over the business cycle: The case of young Australians. Mimeo, School of Economics, University of New South Wales and Research School of Social Sciences, Australian National University.

Ellwood, D. T. (1982). Teenage unemployment: Temporary blemish or permanent scar? In R. B. Freeman and D. A. Wise (Eds.), *The Youth Labor Market Problem: Its Nature, Causes and Consequences*, pp. 349–390. Chicago: University of Chicago Press.

Gregg, P. (2001). The impact of youth unemployment on adult unemployment in the ncds. *Economic Journal 111*(475), F626–F653.

Gritz, R. M. (1993). The impact of training on the frequency and duration of employment. *Journal of Econometrics 57*(1–3), 21–51.

Hall, R. E. (2005). Employment efficiency and sticky wages: Evidence from flows in the labor market. Technical report, National Bureau of Economic Research Working Paper No. 11183.

Ham, J. C. and R. J. LaLonde (1996). The effect of sample selection and initial conditions in duration models: Evidence from experimental data on training. *Econometrica 64*(1), 175–205.

Heckman, J. J. and G. J. Borjas (1980). Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica 47*, 247–283.

Kalbfleisch, J. D. and R. L. Prentice (1980). *The Statistical Analysis of Failure Time Data*. New York: Wiley.

Korenman, S. and D. Neumark (2000). Cohort crowding and youth labor markets: A cross-national analysis. In G. Blanchflower, David and R. B. Freeman (Eds.), *Youth Employment and Joblessness in Advanced Countries*, NBER Comparative Labor Markets Series, pp. 58–106. Chicago: University of Chicago Press.

Neumark, D. (2002). Youth labor markets in the United States: Shopping around vs. staying put. *Review of Economics and Statistics 84*(3), 462–482.

Ridder, G. (1986). An event history approach to the evaluation of training, recruitment and employment programmes. *Journal of Applied Econometrics 1*(2), 109–126.

Ryan, P. (2001). The school-to-work transition: A cross-national perspective. *Journal of Economic Literature 39*, 34–92.

Topel, R. H. and M. P. Ward (1992). Job mobility and the careers of young men. *Quarterly Journal of Economics 107*(2), 439–479.

Wolpin, K. I. (1987). Estimating a structural search model: The transition from school to work. *Econometrica 55*, 801–817.

Table 1: Data overview

	Origin state			Total
	O	U	E	
Number of histories				
Total				5439
Time under observation (days)				
Total	921545	754913	3099619	4776077
Average per person	169	139	570	878
Maximum history length				2111
Number of spells				
Total	6432	7066	9427	22925
Right-censored	744	846	3849	5439
Uncensored	5688	6220	5578	17486
Destination state				
O	0	1792	2735	4527
U	3038	0	2843	5881
E	2650	4428	0	7078
Duration quantiles (days)				
10%	7	7	14	
20%	14	14	41	
30%	28	28	76	
40%	48	41	134	
50%	70	61	273	
60%	119	90	517	
70%	181	131	1033	
80%	272	202	1723	
90%	433	328	2048	

Legend: O: out of the labor force; U: unemployed; E: employed. *Notes:* Quantiles based on the Kaplan-Meier product limit estimator.

Table 2: Parameter estimates

	O→U	O→E	U→O	U→E	E→O	E→U
Elapsed duration						
$\ln \alpha$	0.10*	−0.07*	0.11*	0.07*	−0.15*	−0.23*
	0.02	*0.02*	*0.03*	*0.02*	*0.02*	*0.02*
Cumulative previous history (base: persons with no history)						
Cum prv O spells	−0.24*	−0.23*	0.11*	−0.06	0.18*	−0.08*
	0.04	*0.04*	*0.05*	*0.04*	*0.04*	*0.05*
Cum prv U spells	0.14*	−0.05	−0.31*	−0.23*	0.01	0.12*
	0.04	*0.05*	*0.05*	*0.03*	*0.05*	*0.05*
Cum prv E spells	0.00	0.16*	0.02	0.16*	−0.25*	−0.18*
	0.04	*0.04*	*0.04*	*0.03*	*0.06*	*0.05*
Cum prv O duration	0.04*	0.04*	−0.01	−0.01	0.01*	0.01
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Cum prv U duration	0.00	−0.01	0.06*	0.02*	−0.02*	0.02*
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Cum prv E duration	−0.01	0.01	0.00	0.01*	0.01*	0.01*
	0.01	*0.01*	*0.01*	*0.00*	*0.01*	*0.00*
Previous spell (base: persons with no previous spell)						
Previous O spell			−0.08	0.20*	0.52*	−0.09
			0.10	*0.07*	*0.08*	*0.09*
Previous U spell	−0.22*	0.62*			0.12	0.68*
	0.08	*0.09*			*0.08*	*0.08*
Previous E spell	0.07	0.24*	−0.45*	0.13*		
	0.07	*0.08*	*0.11*	*0.07*		
Previous O duration			0.00	−0.01*	0.02*	0.01
			0.01	*0.01*	*0.01*	*0.01*
Previous U duration	0.00	−0.03*			0.00	0.02*
	0.01	*0.02*			*0.02*	*0.01*
Previous E duration	0.01*	0.00	0.00	−0.01*		
	0.01	*0.01*	*0.01*	*0.00*		
Local unemployment rate						
U-rate (per 1000)	0.01	−0.08*	−0.02	−0.16*	−0.06	0.05
	0.04	*0.04*	*0.05*	*0.03*	*0.04*	*0.04*

