Institute for Fiscal Studies

The effects of social policies on the working careers of Europeans

IFS Working Paper W20/18

Agar Brugiavini
Giuseppe De Luca
Thomas MaCurdy
Guglielmo Weber

Economic and Social Research Council

The effects of social policies on the working careers of Europeans*

Agar Brugiavini
Ca' Foscari University of Venice, Italy, and IFS

Giuseppe De Luca
University of Palermo, Italy

Thomas MaCurdy
Stanford University, USA

Guglielmo Weber
University of Padua, Italy, and IFS

November 25, 2019

Abstract

We analyse the pattern of work and other labour market states, such as unemployment and out-of-labour-force, over the life course, by making use of a long retrospective panel of older Europeans. Based on stochastic simulations of a reduced form transition probability model, we document to what extent social policies over the life course affect employment trajectories both in the long run and in the short run. We focus on two types of reforms that have taken place in various European countries over the lifetime of the panel participants: increases in compulsory school age and increases in pension eligibility age.

Keywords: Employment histories, path dependence, education policies, pension reforms

JEL classification: J22, J26, J64,

* Corresponding author: Guglielmo Weber (email: guglielmo.weber@unipd.it). An earlier version of this work was circulated as "Workability of the young old and scarring effects: evidence from SHARE". We thank seminar audiences at the Institute for Fiscal Studies and the University of Padua for comments and suggestions. We are particularly grateful to Richard Blundell for in-depth discussions. Two of the authors wish to thank the Economics Department of the University College London and the Institute for Fiscal Studies for generous hospitality and for providing a stimulating work environment. Agar Brugiavini, Giuseppe De Luca and Guglielmo Weber acknowledge financial support from MIUR: PRIN 2015FMRE5X.

1 Introduction

In this paper we analyse the pattern of work and other labour market states, such as unemployment and out-of-labour-force, by making use of a long retrospective panel of elderly Europeans drawn from the Survey on Health, Ageing and Retirement in Europe (SHARE).[1] Thanks to our ability to follow individuals over their whole life course we can address some questions of direct policy interest that are normally outside the scope of empirical analysis. In particular, we investigate the life-course effects of increasing school-leaving age on work (and retirement) and the consequences for work, retirement and other labour market states of postponing pension eligibility age by one or more years.

The first issue relates to the effects of education policies on work careers. Since World War II a number of educational reforms have come into force that increased school-leaving age for both boys and girls. There is a vast literature on returns of education that exploits the variability in educational attainments associated to these (and other) reforms - see Card (2001) and Heckman et al. (2006) for reviews. Two recent papers (Haider and Solon 2006; Bhuller et al. 2011) stress that long-term effects can differ from short-term effects, and this argument makes the use of a retrospective panel particularly attractive. Indeed, Brunello et al. (2017) look at the causal effects of education on life-time earnings of men exploiting educational reforms and the very data that we use in this paper. The focus of this literature is typically on the effects on earnings of the extra years of schooling and the analysis focuses on men (who typically work in prime age) rather than on women, many of which never entered the labour market and whose careers are otherwise often characterised by interruptions due to marriage, child bearing and child rearing. By focusing on labour market participation decisions, we address a different set of questions: First of all, to what extent can these reforms explain the marked increase in labour force participation among women? Secondly, what are the effects on work at older ages of the postponed entry into the labour market that is associated to an increase in school-leaving age?

[1] This paper uses data from SHARE Waves 1, 2, and 3 (DOIs: 10.6103/SHARE.w1.700, 10.6103/SHARE.w2.700, 10.6103/SHARE.w3.700), see Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N° 211909, SHARE-LEAP: N° 227822, SHARE M4: N° 261982). Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org). This paper also uses data from the generated Job Episodes Panel (DOI: 10.6103/SHARE.jep.600), see Brugiavini et al. (2013) and Antonova et al. (2014) for methodological details.

The second issue relates to the effects of pension reforms on work and retirement among the young old. Since the 1990s a number of pension reforms have come into force in European countries that have increased eligibility age (and reduced the financial incentives) for both men and women. We investigate the consequences for work, retirement and other labour market states of (further) postponing pension eligibility age by one or more years, under the implicit and common assumption that pension reforms are completely unexpected. Our analysis relates to the research agenda of the International Social Security programme of the NBER that evaluates the short-term effects of pension systems on work by the young old. In particular, Wise (1999) and Gruber and Wise (2003) show the importance of pension systems institutional arrangements and eligibility rules in determining retirement decisions in a host of developed countries. They report that an effect of increased eligibility ages in the last decades has been the increase in participation rates of individuals in their 50s and 60s. In this paper we follow a different methodology to address the same issue, distinguishing between changes in eligibility rules to early retirement pension schemes and to old age (or statutory) pension ages.

We look at all these effects using life-history data from the third (2008-09) wave of SHARE. This data set, known as SHARELIFE, contains information on life conditions in childhood and life-long family, housing, health and employment histories of individuals aged 50+ in a host of European countries. By combining SHARELIFE with the first two regular waves of SHARE we construct a long retrospective "job episodes panel" which records major events and labour market activities experienced by a sample of elderly Europeans over their entire life course. The respondents of this retrospective panel have been exposed to common shocks in some countries (such as recessions, famines or even wars), but also to individual shocks (such as unemployment and out-of-labour-force spells). Moreover, the fact that respondents belong to different countries and different cohorts makes it possible to exploit the additional variation in the national welfare systems which individuals have enjoyed at different stages of their lifetimes.

Our econometric analysis draws upon the multiple-state transition probability model (TPM) introduced by Gritz and MaCurdy (1992) to study labour-market mobility of US men among low-wage jobs, high-wage jobs, training activities and nonemployment in the first ten years of their work careers. Unlike Gritz and MaCurdy (1992), we study the individuals' transition paths across five labour market states that are relevant for our research questions: schooling, work, unemployment, out-of-labour-force and retirement. Coherently with the contextual information about different cohorts and countries, we assume that the set of states available during the life course depends on respondents' age. All individuals exit the initial schooling state before age 31 and up to age 44 they can only transit among the work, unemployment and out-of-labour-force states. Transitions into retirement, which is treated as an absorbing state, are allowed only from 45 years of age.

Our TPM consists of three building blocks: the initial transition probabilities describe the likelihood of starting a career in the various states, the discrete-time duration distributions describe the likelihood of spending a number of years uninterruptedly in a particular state given initial entry in that state, and the exit transition probabilities describe the likelihood of entering a new state upon the termination of a spell in another state. These components of the model are estimated separately for men and women by conventional maximum likelihood methods based on the assumption that labour market spells are independent conditional on a large set of socio-demographic characteristics and history variables. This assumption rules out individual unobserved heterogeneity, but we allow flexible forms of duration dependence to vary across population groups by using nonseparable specifications of the hazard rates which are indistinguishable from a multi-spell proportional hazard model with unobserved heterogeneity (Heckman 1991).

In addition to assessing the goodness-of-fit of the key relationships, we evaluate the predictive performance of our TPM by an out-of-sample prediction experiment based on stochastic simulation methods. Similarly, we investigate the effects of policy reforms about compulsory school-leaving age and public pension age-eligibility rules by comparing the labour market histories generated by our Monte Carlo prediction algorithm under suitable configurations of the exogenous components of the model.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 provides an overview of the policy reforms about compulsory school-leaving age and public pension eligibility ages that are relevant for the SHARE respondents. Section 4 discusses our TPM and assesses the goodness-of-fit of its building blocks. Section 5 evaluates the predictive performance of our model. Section 6 presents the simulation of our education and pension reforms. Section 7 concludes. Appendix A contains additional details on the empirical specification of our TPM.

2 Data

Ideally, analyzing the long-term impact of different social policy reforms would require longitudinal data that follow individuals from school-leaving age to old age. Since this is very difficult due to time and cost restrictions, some surveys of the elderly population collect life-history data retrospectively by asking respondents to provide subjective assessments of their living conditions at various points during their lifetime. Examples include the U.S. Health and Retirement Survey (HRS), the English Longitudinal Study on Aging (ELSA), and the Survey of Health, Ageing and Retirement in Europe (SHARE). The common objective of the life-history data collection methods implemented in these studies is to obtain information on the lives of respondents before the baseline year of interview of each survey.

2.1 Life-history data from SHARE

Our paper is based on data from release 6.0.0 of the first three waves of SHARE, a multidisciplinary and cross-national biannual panel survey covering nationally representative samples of the elderly European population. The first two regular waves of SHARE, conducted in 2004 and 2006 respectively, provide detailed information on current living circumstances of respondents aged 50 years and over and their (possibly younger) partners in fourteen European countries (Austria, Belgium, Czech Republic, Denmark, France, Germany, Greece, Ireland, Italy, the Netherlands, Poland, Spain, Sweden and Switzerland). The data from these two waves cover a wide range of topics (physical and mental health, cognitive abilities, economic and non-economic activities, income and wealth, consumption and health expenditures, expectations, life satisfaction and well-being) and give two broad pictures of the life of respondents after the age of 50 years.