Continued next page.

Table 2 continued

	O→U	O→E	U→O	U→E	E→O	E→U
Calendar year (base: 1991)						
Year 1989	0.34*	0.53*	1.11*	0.56*	0.62*	0.05
	0.14	*0.13*	*0.16*	*0.12*	*0.13*	*0.15*
Year 1990	0.25*	0.25*	0.39*	0.32*	0.20*	−0.06
	0.07	*0.08*	*0.10*	*0.07*	*0.08*	*0.08*
Year 1992	0.02	−0.04	−0.13	0.03	−0.08	−0.11
	0.06	*0.07*	*0.08*	*0.06*	*0.07*	*0.07*
Year 1993	−0.01	0.04	−0.19*	0.07	−0.07	−0.18*
	0.07	*0.08*	*0.10*	*0.06*	*0.08*	*0.07*
Year 1994	0.11	0.18*	−0.06	0.21*	−0.12	−0.29*
	0.08	*0.09*	*0.11*	*0.07*	*0.08*	*0.08*
Student status (base: nonstudent)						
Part-time study	−0.09	0.36*	−0.20	−0.05	−0.61*	−0.57*
	0.13	*0.14*	*0.15*	*0.08*	*0.12*	*0.10*
Full-time study	−1.04*	−0.80*	1.15*	−0.09	0.57*	−0.47*
	0.07	*0.07*	*0.08*	*0.06*	*0.06*	*0.07*
Apprentice/Trainee	−0.22	1.94*	1.34*	1.68*	−1.62*	−1.72*
	0.21	*0.11*	*0.21*	*0.10*	*0.13*	*0.12*
Multiple studies	−0.70*	−0.19	0.48*	0.22*	0.24	−0.69*
	0.15	*0.14*	*0.20*	*0.12*	*0.15*	*0.20*
Highest qualification obtained (base: year 12)						
Education unknown	0.13	0.56*	0.57	−0.10	−0.03	1.37*
	0.57	*0.30*	*0.44*	*0.69*	*0.54*	*0.36*
Year 10	−0.05	−0.39*	−0.40*	−0.56*	−0.22	0.44*
	0.15	*0.16*	*0.15*	*0.09*	*0.14*	*0.12*
Year 11	0.18*	−0.03	−0.28*	−0.29*	−0.21*	0.30*
	0.10	*0.10*	*0.11*	*0.07*	*0.09*	*0.08*
Other post-SS	0.59*	0.48*	−0.15	−0.08	0.01	0.15
	0.12	*0.14*	*0.15*	*0.09*	*0.12*	*0.11*
Other certificate	0.61*	0.52*	−0.07	0.31*	−0.24*	−0.02
	0.10	*0.12*	*0.13*	*0.08*	*0.10*	*0.08*
Trade certificate	0.28	0.25	0.18	0.27*	−0.33	0.03
	0.26	*0.25*	*0.24*	*0.13*	*0.21*	*0.15*
Diploma	0.37*	0.56*	−0.06	0.29*	−0.18	−0.49*
	0.19	*0.19*	*0.24*	*0.16*	*0.16*	*0.17*
Bachelor or higher	0.49*	0.97*	0.45*	0.79*	−0.22	0.14
	0.18	*0.16*	*0.25*	*0.14*	*0.20*	*0.18*

Continued next page.

Table 2 continued

	O→U	O→E	U→O	U→E	E→O	E→U
Sex and marital status (base: male, unpartnered)						
Female, single	−0.07	−0.22*	0.06	0.01	−0.27*	−0.31*
	0.05	*0.05*	*0.07*	*0.05*	*0.05*	*0.05*
Male, partnered	0.13	0.06	−0.14	−0.10	−0.40*	−0.17
	0.23	*0.26*	*0.27*	*0.15*	*0.20*	*0.16*
Female, partnered	−0.86*	−1.06*	0.71*	0.05	0.28*	0.05
	0.15	*0.17*	*0.13*	*0.10*	*0.11*	*0.12*
Age (base: age 18)						
Age $\leq$ 16	0.16	0.45*	0.46*	0.56*	0.07	0.17
	0.14	*0.14*	*0.16*	*0.10*	*0.14*	*0.11*
Age 17	−0.07	0.03	0.07	0.20*	0.07	−0.07
	0.07	*0.07*	*0.08*	*0.05*	*0.06*	*0.06*
Age 19	−0.08	0.06	0.06	−0.04	−0.24*	−0.18*
	0.06	*0.07*	*0.08*	*0.05*	*0.06*	*0.07*
Age 20	−0.12	−0.03	0.00	−0.08	−0.40*	−0.30*
	0.09	*0.10*	*0.11*	*0.08*	*0.08*	*0.09*
Age 21	−0.17	−0.12	−0.11	−0.13	−0.52*	−0.42*
	0.12	*0.15*	*0.16*	*0.11*	*0.12*	*0.11*
Age 22	−0.24	−0.12	0.03	−0.23	−0.35*	−0.57*
	0.17	*0.19*	*0.21*	*0.15*	*0.15*	*0.17*
Age $\geq$ 23	−0.57*	0.22	−0.36	−0.23	−0.61*	−1.19*
	0.30	*0.34*	*0.43*	*0.25*	*0.25*	*0.30*
Language background (base: English)						
Non-English	−0.38*	−0.71*	0.09	−0.46*	0.14	0.00
	0.08	*0.09*	*0.10*	*0.08*	*0.10*	*0.10*
Log likelihood	−21.38					

Legend: O: out of the labor force; U: unemployment; E: employment; other post-SS: other post-secondary school studies; Cum prv X spells: cumulative number of previous spells in state X; Cum prv X duration: cumulative previous duration of X spells in months; U-rate: unemployment rate. *Notes:* Parameters (except α) are approximately the proportional change in the transition intensities per unit change in the corresponding explanatory variable. Cluster-robust standard errors in italics (in particular, the standard errors remain consistent in the case of correlation between multiple spells for the same person). A star indicates statistical significance at the 5% level using the asymptotic distribution. The model also includes dummies for state, calendar month, month in which a qualification was obtained and each of the two adjacent months, rural/urban areas (three dummies), two variables capturing breaks in the unemployment series in certain regions prior to 1992, and 27 unknown parameters the distribution of the random effects.

Table 3: Model fit

	Origin state			Total
	O	U	E	
Number of histories				
Total				5439
Time under observation (days)				
Total	844708	687397	3243971	4776077
Average per person	155	126	596	878
Maximum history length				2111
Number of spells				
Total	7932	8233	11259	27424
Right-censored	637	661	4141	5439
Uncensored	7295	7572	7118	21985
Destination state				
O	0	2232	3781	6013
U	3687	0	3337	7024
E	3608	5340	0	8948
Duration quantile (days)				
10%	6	7	14	
20%	14	15	40	
30%	25	24	76	
40%	39	35	131	
50%	56	48	217	
60%	81	67	358	
70%	119	94	653	
80%	185	137	1352	
90%	312	231	2055	

Legend: O: out of the labor force; U: unemployed; E: employed. *Notes:* Quantiles based on the Kaplan-Meier product limit estimator. Predictions calculated by simulating a single history for each person in the analysis sample. Simulating two paths for each person yields very similar results.