The third wave of SHARE, conducted in 2008-09 and known as SHARELIFE, is different because of the retrospective nature of its life-history interview. In addition to self-reported measures of health and socio-economic status in childhood (centered around age ten), SHARELIFE collects data on life-long family, housing, health and employment histories of about 28,500 respondents who had participated in one of the two previous waves. For detailed information on survey design, fieldwork procedures and nonresponse errors we refer to Schröder (2011).[2]

We organize the available data as a long retrospective panel, the so-called "Job Episodes Panel" (JEP), in which each respondent contributes as many observations as there are years of age from birth to the age in 2008 (when they are interviewed). As discussed in Brugiavini et al. (2013) and

[2] Four additional waves of SHARE were fielded in 2011, 2013, 2015 and 2017, respectively, covering new countries of Continental Europe as well as new refreshment samples in the countries that have already participated in the previous waves. Specifically, waves 4, 5 and 6 are regular panel waves focused on current living circumstances of respondents in their baseline year of interview, while the most recent wave 7 combines the collection of retrospective life-history data for respondents who have not participated in wave 3 with the regular panel interview for respondents who already had done their SHARELIFE interview in Wave 3 (Bergmann et al. 2019). Although the life-history data collected in waves 3 and 7 could be combined to achieve both a larger sample size and a greater country coverage (Brugiavini et al. 2019), we focus on the SHARELIFE data of wave 3 to avoid modelling cross-country differences in survey participation and other important changes in the national labour market policies implemented between 2008 and 2017.

Antonova et al. (2014), the SHARE-JEP uses the information collected in the first three waves of SHARE to provide binary indicators for full-time education, employment, unemployment and retirement that span the entire life of respondents. This allows us to distinguish five exhaustive and mutually exclusive labour market states: schooling ($\mathcal{S}$), work ($\mathcal{W}$), unemployment ($\mathcal{U}$), out-of-labour-force (but not retired) ($\mathcal{O}$) and retirement ($\mathcal{R}$). In those cases where an individual reports two labour market states for the same year (about 3% of the sample), we give priority to $\mathcal{S}$ between 10 and 15 years of age, to $\mathcal{W}$ and $\mathcal{U}$ between 16 and 44 years of age, and to $\mathcal{R}$ at 45+ years of age. Independently of age, we assign lowest priority to the $\mathcal{O}$ status that is defined as a residual category starting from the binary indicators for the other labour market states. According to the definitions adopted in the SHARE-JEP, this residual category includes home-making, maternity leave, military service, apprenticeship and training, and disability insurance for older workers.

2.2 Data issues and sample selection rules

We drop from our sample three of the fourteen countries included in the original SHARELIFE sample of wave 3: Ireland, because of the small sample and the lack of sampling design information which raises serious concerns about sample representativeness, Czech Republic and Poland because of the very different labour market institutions up until 1991. For the same reason, we also drop respondents from East Germany. Given the high level of comparability of the SHARE data, we group the remaining eleven countries in four European macro-regions: Germanic (AT, CH, West-DE and NL), Nordic (DK and SE), French (BE and FR), and Southern (GR, IT and ES). In the econometric analysis, we pool data from the various countries but employ country dummies and interactions between macro-region dummies and other explanatory variables to capture unobserved heterogeneity at the country and macro-region levels. Pooling the data allows us to increase efficiency of estimation and helps reduce problems of collinearity due to the limited within-country variability of contextual variables such as eligibility rules for old age and early retirement pensions.

To reduce issues of sample representativeness for certain population groups, we further restrict our sample to respondents born between 1927 and 1956 who were aged between 50 and 79 years in 2006 (i.e. the reference year of the second wave of SHARE). The SHARELIFE sample includes respondents aged less than 50 in 2006 only because they are partners of age-eligible respondents, but are relatively few and not representative of the underlying population. For similar reasons, we drop oldest old respondents (i.e. those aged 80+ years in 2006) because of likely coverage errors due to cross-country differences in the sampling procedures for the institutionalized population.

In addition to observing the same initial state (schooling) for all individuals, another attractive feature of this long retrospective panel is the reduced risk of attrition. In our sample, the cross-country average of the attrition rate is about 17% between the first two waves and about 18% between waves 2 and 3. Hence, the cumulative attrition rate of retrospective life-history data covering at least 50 years is at most 35% percent. Although these attrition errors are not negligible, they are considerably lower those faced in conventional panel surveys that follow nationally representative samples of individuals for a long time. To give an idea, the cumulative attrition rate in the first nine waves of the 1970 British Cohort Study is about 80% (Mostafa and Wiggins 2015). Moreover, this type of surveys are generally available for a limited number of countries and cohorts.

Of course, retrospective data collection is also subject to important disadvantages. Two serious concerns are item nonresponse and measurement errors on the respondents' assessments of their past events. Previous validation studies suggest that these types of nonsampling errors can be systematically related to specific characteristics of the respondents, the method of data collection, the type of data collected, the period of recall and the saliency of each event (see, e.g., Akerlof and Yellen 1985; Mathiowetz and Duncan 1988; Peters 1988; Jürges 2007; and Manzoni et al. 2009). Based on insights from this literature and a previous pilot study from ELSA, the SHARELIFE interview was designed on methods and principles that are considered most effective in improving respondents' recall ability.[3] Concerns about item nonresponse and measurement errors lead us to ignore the available information on first monthly earnings for each job and final earnings for the main current job, as both variables are collected through a number of open-ended and retrospective questions that are sensitive and difficult to answer precisely. After excluding from our analysis individuals with rare or unlikely work careers, we study instead individual labour market histories from a minimum of age 10 to a maximum of age 70 under the assumption that information on spells lasting at least six months is correctly reported.

In our model, all individuals start life with some schooling ($\mathcal{S}$), until at least the age of 9. At age 10, they can either continue their education or transit into work ($\mathcal{W}$), unemployment ($\mathcal{U}$), or out-of-labour-force ($\mathcal{O}$). Individuals are allowed to stay in $\mathcal{S}$ up to age 30 at most, but they cannot come back in this state after interrupting education. Until age 45, individuals can only transit among

[3] As discussed in Schröder (2011), the method of data collection is computer assisted personal interviews (CAPI) and the interview process adopts an event history calendar method which allows both the respondent and the interviewer to watch on the screen important events of different areas (such as children, health and jobs) that are sequentially recorded through the interview. Moreover, the order of the various interview modules can be changed according to what is deemed most important for the respondent. For validation studies on the SHARELIFE data see also Garrouste and Paccagnella (2010) and Havari and Mazzona (2015).

the states $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$. Between ages 45 and 70, those with at least 15 years of $\mathcal{W}$ can also transit into $\mathcal{R}$, an absorbing state that includes retirement from work. To enforce these rules, we dropped from the original SHARE-JEP sample about 3% of respondents with either back-transitions into $\mathcal{S}$, exit-transitions from $\mathcal{S}$ after age 30, entry-transitions into $\mathcal{R}$ before age 45, or exit-transitions from $\mathcal{R}$, about 3% of respondents with entry-transitions into $\mathcal{R}$ with less than 15 years of $\mathcal{W}$, and about 10% of respondents with missing values on the covariates of interest.

2.3 Summary statistics on labour market history data

Table 1 presents, separately by gender and age-group, the number of censored and uncensored spells in the not absorbing origin states $\{\mathcal{S}, \mathcal{W}, \mathcal{U}, \mathcal{O}\}$, the transition frequencies between the not absorbing origin states $\{\mathcal{S}, \mathcal{W}, \mathcal{U}, \mathcal{O}\}$ and the admissible destination states $\{\mathcal{S}, \mathcal{W}, \mathcal{U}, \mathcal{O}\}$, and the number of year/spell observations available for the various origin states. In total, our final working sample contains 23,364 spells from 8,304 men and 31,222 spells from 9,260 women. By setting the right-censoring age-limit equal to the minimum between the years of age in 2008 and the upper bound of 70 years of age, the proportion of right-censored spells is 14% for men and 19% for women. This difference is mostly due to the considerably larger number of right-censored $\mathcal{O}$ spells among women, which is insensitive to the choice of age 70 as upper bound. Another noticeable feature of the transition matrix for uncensored spells is that, at school-leaving age, men transit more often than women from $\mathcal{S}$ to either $\mathcal{W}$ or $\mathcal{U}$, while women transit more often than men from $\mathcal{S}$ to $\mathcal{O}$. At child-bearing and child-rearing ages, women also have a considerably larger number of labour market transitions than men. On the other hand, at old ages, men transit more easily than women into $\mathcal{R}$ regardless of the origin status. For men, the number of year/spell observations in the state $\mathcal{W}$ is substantially larger with respect to both $\mathcal{U}$ and $\mathcal{O}$. A much larger number of year/spell observations in the state $\mathcal{O}$ is available only for women, whereas the state $\mathcal{U}$ is a relatively rare outcome for both men and women. Since women seem to have more often interrupted careers than men, we shall model their labour market histories separately.