Table 4: Expected number of days in each labor force state by educational path (males)

Age	16	17	18	19	20	21	22	23	24	20–24
I: Left school after year 10, no further education										
O	55	30	25	22	22	21	23	18	16	100
U	103	108	124	118	111	104	100	76	63	453
E	208	226	216	225	233	241	242	271	286	1273
II: Left school after year 11, no further education										
O		54	25	20	17	16	16	14	12	74
U		96	100	94	83	77	72	52	42	326
E		215	241	251	265	273	277	300	311	1425
III: Left school after year 12, no further education										
O			60	30	24	20	22	18	16	100
U			83	65	56	50	45	32	24	206
E			222	270	286	295	298	315	325	1519
IV: Left school after year 10, 4 years apprenticeship, trade certificate										
O	17	3	2	1	9	12	14	12	11	58
U	14	4	5	4	19	24	24	16	13	96
E	335	358	358	360	337	330	327	337	341	1671
V: Left school after year 12, 1 year full-time study, other certificate										
O			132	30	12	11	11	8	8	50
U			55	67	49	41	36	23	18	166
E			179	268	304	313	318	334	339	1609
VI: Left school after year 12, 2 years part-time study, other certificate										
O			48	18	11	9	11	8	7	46
U			69	45	43	35	32	20	15	145
E			248	302	311	321	323	337	342	1634
VII: Left school after year 12, 2 years full-time study, diploma										
O			133	119	30	14	14	11	10	80
U			52	40	51	36	29	19	14	149
E			180	206	283	316	322	335	341	1597
VIII: Left school after year 12, 3 years full-time study, bachelor degree										
O			133	120	107	23	12	8	7	157
U			52	39	39	44	29	18	14	143
E			180	207	219	298	324	340	344	1525
IX: Left school after year 12, 2 years nonstudent, 1 year full-time study, o.c.										
O			60	30	59	20	11	9	8	107
U			83	65	39	47	36	24	18	164
E			222	270	267	298	318	332	339	1554

Legend: O: out of the labor force; U: unemployed; E: employed. *Notes:* Expected values are computed by averaging over 6000 simulated histories for each educational path, implying simulation standard errors less than 4 days and less than 0.5 percentage points.

Table 5: Expected number of days in each labor force state by educational path (females)

Age	16	17	18	19	20	21	22	23	24	20–24
I: Left school after year 10, no further education										
O	58	31	25	22	21	20	23	20	17	101
U	90	89	100	98	92	86	81	60	50	369
E	217	245	240	245	252	259	261	285	298	1355
II: Left school after year 11, no further education										
O		56	25	19	16	15	16	13	11	71
U		86	83	75	67	62	58	42	33	263
E		222	256	270	282	288	291	310	321	1491
III: Left school after year 12, no further education										
O			62	31	23	19	21	17	15	95
U			75	55	45	40	36	25	19	166
E			227	279	297	306	308	323	330	1564
IV: Left school after year 10, 4 years apprenticeship, trade certificate										
O	19	3	2	1	8	11	13	10	10	53
U	13	3	4	3	14	18	19	13	10	74
E	332	359	359	361	342	336	333	342	344	1698
V: Left school after year 12, 1 year full-time study, other certificate										
O			131	31	12	10	11	8	8	48
U			50	60	42	33	30	19	15	138
E			184	273	311	322	325	338	342	1638
VI: Left school after year 12, 2 years part-time study, other certificate										
O			51	19	10	8	10	7	7	43
U			64	40	36	28	24	15	12	115
E			250	306	319	329	330	343	346	1666
VII: Left school after year 12, 2 years full-time study, diploma										
O			132	117	30	12	13	10	9	74
U			48	36	48	32	26	17	11	134
E			185	212	287	320	327	339	345	1617
VIII: Left school after year 12, 3 years full-time study, bachelor degree										
O			132	118	103	24	11	7	7	152
U			48	34	35	40	25	16	11	126
E			185	213	227	302	329	343	347	1548
IX: Left school after year 12, 2 years nonstudent, 1 year full-time study, o.c.										
O			62	31	55	20	11	7	7	100
U			75	55	32	39	29	19	15	133
E			227	279	279	307	325	339	343	1592

See table 4 for legend and notes.

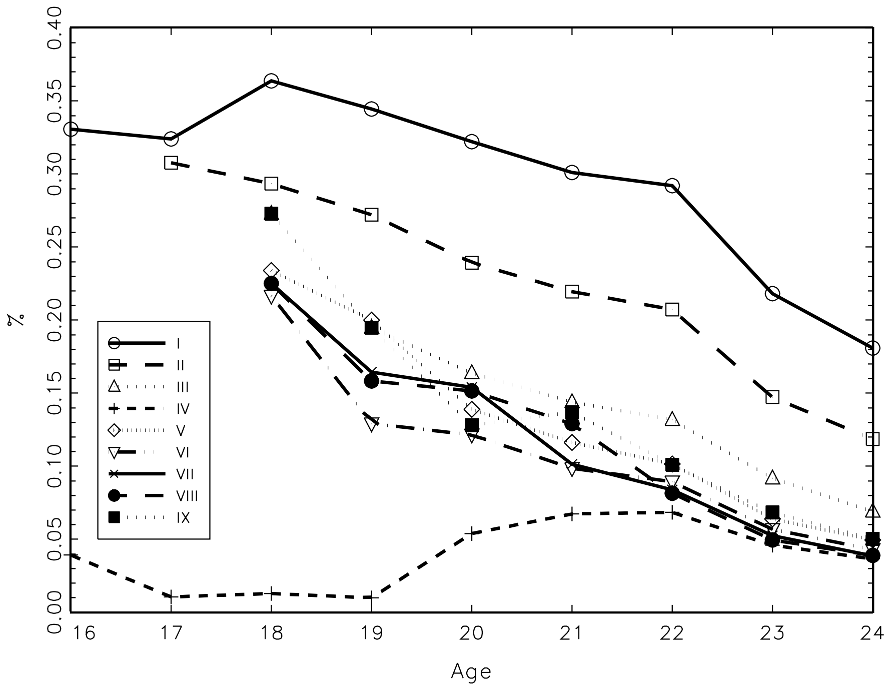

Figure 1: Expected unemployment rates
(males; see table 4)

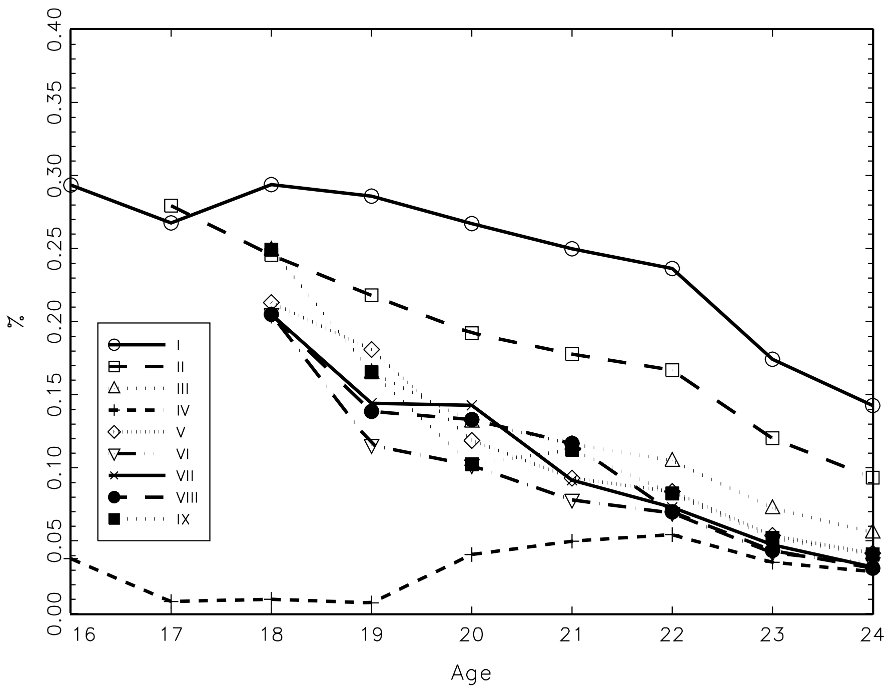

Figure 2: Expected unemployment rates
(females; see table 5)

Table 6: The effect of the recession

	Labor force state			
	O	U	E	Total
Observed outcomes				
Total	921545	754913	3099619	4776077
Percentage	19.3	15.8	64.9	100.0
Predicted outcomes if no recession				
Total	1055971	470916	3249190	4776077
Percentage	22.1	9.9	68.0	100.0

Legend: O: out of the labor force; U: unemployed; E: employed. *Notes:* Predicted outcomes are computed by averaging over one simulated history for each respondent in the analysis sample, setting yearly effects to 1989 and local unemployment rates to their (overall) 1989 time-weighed average.