Table 2 provides additional evidence on the labour market careers of men and women by showing their top-20 transition sequences. Not surprisingly, the most common sequence for men is from school to work and then to retirement ($\mathcal{SWR}$, 27%), followed by the simpler sequence from school to work ($\mathcal{SW}$, 22%) which is typical of respondents who were not yet eligible for pension at the right-censoring age-limit. The next six most common sequences among men involve one or two out-of-labour-force spells ($\mathcal{SWOR}$, 10%; $\mathcal{SOWR}$, 9%; $\mathcal{SOW}$, 5%; $\mathcal{SWOWR}$, 4%; $\mathcal{SWOW}$, 3%; $\mathcal{SOWOR}$, 2%), while the first most common sequence with at least one unemployment spell is $\mathcal{SUWR}$ with a relative frequency of 2%. For women, the picture is quite different and more heterogenous: the most common sequence is from school to out-of-labour-force ($\mathcal{SO}$, 16%); the cumulative frequencies of their sequences are substantially lower with respect to men; and the sequences $\mathcal{SW}$ and $\mathcal{SWR}$ that are most common among men now rank in the second and fourth places with relative frequencies of 11% and 9%, respectively. The occurrence of $\mathcal{U}$ spells is similar across men and women: about 10% of male and female respondents have a work career interrupted by some $\mathcal{U}$ spell. Nevertheless, work careers of women have more interruptions than men because of $\mathcal{O}$ spells.

Figure 1 shows a box-plot on the observed length of $\mathcal{S}$, $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$ spells by gender. The length of $\mathcal{S}$ and $\mathcal{U}$ spells are similar across men and women, but their labour market histories are characterized by striking differences in the length of $\mathcal{W}$ and $\mathcal{O}$ spells. The median length of $\mathcal{W}$ spells is equal to 37 years for men and 16 years for women, while the median length of $\mathcal{O}$ spells is 3 years for men and 10 years for women. In addition, the duration distributions of $\mathcal{W}$ and $\mathcal{O}$ spells exhibit a considerably greater dispersion for women than for men. These differences in labour market attachments confirm again the importance of keeping the analysis completely separate for men and women.

3 Education and pension policy reforms in Europe

In this paper we analyze working careers of individuals starting from the schooling experience: compulsory schooling arrangements, which regulate the minimum duration of schooling through the entry age and the minimum exit age, have a direct impact on the working patterns over the life-course. Table 3 lists the compulsory education rules which are relevant for our sample of SHARE respondents (see Brunello et al. 2017), namely the time-window which covers the cohorts born between 1927 and 1956, the entry age, the minimum exit age and the minimum duration of schooling. Because the entry age is typically six years and the exit age is at most sixteen, we cover the time-window 1933 to 1974, as to provide the information on the respondents which were actually affected by a given educational reforms, as they were becoming of age. For most countries the important changes took place during the 1950s and 1960s, typically increasing the minimum exit age and imposing a longer duration of schooling. In some countries reforms took place earlier. The Netherlands provide an interesting pattern as duration increased from 7 years to 8 years for the cohorts born between 1929 and 1933 (during the war years), but decreased to 7 years after the war for the cohorts 1934-36 and increased again to a duration of 9 years for the cohorts 1937-59.

A crucial role in the working life of individuals is played by pension arrangements and how pension provisions are made available for insuring income in the *post*-retirement years. European countries show a marked variability of welfare provisions, including pension benefits and eligibility rules: Tables 4 and 5 show the eligibility rules for old age pensions (OAP) and early retirement pensions (ERP), respectively. In both tables we distinguish by country and gender, because traditionally there are significant gender differences in pension arrangements in most countries. In Table 4 we present the main eligibility rules for OAP that workers experienced in different periods of time: in most countries the statutory retirement age was 65 for men, but in some countries such as Italy, it was as low as 60 in the time window 1972-93. Also for women a significant gradient in OAP ages was in place moving from the Nordic countries to the Southern countries (from age 63 or 65 to age 55). The same pattern can be observed in Table 5 where eligibility rules are presented in terms of age and seniority, as in many countries workers could retire at relatively young ages (for example, in Austria age 60 for men or age 55 for women until 2000) provided a seniority requirement was fulfilled, for example (still in Austria) fifteen years of contributions had been paid to the social security administration. During the last thirty years a flurry of reforms took place in most countries raising the OAP retirement age and reducing the windows of opportunities for early retirement, making pension systems less generous: these policies were typically based on a grand-fathering approach, which introduced tighter rules for younger generations while preserving the *status quo* for older generations. This differential treatment by cohort was clearly present in the Southern countries, for example imposing a higher seniority requirement and a higher age in more recent years, but it is also visible in other regions and countries, such at the Netherlands or Belgium.

4 Transition probability model

Following Gritz and MaCurdy (1992), we analyse the dynamic process generating the observed labour market histories by a transition probability model (TPM) that consists of three modular building blocks. In the first module, we take the duration of schooling as exogenous and model the exit transitions from school $\mathcal{S} \to \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ that characterize the initial conditions of the process at school-leaving age. In the second module, we consider separate discrete-time duration models for the length of $\{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ spells that may occur at different stages of individuals' lifetimes. In the third and last module, we consider a set of logit models for the exit transitions across the labour market states $\{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ that may occur in the $10 - 44$ age range and a set of multinomial logit models for the exit transitions across the labour market states $\{\mathcal{W}, \mathcal{U}, \mathcal{O}, \mathcal{R}\}$ that may occur in the $45 - 70$ age range. Notice that, rather than calendar time, the relevant time measure used in this dynamic model is the age of the respondents at different points of their life-course.

Out TPM is based on a parametric setup and requires accurate fine-tuning in the specification of its components, but it gives great flexibility in modelling the observed labour market patterns and could therefore be used as an auxiliary model in the estimation of 'semi-structural' life-cycle models by indirect inference (see, e.g., Altonji et al. 2013). This modular approach does not account for unobserved heterogeneity, but it allows for flexible effects of duration dependence and other forms of state dependence by using a nonseparable specification of the hazard functions and a large set of socio-demographic characteristics and history variables to the point that unobservable components would have negligible effects.

Below, we provide a detailed description of the discrete choice models estimated in the three modules of our TPM. Like most other multi-state transition models, the interpretation of the estimated coefficients is complicated by the nonlinear nature of the models employed in each module, the constraints imposed in the case of rare transitions, the large set of explanatory variables, as well as the many different ways these variables are allowed to operate in our TPM. To deal with this issue, we first evaluate the key relationships that serve as sequential building blocks in the dynamic process for characterizing the observed labour market histories in terms of their goodness-of-fit.[4] Next, in Section 5, we also show how to use the estimated building blocks for evaluating the overall predictive performance of our TPM by means of stochastic simulation methods.

4.1 Initial transitions from school

Taking the duration of schooling as exogenous, we first consider a multinomial logit model for the exit transitions from school $\mathcal{S} \to \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$. In our model, all individuals exit the initial state $\mathcal{S}$ between 10 and 30 years of age and transit into one of the three admissible labour market states with multinomial logit probabilities of the form

$$\Pr(\mathcal{S} \to j | X_{\mathcal{S}}) = \pi_{\mathcal{S}j}(X_{\mathcal{S}}; \alpha) = \frac{\exp(X_{\mathcal{S}}^\top \alpha_j)}{\sum_{\hbar \in \mathcal{J}} \exp(X_{\mathcal{S}}^\top \alpha_{\hbar})}, \tag{1}$$

where $j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ indexes the destination states of the initial transition from school, $X_{\mathcal{S}}$ is a vector of explanatory variables measured at school-leaving age (or earlier), and $\alpha = (\alpha_{\mathcal{U}}^\top, \alpha_{\mathcal{O}}^\top)^\top$ is the associated vector of unknown and identifiable coefficients when $\mathcal{S} \to \mathcal{W}$ is used as base category

[4] Point estimates and standard errors of the coefficients of each model are available from the authors upon request.

(i.e. under the normalization $\alpha_{\mathcal{W}} = 0$). In what follows, we shall refer to the $\pi_{\mathcal{S}j} = \pi_{\mathcal{S}j}(X_{\mathcal{S}}; \alpha)$ as "initial transition probabilities" because they represent the initial conditions of the dynamic process that characterizes the individual labour market histories after leaving school.

Although this is not explicitly shown in the notation, we consider separate multinomial logit models for men and women. Since we observe only one exit transition from school for each individual, the underlying samples consist of 8,304 men and 9,260 women. The explanatory variables in the model for men include an intercept, a linear age-spline with seven knots at 12, 15, 17, 20, 24, 26 and 28 years of age, two cohort dummies (1937-46 and 1947-56), two family composition variables (if married at school-leaving age and total number of children), eight dummies for socio-economic conditions at 10 years of age (at most 10 books, good math and language performance in school, type of occupation of main breadwinner and features of accommodation), two dummies for medium and high educational attainments, ten country dummies and their interactions with the two cohort dummies. The model for women contains the same explanatory variables, plus an additional dummy for having new natural children in the last three years before school-leaving age. In both models, the information on educational attainments has been recoded using the 1997 International Standard Classification of Education (ISCED-97) to ensure cross-country comparability. Due to the small numbers of exit transitions from school to unemployment, namely 330 for men and 243 for women, we restrict some coefficients of $\alpha_{\mathcal{U}}$ to be zero (see Appendix A). The remaining coefficients of α are estimated by constrained maximum likelihood (ML).