Table 7: Expected outcomes for policy experiments
(males; average over age range 20–24)

	Days O	Days U	Days E		PR	UR
A. Model with state dependence:						
Left school after year 10, no further education						
Base	19.9	90.5	254.6		94.5	26.2
Successful job search	−9.5	−50.3	59.8		2.6	−14.9
Subsidized job (30 days)	−13.4	−14.2	27.7		3.7	−5.0
30 days training (pessimistic)	2.3	9.3	−11.6		−0.6	2.9
Left school after year 12, no further education						
Base	20.0	41.3	303.7		94.5	12.0
Successful job search	−3.6	−21.4	25.0		1.0	−6.3
Subsidized job (30 days)	−6.9	−4.6	11.5		1.9	−1.5
30 days training (pessimistic)	0.2	2.4	−2.6		−0.1	0.7
Left school after year 12, 2 years full-time study, diploma						
Base	15.9	29.7	319.4		95.6	8.5
Successful job search	−1.6	−16.1	17.7		0.4	−4.6
Subsidized job (30 days)	−3.5	−4.0	7.6		1.0	−1.2
30 days training (pessimistic)	0.3	3.1	−3.4		−0.1	0.9
B. Model without state dependence:						
Left school after year 10, no further education						
Base	21.5	93.6	249.9	94.1	27.2	
Successful job search	−2.6	−49.7	52.3	0.7	−14.6	
Subsidized job (30 days)	0.6	−8.0	7.5	-0.2	−2.3	
30 days training (pessimistic)	−0.5	5.5	−5.0	0.1	1.6	
Left school after year 12, no further education						
Base	22.1	44.1	298.9	94.0	12.8	
Successful job search	−1.4	−21.2	22.6	0.4	−6.2	
Subsidized job (30 days)	0.2	−3.1	2.9	-0.1	−0.9	
30 days training (pessimistic)	−0.7	2.5	−1.8	0.2	0.7	
Left school after year 12, 2 years full-time study, diploma						
Base	15.8	32.9	316.3	95.7	9.4	
Successful job search	−0.7	−15.2	16.0	0.2	−4.4	
Subsidized job (30 days)	0.4	−2.1	1.6	-0.1	−0.6	
30 days training (pessimistic)	−0.1	2.6	−2.5	0.0	0.7	

Legend: O: out of the labor force; U: unemployed; E: employed; PR: average participation rate; UR: average unemployment rate; Base: expected outcomes predicted by model; Real job, 30 days training (pessimistic), 30 days training (optimistic): see main text. *Notes:* Expected values are computed by averaging over 6000 simulated histories for each scenario, implying simulation standard errors less than 4 days and less than 0.5 percentage points. Base shows expected number of days spent in each labor force state and the corresponding participation and unemployment rates, averaged over age range 20–24. The effect of the policy experiments are differences from base (the "average treatment effect").

Table 8: Expected outcomes for policy experiments
(females; average over age range 20–24)

	Days O	Days U	Days E		PR	UR
A. Model with state dependence:						
Left school after year 10, no further education						
Base	20.2	73.7	271.0		94.5	21.4
Successful job search	−9.6	−42.8	52.5		2.6	−12.7
Subsidized job (30 days)	−13.0	−13.4	26.4		3.6	−4.5
30 days training (pessimistic)	1.4	5.4	−6.8		−0.4	1.7
Left school after year 12, no further education						
Base	19.1	33.2	312.7		94.8	9.6
Successful job search	−3.6	−17.5	21.1		1.0	−5.1
Subsidized job (30 days)	−6.2	−3.3	9.5		1.7	−1.1
30 days training (pessimistic)	0.9	3.8	−4.7		−0.2	1.1
Left school after year 12, 2 years full-time study, diploma						
Base	14.8	26.8	323.4		95.9	7.6
Successful job search	−1.9	−15.2	17.1		0.5	−4.4
Subsidized job (30 days)	−3.2	−3.8	7.0		0.9	−1.2
30 days training (pessimistic)	0.3	1.7	−2.0		−0.1	0.5
B. Model without state dependence:						
Left school after year 10, no further education						
Base	19.5	73.3	272.2	94.7	21.2	
Successful job search	−3.0	−41.2	44.2	0.8	−12.0	
Subsidized job (30 days)	0.1	−7.3	7.2	0.0	−2.1	
30 days training (pessimistic)	−0.1	3.4	−3.3	0.0	1.0	
Left school after year 12, no further education						
Base	19.4	34.0	311.6	94.7	9.8	
Successful job search	−1.6	−17.0	18.6	0.4	−4.9	
Subsidized job (30 days)	0.3	−2.8	2.4	-0.1	−0.8	
30 days training (pessimistic)	−0.1	2.7	−2.5	0.0	0.8	
Left school after year 12, 2 years full-time study, diploma						
Base	15.2	26.1	323.7	95.8	7.5	
Successful job search	−0.9	−12.4	13.3	0.2	−3.5	
Subsidized job (30 days)	−0.1	−1.5	1.6	0.0	−0.4	
30 days training (pessimistic)	−0.5	2.3	−1.8	0.1	0.7	

See table 7.