Figure 2 illustrates the observed and estimated age-profiles of the initial transition probabilities for men and women. Although the school-leaving age distribution does not differ much between men and women, we find striking differences in the age-profiles of their initial transition probabilities when school-leaving age is below 20 years: $\mathcal{S} \to \mathcal{W}$ and $\mathcal{S} \to \mathcal{U}$ are more likely for men than for women, while $\mathcal{S} \to \mathcal{O}$ is relatively more likely for women. The age-profile of $\mathcal{S} \to \mathcal{W}$ is rather steep until age 15 for both men and women, but there are important differences in the other exit transitions from school. For men, we observe a sharp decline in the average probability of $\mathcal{S} \to \mathcal{U}$ from 0.12 to 0.03 and in the average probability of $\mathcal{S} \to \mathcal{O}$ from 0.70 to 0.15. For women, the average probability of $\mathcal{S} \to \mathcal{U}$ is about 0.03 and we observe only a sharp decline in the average probability of $\mathcal{S} \to \mathcal{O}$ from 0.94 to 0.40. The resulting age-profiles are highly nonlinear for both men and women, but these nonlinearities are well captured by the linear age-splines thanks to the large set of knots.

4.2 Discrete-time duration distributions

In the second module of out TPM, we consider a set of discrete-time duration models for the number of years that men and women spend uninterruptedly in the $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$ labour market states, given initial entry in one of these admissible and not absorbing states.

Let T_j be a discrete random variable for the duration of a generic spell in state $j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$, which takes positive integer values τ with probability mass function

$$f_j(\tau) = \Pr(T_j = \tau) = S_j(\tau - 1)\lambda_j(\tau), \qquad \tau = 1, 2, \ldots, \tag{2}$$

where $S_j(\tau - 1) = \Pr(T_j > \tau - 1) = \prod_{t=1}^{\tau-1}[1 - \lambda_j(t)]$ is the discrete-time survivor function and $\lambda_j(t) = \Pr(T_j = t | T_j \geq t)$ is the discrete-time hazard function. The marginal distribution of each T_j can be fully characterized in terms of its hazard or suitable transformations thereof. Like Gritz and MaCurdy (1992), we focus on the complement to the hazards, that is $\pi_j(t) = 1 - \lambda_j(t) = \Pr(T_j \geq t + 1 | T_j \geq t)$. Below, we refer to the $\pi_j(t)$ as "instantaneous survival functions" because they describe the conditional probabilities of continuing the current spell in state j given survival up until time $t - 1$. Independently of calendar time, the starting time of each duration distribution varies across individuals depending on the year in which a previous transition ends in state j.

As argued by Allison (1982) and Jenkins (1995), a discrete-time duration analysis is equivalent to a panel data approach for binary responses in which each spell contributes as many observations as the number of years at risk of a given event. Specifically, to model $\pi_j(t) = 1 - \lambda_j(t)$, we define a binary outcome variable y_{jt} that takes value one if the current spell in state j is still in progress at time t and value zero otherwise. Hence, an uncensored spell lasting $\tau > 1$ years yields a sequence of the form $(y_{j1} = 1, \ldots, y_{j,\tau-1} = 1, y_{j\tau} = 0)$, a one-year spell yields a single observation with $y_{j1} = 0$ (and $y_{j0} = 1$), and a right-censored spell yields a sequence of $y_{jt} = 1$ for all t in the period of observation. In addition to providing a clear setup for the discrete nature of the observed duration data, this approach allows us to account for both flexible specifications of duration dependence (i.e. the dependence of each $\pi_j(t)$ on t) and the contribution of regressors that may change over time at yearly steps. Estimation procedures are commonly based on ML methods by assuming conditional independence of the right-censoring mechanism. Given a vector of explanatory variables Z_{jt}, the relevant outcome probabilities are $\Pr(y_{jt} = 1 | y_{j,t-1} = 1, Z_{jt}) = \Pr(T_j \geq t + 1 | T_j \geq t, Z_{jt}) = \pi_j(t, Z_{jt}; \theta_j)$ and $\Pr(y_{jt} = 0 | y_{j,t-1} = 1, Z_{jt}) = 1 - \pi_j(t, Z_{jt}; \theta_j)$. This implies that, after choosing a functional form for $\pi_j(t, Z_{jt}; \theta_j)$, one can build up a partial log-likelihood function that describes the distribution of y_{jt} given $(y_{j,t-1}, \ldots, y_{j,1})$ and $(Z_{jt}, \ldots, Z_{j1})$. If the model is correctly specified, including the assumptions on the right-censoring mechanism and the functional form of $\pi_j(t, Z_{jt}; \theta_j)$, then the conditional density of y_{jt} given Z_{jt} is dynamically complete and conventional ML estimators are asymptotically valid (see, e.g., Wooldridge 2010, Section 20.4).

Our discrete-time duration analysis assumes that the lengths of either subsequent spells in different states or repeated spells in the same state are independent after conditioning on the explanatory variables Z_{jt}. At a first glance, this assumption may seem restrictive as it rules out the presence of unobserved heterogeneity terms that may lead to correlated durations of the spells and would therefore require a complex competing-risks model to estimate all building blocks of our TMP jointly (see, e.g., Mealli and Pudney 1996). However, as pointed out by Heckman (1991), the ability to distinguish between unobserved heterogeneity and duration dependence in single-spells duration models rests critically on maintaining explicit assumptions about the way unobservables and observables interact (an extended discussion of the identification conditions can be also found in Lancaster 1990 and Van den Berg 2001). The key identification issue is that, without imposing separable models for the hazard functions, unobserved heterogeneity is indistinguishable from simply allowing for more flexible forms of duration dependence. Thus, instead of modelling unobserved heterogeneity, we follow the easier approach of specifying the various $\pi_j(t, Z_{jt}; \theta_j)$ according to a set of nonseparable models that include a number of interaction terms between t and Z_{jt}. In principle, multiplicative forms of unobserved heterogeneity could be identified under fairly weak conditions by the information from repeated spells data on the same state (see, e.g., Honoré 1993; Van den Berg 2001). In our application, however, this source of information plays a minor role due to the small percentages of respondents reporting repeated spells data in the various states (between 11% and 16% for man and between 16% and 38% for women).

Based on this setup, our empirical strategy consists of estimating the duration distributions of interest by separate staked logit models of the form

$$\pi_j(t, Z_{jt}; \theta_j) = [1 + \exp(-\eta_j(t, Z_{jt}; \theta_j))]^{-1}, \qquad j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}, \tag{3}$$

where $\eta_j(t, Z_{jt}; \theta_j) = Z_{jt}^\top \beta_j + g_j(t, Z_{jt}; \gamma_j)$, $\theta_j = (\beta_j^\top, \gamma_j^\top)^\top$, and $g_j(t, Z_{jt}; \gamma_j)$ is an unknown function determining both the duration dependence of a spell in state j and the way in which this dependence is allowed to vary with the observed regressors Z_{jt}.

These models are estimated separately for men and women by using two subsets of regressors, that is $Z_{jt} = (X_{jt}^\top, H_{jt}^\top)^\top$, where X_{jt} contains a vector of socio-demographic characteristics and H_{jt} contains a vector of history variables summarizing the labour market activities experienced up to time t. Most socio-demographic characteristics in X_{jt} coincide with the explanatory variables

X_S employed to model the initial transition probabilities, but they are now measured at different points in time rather than at school-leaving age. As discussed in Appendix A, these two sets of variables differ in three major respects. First, X_{jt} contains a linear spline in current age (instead of school-leaving age) with state and gender-specific lists of predetermined knots (between 3 and 10 knots in the 20-66 age range). Second, X_{jt} contains only macro-region dummies (instead of country dummies), but it also includes a number of additional controls such as interaction terms between age-spline components and macro-region dummies, indicators for disability and health problems, and time-varying eligibility dummies for ERP and OAP. Third, given the larger sample size, the duration models for $\mathcal{W}$ spells are based on a less parsimonious specification with respect to $\mathcal{U}$ and $\mathcal{O}$ spells. The model for $\mathcal{W}$ spells of women includes a set of four (instead of two) cohort dummies (1937-41, 1942-46, 1947-51 and 1952-56), plus their interactions with the macro-region dummies. In the model for $\mathcal{W}$ spells of men, we also replace the macro-region dummies and their interactions with the cohort dummies with a full set of dummies and interaction terms at the country level.

The history variables in H_{jt} contains two time-invariant dummies for the labour market states held before the start of the current spell in state j and six time-varying variables measuring, respectively, the fractions of active live, last ten years, and last 5 years spent in the other two labour market states different from j. In the models for $\mathcal{U}$ and $\mathcal{O}$ spells, we restrict the coefficients of β_j associated with some time-varying history variables to be zero to avoid collinearity problems.

For each type of spell, we approximate the function $g_j(t, Z_{jt}; \gamma_j)$ by a restricted cubic spline in t with 3-4 knots at Harrell's (2001) recommended percentiles, plus interactions between the t-spline components and some of the socio-demographic characteristics X_{jt} (e.g. cohort, macro-region, education attainments, family composition and health condition variables). Additional interactions between the t-spline components and the history variables H_{jt} are excluded from the approximation because of convergence problems faced in estimating the underlying elements of γ_j. After restricting these coefficients to be zero, this approximation gives us a set of flexible parametric models which admit nonmonotonic forms of duration dependence and variation of duration dependence across population groups. In addition, since each $\eta_j(t, Z_{jt}; \theta_j)$ is in fact a linear predictor, the free coefficients of $\theta_j = (\beta_j^\top, \gamma_j^\top)^\top$ can be easily estimated by ML.

The three top panels of Figure 3 show the observed and estimated age-profiles of the instantaneous survival probabilities for men and women. On average, the instantaneous survival probability of $\mathcal{W}$ spells is close to unity from age 10 to age 50, even though it is visibly lower for women than for men in the 20-35 age range, that is during the child bearing and rearing period. For both men and women this probability falls to about 0.8 around age 54, and a more marked drop (to about 0.5) is observed in the mid-sixties. Our models capture these sudden changes remarkably well thanks not only to pension eligibility indicators but also to linear age-splines with a large number of knots in the 50-66 age range.

In the case of $\mathcal{U}$ spells, the smaller sample size leads to a considerably greater variability of the average instantaneous survival probabilities. Since data show a clear U-shaped profile up to age 55 (especially for men), we fixed the knots of the linear age-splines at 25, 35 and 50 years of age for women, plus an additional knot at 55 years of age for men. Up to age 55, the estimated age-profiles capture the observed patterns reasonably well. Thereafter, the in-sample fit of our models deteriorates due to the extremely large dispersion of the observed data.

The age-profiles of $\mathcal{O}$ spells highlight other striking differences in the labour market patterns of men and women. Except for two small falls near retirement age (0.92 at age 60 and 0.88 at age 64), the average instantaneous survival probability of $\mathcal{O}$ spells for women is about 0.97 at all ages. For men, we observe instead a U-shaped age-profile between late childhood and early adulthood with a minimum of 0.59 at age 21, a slightly increasing age-profile in midlife with a maximum of 0.96 at age 53, and three marked falls around retirement age with a minimum of 0.39 at age 64. Like $\mathcal{W}$ spells, the in-sample fit of our duration models is remarkably good thanks to both pension eligibility indicators and linear age-splines.

In the three bottom panels of Figure 3, we also show the observed and estimated time-profiles of the instantaneous survival probabilities. The choice of modelling duration-dependence by restricted cubic spline (instead of linear splines) is primarily motivated by the smooth shape of these relationships. As before, our duration models fit extremely well the time persistence of $\mathcal{W}$ and $\mathcal{O}$ spells. Beyond the first decade, the in-sample fit for $\mathcal{U}$ spells is less good due to the short duration of this type of spells.

4.3 Exit transitions from the current state

In the third and last module of our TPM, we model the probabilities of the exit transitions upon the termination of a spell in one of the three admissible and not absorbing labour market states $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$. Conditional on concluding a spell of τ_j years in state j, we write the probability of transiting into a generic state $\mathcal{k} \neq j$ as

$$\pi_{j\mathcal{k}} = \pi_{j\mathcal{k}}(\tau_j, V_j) = \Pr\{j \to \mathcal{k} | \tau_j, V_j\},$$

where j and ℓ index, respectively, the origin and destination states, τ_j is the duration of the spell just ended, and $V_j = (X_j^\top, H_j^\top)^\top$ is a vector of explanatory variables containing both socio-demographic characteristics and additional history variables (other than τ_j) measured at the time of each transition. Notice that, in our model, all labour market transitions after schooling-leaving age may occur at different stages of individuals' lifetime, but back-transitions into the initial state $\mathcal{S}$ are always inadmissible and exit-transitions into the absorbing state $\mathcal{R}$ are admissible only from 45 years of age. These rules imply that the set of origin states is always $\mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$, while the set of destination states changes once individuals reach 45 years of age. Defining $\mathcal{K}^{10-44} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ for the transitions occurring in the 10-44 age range and $\mathcal{K}^{45-70} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}, \mathcal{R}\}$ for the transitions occurring in the 45-70 age range, we can then distinguish two sets of exit transition probabilities:

$$\begin{aligned}
\pi_{j\ell}^{10-44} &= \pi_{j\ell}^{10-44}(\tau_j, V_j) = \Pr\{j \to \ell | \tau_j, V_j\}, \qquad j \neq \ell,\ j \in \mathcal{J},\ \ell \in \mathcal{K}^{10-44}, \\
\pi_{j\ell}^{45-70} &= \pi_{j\ell}^{45-70}(\tau_j, V_j) = \Pr\{j \to \ell | \tau_j, V_j\}, \qquad j \neq \ell,\ j \in \mathcal{J},\ \ell \in \mathcal{K}^{45-70},
\end{aligned}$$

which, by construction, satisfy the restrictions:

$$\sum_{\ell \in \mathcal{K}^{10-44}} \pi_{j\ell}^{10-44} = 1, \qquad \sum_{\ell \in \mathcal{K}^{45-70}} \pi_{j\ell}^{45-70} = 1.$$

For the first set of transitions, we consider three logit models: $\mathcal{W} \to \{\mathcal{U}, \mathcal{O}\}$ with $\mathcal{W} \to \mathcal{O}$ as base category, $\mathcal{U} \to \{\mathcal{W}, \mathcal{O}\}$ with $\mathcal{U} \to \mathcal{W}$ as base category, and $\mathcal{O} \to \{\mathcal{W}, \mathcal{U}\}$ with $\mathcal{O} \to \mathcal{W}$ as base category. If ℓ_j^* is the destination state used as baseline category in the logit model for the origin state j, then the exit transition probability of $j \to \ell_j^*$ takes the form

$$\pi_{j\ell_j^*}^{10-44}(\tau_j, V_j; \delta_j) = \left[1 + \exp\left(V_j^\top \psi_j + p_j(\tau_j; \varphi_j)\right)\right]^{-1}, \tag{4}$$

where $\delta_j = (\psi_j^\top, \varphi_j^\top)^\top$ is a vector unknown coefficients and $p_j(\tau_j; \varphi_j)$ is an unknown function that describes the way in which the exit transition probabilities from state j depend on the duration of the spell just ended. Notice that, unlike the staked logit models employed in the context of duration analysis, we do not allow $p_j(\tau_j; \varphi_j)$ to depend on V_j. Here, the contribution of the socio-demographic characteristics and other history variables to the exit transition probabilities is fully captured by the vector of coefficients ψ_j.

Similarly, for the second set of transitions, we consider three multinomial logit models: $\mathcal{W} \to \{\mathcal{U}, \mathcal{O}, \mathcal{R}\}$, $\mathcal{U} \to \{\mathcal{W}, \mathcal{O}, \mathcal{R}\}$, and $\mathcal{O} \to \{\mathcal{W}, \mathcal{U}, \mathcal{R}\}$, each of which with the same base category ℓ_j^* as before. In this case, the exit transition probabilities can be written as

$$\pi_{j\ell}^{45-75}(\tau_j, V_j; \delta_j) = \frac{\exp\left(V_j^\top \psi_{j\ell} + p_j(\tau_j; \varphi_{j\ell})\right)}{\sum_{h \in \mathcal{K}^{10-44}} \exp\left(V_j^\top \psi_{jh} + p_j(\tau_j; \varphi_{jh})\right)}, \tag{5}$$

where δ_j is the vector of unknown coefficients obtained by staking on the top of each other the two vectors of equation-specific coefficients $\delta_{jk} = (\psi_{jk}^\top, \varphi_{jk}^\top)^\top$ for $k \neq j$, $k \neq k_j^*$ and $k \in \mathcal{K}^{45-70}$, and $\delta_{jk_j^*} = 0$ in the case of the baseline category $k = k_j^*$.

All these models are estimated again by ML, separately for men and women. As discussed in Appendix A, the explanatory variables V_j include most of the socio-demographic characteristics and history variables employed in the estimation of duration models, but we now impose a number of equation-specific restrictions on the coefficients δ_j for taking into account the smaller sample size available in each model. Our empirical specification of the exit transition probabilities in (4) and (5) is subject to four major simplifications. First, the transitions $\mathcal{U} \to \mathcal{O}$ and $\mathcal{O} \to \mathcal{U}$ are so rare that we have to estimate $\pi_{\mathcal{UO}}^{10-44}$, $\pi_{\mathcal{OU}}^{10-44}$, $\pi_{\mathcal{UO}}^{45-70}$ and $\pi_{\mathcal{OU}}^{45-70}$ through a set of constant probability models (i.e. all elements of δ_j and δ_{jk}, except their intercept coefficients, are restricted to be zero). Second, we restrict the linear predictors of $\pi_{\mathcal{UR}}^{45-70}$ and $\pi_{\mathcal{OR}}^{45-70}$ to depend on respondent's age linearly. More flexible age effects are allowed only in the exit transitions from $\mathcal{W}$ by using a linear age-spline with 4 knots at 20, 25, 35 and 40 years in the linear predictor of $\pi_{\mathcal{WU}}^{10-44}$ and a linear age-spline with 5 knots at 50, 55, 60, 64 and 66 years of age in the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$. Third, to model the dependence of the exit transition probabilities from τ_j, we approximate the functions $p_j(\tau_j; \varphi_j)$ and $p_j(\tau_j; \varphi_{jk})$ through restricted cubic splines with 3-4 knots at Harrell's (2001) recommended percentiles. In addition to $\pi_{\mathcal{UO}}^{10-44}$, $\pi_{\mathcal{OU}}^{10-44}$, $\pi_{\mathcal{UO}}^{45-70}$ and $\pi_{\mathcal{OU}}^{45-70}$ (which are kept constant), there are only two exceptions: the linear predictors of $\pi_{\mathcal{UR}}^{45-70}$ for men and women depend on $\tau_{\mathcal{U}}$ linearly, and the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ for men depends on $\tau_{\mathcal{O}}$ quadratically. Fourth, we also restrict the way in which other socio-demographic characteristics and history variables enter the linear predictors of the various exit transition probabilities for men and women. The details of these equation-specific exclusion restrictions can be found in Appendix A.

Figure 4 shows the observed and estimated age-profiles of the exit transition probabilities with origin state $\mathcal{W}$. The two upper panels refer to the transitions occurring in the 10-44 age range (i.e. $\pi_{\mathcal{WU}}^{10-44}$ and $\pi_{\mathcal{WO}}^{10-44}$), while the three bottom panels refer to the transitions occurring in the 45-70 age range (i.e. $\pi_{\mathcal{WU}}^{45-70}$, $\pi_{\mathcal{WO}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$). In the first part of life, where there are 1,387 transitions for men and 4,951 transitions for women, the observed age-profiles for men have greater dispersion with respect to women (especially at very young ages). From age 20, the age-profile of $\pi_{\mathcal{WO}}^{10-44}$ is decreasing (hence $\pi_{\mathcal{WU}}^{10-44}$ is increasing) for both men and women, but women are more likely than men to transit into $\mathcal{O}$ at child bearing and rearing ages. In the second part of life, we observe 5,574 transitions for men and 4,168 for women. The age-profile of $\pi_{\mathcal{WU}}^{45-70}$ decreases smoothly for both men and women, while $\pi_{\mathcal{WR}}^{45-70}$ presents an increasing age-profile with two major peaks at 60 and 65 years of age. Overall, our model does a good job in fitting the observed patterns of the exit transitions from $\mathcal{W}$. Similarly to duration models, linear age-splines and pension eligibility indicators capture most of the discontinuities due to institutional constraints of the national pension schemes. On average, our model understates the two peaks in $\pi_{\mathcal{WR}}^{45-70}$ at age 60 and 65, respectively, by 9 and 5 percentage points for men and by 12 and 6 percentage points for women.

5 Predictive performance

The discrete choice models estimated in the three modules of our TPM provide the key short-term relationships required for characterizing the likelihood of any given sequence of labour market episodes. We now introduce stochastic simulation methods that exploit these short-term relationships within a sequential process to uncover the most likely labour market histories implied by the estimated TPM.

5.1 Monte Carlo predictions

In this section, we describe a Monte Carlo algorithm that exploits the estimated coefficients of our TPM to predict the dynamic sequence of labour market activities experienced by a single individual with given socio-demographic characteristics over the different years of his life-course after leaving school. Our Monte Carlo prediction algorithm is based on three logical steps. First, we fix the overall length of the sequence on the basis of the individual's age in the year of the interview (eventually censured at 70 years of age). Second, we determine the initial schooling state exogenously by using the available information on school-leaving age. Third, we complete the sequence of the labour market states by comparing sequentially independent draws from the uniform distribution with the estimated probabilities of the discrete outcome variables which are relevant at each year of the time-span. Throughout this process, we keep constant the entire time-path of the socio-demographic characteristics employed as exogenous explanatory variables in the three modules of our TPM, but we repeatedly update the predetermined history variables according to the labour market careers simulated up to each point in time.

Our Monte Carlo prediction algorithm is implemented in Stata. Indexing the individual-specific explanatory variables and generated outcomes with the additional subscript i, the core of the routine relies on the following three-step iterative procedure:

1. In the first step, we predict the initial transition from school $\mathcal{S} \to j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ at

the observed school-leaving age. Specifically, given the socio-demographic characteristics $X_{i,\mathcal{S}}$ and the ML estimates $\widehat{\alpha}$ of α, we first estimate the probabilities of all admissible transitions from school $\widehat{\pi}_{i,\mathcal{S}j} = \pi_{\mathcal{S}j}(X_{i,\mathcal{S}};\widehat{\alpha})$, $j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$. Based on a pseudo-random draw ν_i from a uniform distribution, we then set the predicted transition from school equal to $\mathcal{S}_i \to \mathcal{W}_i$ if $\nu_i \leq \widehat{\pi}_{i,\mathcal{S}\mathcal{W}}$, $\mathcal{S}_i \to \mathcal{U}_i$ if $\widehat{\pi}_{i,\mathcal{S}\mathcal{W}} \leq \nu_i \leq \widehat{\pi}_{i,\mathcal{S}\mathcal{W}} + \widehat{\pi}_{i,\mathcal{S}\mathcal{U}}$, and $\mathcal{S}_i \to \mathcal{O}_i$ otherwise.

2. In the second step, we predict the duration of the current spell in the destination state $j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ as predicted in the last exit transition. After setting $t = 1$ and initializing the explanatory variables $Z_{i,jt}$ according to the calendar year of the current spell, we use the ML estimates $\widehat{\theta}_j$ of θ_j to estimate the instantaneous survival probability $\widehat{\pi}_{i,jt} = \pi_j(t, Z_{i,jt}; \widehat{\theta}_j)$. Given a new pseudo-random draw ν_i from the uniform distribution, we set the predicted duration equal to $\widehat{\tau}_{i,j} = 1$ if $\nu_i > \widehat{\pi}_{i,jt}$ and $\widehat{\tau}_{i,j} > 1$ otherwise. In the latter case, we repeat the same procedure iteratively by updating at each iteration the time-index t and the time-varying regressors of $Z_{i,jt}$ for one additional year spent in the state j. This iterative procedure is interrupted either when $\nu_i > \widehat{\pi}_{i,jt}$, or when individual's age reaches the maximum age-limit (i.e. the minimum between the years of age in 2008 and the right-censoring age-limit of 70 years). In both cases, we set the predicted duration equal to the value of the time-index recorded in the last iteration, that is $\widehat{\tau}_{i,j} = t$. If the current spell ends because of the first exit condition, then we proceed with the third step of the algorithm. If exit is instead due to the second condition, then we terminate the algorithm because the current spell in state j is right-censored.

3. In the third step, we predict the new exit transition from the origin state $j \in \mathcal{J} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ of spell just ended towards a destination status $k \neq j$, with either $k \in \mathcal{K}^{10-44} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}\}$ if the transition occurs in the 10-44 age range or $k \in \mathcal{K}^{45-75} = \{\mathcal{W}, \mathcal{U}, \mathcal{O}, \mathcal{R}\}$ if the transition occurs in the 45-70 age range. For brevity, we focus on an exit transition from work for an older worker (such that $j = \mathcal{W}$ and $k \in \mathcal{K}^{45-75} = \{\mathcal{U}, \mathcal{O}, \mathcal{R}\}$). After initializing the explanatory variables $V_{i,\mathcal{W}}$ according to the calendar year of the new exit transition from $\mathcal{W}$, we use the ML estimates $\widehat{\delta}_{\mathcal{W}}$ of $\delta_{\mathcal{W}} = (\delta_{\mathcal{W}\mathcal{U}}^\top, \delta_{\mathcal{W}\mathcal{R}}^\top)^\top$ and the simulated duration $\widehat{\tau}_{i,\mathcal{W}}$ of the $\mathcal{W}$ spell just ended to estimate the probabilities of all admissible transitions $\widehat{\pi}_{i,\mathcal{W}k}^{45-75} = \pi_{\mathcal{W}k}^{45-75}(\widehat{\tau}_{i,\mathcal{W}}, V_{i,\mathcal{W}}; \widehat{\delta}_{\mathcal{W}})$, $k \in \mathcal{K}^{45-75} = \{\mathcal{U}, \mathcal{O}, \mathcal{R}\}$. Based on a new pseudo-random draw ν_i from the uniform distribution, we then set the predicted transition from $\mathcal{W}$ equal to $\mathcal{W}_i \to \mathcal{U}_i$ if $\nu_i \leq \widehat{\pi}_{i,\mathcal{W}\mathcal{U}}^{45-75}$, $\mathcal{W}_i \to \mathcal{O}_i$ if $\widehat{\pi}_{i,\mathcal{W}\mathcal{U}}^{45-75} \leq \nu_i \leq \widehat{\pi}_{i,\mathcal{W}\mathcal{U}}^{45-75} + \widehat{\pi}_{i,\mathcal{W}\mathcal{O}}^{45-75}$, and $\mathcal{W}_i \to \mathcal{R}_i$ otherwise. In the first two cases, we go back to the second step of the algorithm to predict the duration of the new $\mathcal{U}/\mathcal{O}$ spell. In the third

case, we terminate the algorithm because $\mathcal{R}$ is an absorbing state.

5.2 Out-of-sample predictions

The Monte Carlo algorithm described in the previous section provides the basic information needed to perform an out-of-sample prediction experiment for assessing the predictive performance of our TPM. In this experiment, we randomly select 75% of the original respondents by gender and country as training sample and leave out the remaining 25% of respondents as validation sample. Based on this random split of the data, we first re-estimate all building blocks of our TPM by using the training sample only and then predict the labour market histories of the individuals belonging to the validation sample by applying our Monte Carlo prediction algorithm with the estimated coefficients obtained from the training sample. The process is repeated 200 times to account for the randomness due to both the stochastic selection of the training and validation samples and the stochastic nature of our Monte Carlo prediction algorithm. To evaluate the predictive accuracy of the model, we compare observed and predicted labour market histories in terms of average number and duration of the spells, the probabilities of the admissible exit transitions, and the age-profiles of binary indicators for the labour market states.

Table 6 presents the prediction results concerning the number and the length of $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$ spells. On average, the model does a rather good job in predicting these features of the individual labour market careers. For men, the most sizeable prediction error occurs in the persistence of $\mathcal{U}$ spells, which is overstated by 5%. For women, the model tends to overstating the number and understating the length of $\mathcal{W}$ and $\mathcal{O}$ spells, but the discrepancies between predicted and observed outcomes are in general small (less than 3%). The largest prediction error occurs again in the persistence of $\mathcal{U}$ spells, which is now overstated by 9%.

Table 7 presents the prediction results concerning the number and the probabilities of the admissible exit transitions across different periods of the life-course. Again, the general picture emerging from these prediction results is rather satisfactory. In the 45-70 age range, the model overstates the probability of $\mathcal{U} \to \mathcal{W}$ by 3-4 percentage points, mainly at the expenses of $\mathcal{U} \to \mathcal{R}$ which is understated by the same amount. For men the number of exit transitions from $\mathcal{O}$ is understated by 10%, while for women the probability of $\mathcal{O} \to \mathcal{W}$ is overstated by 5 percentage points (again at expenses of $\mathcal{O} \to \mathcal{R}$). Except for these discrepancies, which are probably due to the parsimonious specifications adopted in the case of rare transitions, the predicted outcomes are very close to the observed ones.

Figure 5 shows the observed and predicted age-profiles of binary indicators for the labour market states $\mathcal{W}$, $\mathcal{U}$, $\mathcal{O}$ and $\mathcal{R}$. We see that the model predicts very well the nonlinear age-profiles of the different labour market states for both men and women. The most relevant discrepancies occur in the 60-70 age range, where the average prediction error for $\mathcal{R}$ is about -2 percentage points for men and -3 percentage points for women. In Figures 6 and 7, we also present a breakdown of the observed and predicted age-profiles by cohort and macro-region. The variation across cohorts is much more relevant for women than for men. In the central part of their life, younger cohorts of women tend to have higher levels of $\mathcal{W}$ and lower levels of $\mathcal{O}$ with respect to older cohorts. In turn, between ages 65 and 70, we find that $\mathcal{R}$ is 8 percentage points higher for women born in 1937-46 than for women born in 1927-36. As for the variation across macro-regions, we see that the age-profiles in the Germanic macro-region (AT, CH, West-DE and NL) are quite similar to those obtained in the pooled sample. Differently, the Nordic macro-region (DK and SE) shows much reduced gaps in the age-profiles of men and women, the French macro-region (FR and BE) shows a surge of $\mathcal{U}$ between ages 55 and 60, and the Southern macro-region (ES, GR and IT) shows a surge of $\mathcal{U}$ between ages 10 and 30 and substantially lower levels of $\mathcal{W}$ and $\mathcal{R}$ for women. Overall, the out-of-sample predictions obtained from our TPM reproduces accurately these important sources of population heterogeneity.

6 Simulations

As we saw in Section 3 all European countries under investigation had in place, and changed over time during our very long sample period, at least two types of social policies: a compulsory education requirement up to a legally determined minimum age and a public pension system with gender-specific age-eligibility requirements. The effects of these policies have been investigated in a number of papers, but only few of them could exploit the breadth and depth of information available in our data. Typically, education reforms have been used to identify the causal effect of education on earnings at a given point in the life course. Even those papers that have estimated returns to education in terms of lifetime earnings (like Brunello et al. 2017) have focused on male earnings, because of the interrupted work careers of many women. Pension reforms have been widely used to identify the causal effect of retirement on a number of economic or health outcomes (consumption, as in Battistin et al. 2009, mental health, Celidoni et al. 2017, physical health, Bertoni et al. 2018, etc.), but their effects on the work careers of both men and women has been less extensively investigated. Recent work by the NBER International Social Security group is now investigating the importance of changes in financial incentives brought about by recent pension reforms in a host of countries for the transition probability from work to retirement, but the effects of pension eligibility *per se* are not directly the focus of their analysis.

We contribute to the literature on the labour market effects of these social policies by simulating two types of reforms. The first reform increases compulsory school-leaving age from 9-15 years to 16 years and assign middle education to individuals with low education. As counterfactual scenario, we use the observed schooling choices (*status quo*). The second reform involves three different changes of OAP/ERP age-eligibility requirements: (i) abolition of ERP; (ii) a one-year increase in ERP age-eligibility; and (iii) a one-year increase in OAP age-eligibility. The counterfactual scenario of these pension reforms is based again on the *status quo*, that is the OAP/ERP age-eligibility requirements given in Tables 4 and 5. To simulate the effects generated by each scenario, we employ the Monte Carlo algorithm described in Section 5.1 under a suitable configuration of the exogenous components of the model. For example, the *status quo* scenario corresponds to using the observed schooling choices and the effective OAP/ERP age-eligibility rules. In the education reform scenario, we force the individuals with low education and school-leaving age lower than 16 years to reach a middle level of education by staying in school until age 16. In the pension reform scenarios, we change only the rules determining the time-varying age-eligibility dummies for OAP/ERP. In all these cases, our Monte Carlo prediction algorithm uses the estimated coefficients for men and women obtained from the original sample.

For each policy simulation, we present the age-profiles of the differences between the proportions of individuals in a given labour market state which result from the reform and *status quo* scenarios, respectively. To account for the randomness due to the simulation process we average the estimated policy effects over 30 independent replications of the Monte Carlo algorithm. Moreover, we construct the 95% symmetric confidence bands using the standard errors obtained from a stratified nonparametric bootstrap procedure with 200 replications. The bootstrap algorithm is based on four steps. First, in each bootstrap replication, we sample with replacement individual labour market histories from the original sample of respondents stratified by gender and country. Second, we re-estimate all building blocks of our TPM (separately for men and women) on each stratified bootstrap sample. Third, we run our Monte Carlo algorithm on each bootstrap replication of the estimated coefficients to predict the individual labour market careers under both the reform and *status quo* scenarios. Fourth, we compute the required standard errors as standard deviations over the 200 bootstrap replications of the difference between the simulated outcomes under the reform and *status quo* scenarios.

6.1 Policy reform on compulsory school for people with low education

Economists have long investigated the effects of education on earnings - mostly focusing on earnings of prime age men, who are for the largest part all employed. The effects on women are more difficult to evaluate, because large fractions are out-of-labour-market for long periods of time, and even when they return to paid work, these interruptions have a negative impact on their earnings. But the effects of education on employment are interesting on their own right, and a key component of returns to education for those individuals (some men, many women) whose labour market attachment is not consistently high across the life-cycle.

Figure 8 shows the medium to long-term effects of forcing all individuals to complete at least middle-education and stay in school at least until age 16, compared to the baseline case where some may have left full-time education at ages 10-15. This simulation is effectively imposing a one-off increase in compulsory school leaving age affecting only those with low or little education. To the extent that school leaving age was higher for younger cohorts, the effects are likely to be driven by men and women from the older cohorts who left school relatively early, and these would have typically been children of less educated parents, many of them living in rural areas (as Brunello et al. 2017, report, the effects of compulsory school age reforms on educational attainment is much stronger for men who grew up in rural areas).

In this figure we consider the 30-70 age range - the upper panels show the effect of the reform on men, the lower panels on women. If we look at the effects of the "education reform" on men, we see a small increase in employment all the way up to age 45, and correspondingly a small decrease in the proportion of out-of-labour-force until the same age. Past age 45 there is a decrease in $\mathcal{O}$ and a corresponding increase in $\mathcal{R}$ (even though this is insignificantly different from zero). Thus the increased labour supply attachment of men comes at the expense of being out of the labour force in prime age, but is then compensated by early access to retirement. However, the effects of education on work career are relatively minor, thanks to the high labour market participation of men.

The effects of raising school-leaving age to 16 for all are much more dramatic on women's work careers. Our simulation results suggest that this reform would have major effects on women, whose employment rate would be 15-16% higher at all ages until age 45, and would then gently drop to zero by age 65. The proportion of women who would be out-of-labour-force (home-makers) is much lower in the simulation scenario (around −15% across the whole 30-70 age range). The positive effects on women's employment gently fade, and disappear by age 65, and this pattern is compensated by a steady increase in retirement.

Given the size of the effects of the increased school leaving age on women, it is useful to investigate whether these are mostly driven by those women who had only primary education (that is a large fraction among older cohorts). Figure 9 presents a breakdown of the effects of this schooling reform on women, distinguishing them by their baseline (*status quo*) school-leaving age (9-11, 12-13 and 14-15). We see that by the far the largest effects are for those who left school very early (a common occurrence among the older cohorts) but that the effects are far from negligible even for those who increased schooling only by one or two years (their employment rate is 10% higher in mid-life, and their retirement rate over 10% higher around age 65).

We conclude from this that higher schooling attainment was an important determinant of labour market attachment over the life course. It seems likely that girls who were allowed to continue education until age 16 or above were brought up in less traditional families, where home-making and child rearing were not considered as the most desirable occupation of young women. Our simulation results reveal the importance of investigating the extensive margin effects of education when estimating a returns to education equation for women at times and in countries where female labour force participation was/is substantially lower than for men.

6.2 Policy reforms on early-retirement and old-age pension schemes

In our second set of simulations, we investigate the effects of pension reforms on the workability of the young old. In particular, based on the parameter estimates of our econometric model (that captures the direct effect of pension eligibility, but also allows for several breaks in the age splines in the late fifties and early to mid-sixties), we simulate the consequences for work, retirement and other labour market states of (further) postponing pension eligibility age by one or more years (while keeping the age splines unaffected). We distinguish between changes in eligibility rules to early retirement pension schemes and to old age (or statutory) pension schemes.

Figure 10 illustrates the consequences of abolishing early retirement altogether. To clarify the way the simulation is set up, the early retirement eligibility dummy is set equal to zero until the age when the individual becomes eligible for old-age pension. The effects of such reform on men are to generate an increase (up to 3%) in employment between ages 60 and 65 and a similar decrease in retirement over the same age range. The effects on unemployment and out-of-labour-force are much smaller and insignificant. For women the increase in employment is similar in size and timing, but the effects on retirement and out-of-labour-force are different: we observe a large (around 2%), if insignificant, increase in the proportion of women who are out-of-labour-force around age 65 and a more marked decline in retirement compared to men, some of which persists past age 65.

The complete abolition of early retirement may be too stark a change to be of direct policy interest. For this reason we also consider the more plausible scenario where access to an early retirement scheme is postponed by one year for all. Figure 11 shows the outcome of such a reform (the baseline case is the *status quo*). We see that effects are smaller than in the case considered above. They are also statistically insignificant in all but one case (the drop in retirement around age 62 for women). The point estimates are still sizeable: for men, the employment rate increases by 1% at ages 61 and 62, and the proportion of retired falls by about as much (there is a small, temporary increase in unemployment at age 60). For women (who in some countries and dates could retire at ages below 60, as shown in Table 5) we observe a small surge in employment in their early sixties, and a drop in retirement starting at the same age and deepening around age 62. There is also a small but persistent increase in the proportion of women who are out-of-labour-force.

As explained in Section 3, in all countries individuals who reached a certain age (typically larger than the early retirement eligibility age) become eligible for an old-age pension. Figure 12 displays the effects of postponing old-age pension age by one year for all. We see that this policy reform would have no significant effect for women, but some significant effects for men. The most remarkable effect of this policy reform would be to increase the proportion of men who are out-of-labour-force at age 65, and decrease the proportion of men who are retired at the same age. Effects on men would be almost entirely transitory.

An interesting feature of these pension policy experiments is that we find non-negligible effects at focal ages (such as 60 and 65) despite the presence in several of the estimation modules of the TPM of knots at those ages. Also of great interest are the major differences we find for men and women, that reflect differences in their work careers on the one hand, and in eligibility rules to pension schemes on the other.

7 Conclusions

In this paper we have used a long, retrospective panel on European men and women to estimate and simulate the dynamic processes underlying their work and retirement histories. We adopted the flexible transition probability model put forward in Gritz and MaCurdy (1992) to estimate, separately for men and women, the probability of leaving school and starting a work, unemployment or out-of-labour-force spell, the duration of each labour market spell, and the probability to change state towards one the states previously mentioned or retirement. We have shown that this model provides a good fit both within sample and out of sample (cross validation) and this makes it a useful tool to investigate the long-term effects of changes in the environment individuals face over their life course.

In addition to analyzing specific features of the labour market careers of European men and women, we used the estimated model to simulate the response to two changes that are of direct policy relevance, one affecting the early work years and one more directly affecting the late work years. First of all, we investigated a wide-ranging schooling reform, increasing school-leaving age from 9-15 years to 16 years and assigning middle education to individuals with low education. This reform is assumed to have no effect on those individuals who left school past age 15. This type of reform-induced exogenous variability has been often used in the literature to estimate the returns to education for men, by looking at their earnings in prime age (when almost all are employed) or sometimes over the whole working lives. We find that the effects of the schooling reform on labour market histories are relatively minor for men. They are instead very large and persistent for women, who are induced to participate much more in the labour market. Initially, not all women find jobs, but by age 25 and until age 45-50 the positive effect is entirely on employment. Past age 45-50 there is a steady increase also in the proportion of women who retire from work.

The second change, or set of changes, we consider concerns the public pension system. As we document in the paper, in all countries men and women become eligible for an old-age pension when they reach a set of statutory retirement ages, which are typically higher for men and have been changed over the years for both men and women. In all countries individuals can retire and draw an early retirement pension at earlier ages if they meet certain conditions, such as a long enough work career. Eligibility to these early retirement schemes has changed a lot over the years, to make them less easily accessible to relatively young workers. The first policy change we consider is the abolition of all early retirement pension schemes - this has the effect of increasing the proportion of men and women in their early sixties who still work, but also determines a rise in the proportion of older women who are out-of-labour-force (and not retired). We also simulate a less draconian measure, whereby early retirement schemes remain in operation, but age eligibility is increased by one year for all, and a different policy reform, that leaves early retirement schemes untouched but increases by one year the age eligibility criteria for old-age pensions.

References

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, 13: 61–98.

Altonji, J. G., Smith, A. A., and Vidangos, I. (2013). Modeling earnings dynamics. *Econometrica*, 81: 1395–1454.

Akerlof, G. A., and Yellen, J. (1985). Unemployment through the filter of memory. *Quarterly Journal of Economics*, 100: 747–773.

Antonova, L., Aranda, L., Pasini, G., and Trevisan, E. (2014). Migration, family history and pension: the second release of the SHARE Job Episodes Panel. *SHARE working paper*, No. 18-2014.

Battistin, E., Brugiavini, A., Rettore, E., and Weber G. (2009). The retirement consumption puzzle: evidence from a regression discontinuity approach. *American Economic Review* 99: 2209–2226.

Bell, D., and Blanchflower, D. (2009). What should be done about rising unemployment in the UK. *IZA Working Paper*, No. 4040.

Bergmann, M., Scherpenzeel, A., and Börsch-Supan, A. (2019). *SHARE Wave 7 Methodology: Panel innovations and life histories.* Munich: MEA, Max Planck Institute for Social Law and Social Policy.

Bertoni, M., Brunello, G., and Mazzarella, G. (2018). Does postponing minimum retirement age improve healthy behaviours before retirement? Evidence from middle-aged Italian workers. *Journal of Health Economics*, 58: 215–227.

Bhuller, M., Mogstad, M., and Salvanes, K. G. (2011). Life-cycle bias and the returns to schooling in current and lifetime earnings. *IZA Discussion Paper*, No. 5788.

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., Schaan, B., Stuck, S., and Zuber, S. (2013). Data resource profile: the Survey of Health, Ageing and Retirement in Europe (SHARE). *International Journal of Epidemiology*, 42: 992–1001.

Brugiavini, A., Cavapozzi, D., Pasini, G., and Trevisan, E. (2013). Working life histories from SHARELIFE: a retrospective panel. *SHARE working paper*, No. 11-2013.

Brugiavini, A., Orso, C. E., Genie, M. G., Naci, R., and Pasini, G. (2019). Combining the retrospective interviews of wave 3 and wave 7: the third release of the SHARE Job Episodes Panel. *SHARE Working Paper*, No. 36-2019.

Brunello, G., Weber, G., and Weiss, C. (2017). Books are forever: early life conditions, education and lifetime income. *The Economic Journal*, 127: 271–296.

Card, D. (2001). Estimating the return to schooling: progress on some persistent econometric problems. *Econometrica*, 69: 1127–60.

Celidoni, M., Dal Bianco, C., and Weber G. (2017). Retirement and cognitive decline. A longitudinal analysis using SHARE data. *Journal of Health Economics*, 56: 113-125.

Ellwood, J. T. (1982). Teenage unemployment: permanent scars or temporary blemishes? In Freeman, R. B., and Wise, D. A. (eds.), *The Youth Labour Market Problem: Its Nature, Causes, and Consequences*, pp. 349–390, Chicago: University of Chicago Press.

Garrouste, C., and Paccagnella, O. (2010). Data quality: Three examples of consistency across SHARE and SHARELIFE. In Schröder, M. (ed.) *Retrospective Data Collection in the Survey of Health, Ageing and Retirement in Europe, SHARELIFE Methodology*, pp. 62–72, Mannheim: MEA.

Gritz, R. M., and MaCurdy, T. (1992). Participation in low-wage labour markets by young men. *NLS Discussion Paper*, No. 93-16.

Gruber, J., and Wise, D. A. (2003). *Incentive Effects of Public Pension Systems.* Chicago: University of Chicago Press.

Haider, S., and Solon, G. (2006). Life cycle variation in the association between current and lifetime earnings. *American Economic Review*, 96: 1308–20.

Harrell, F. E., Jr. (2001). *Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis.* New York: Springer.

Havari, E., and Mazzonna, F. (2015). Can we trust older people's statements on their childhood Circumstances? Evidence from SHARELIFE. *European Journal of Population*, 31: 233–257.

Heckman, J. J. (1991). Identifying the hand of past: distinguishing state dependence from heterogeneity. *American Economic Review*, 81: 75–79.

Heckman, J. J., Lochner, L. J., and Todd, P. E. (2006). Earnings functions, rates of return and treatment effects: the Mincer equation and beyond. In Hanushek, E., and Welch, F. (eds.), *Handbook of the Economics of Education*, Vol. 1, pp. 307–458, Amsterdam: Elsevier.

Honoré, B. E. (1993). Identification results for duration models with multiple spells. *Review of Economic Studies*, 60: 241–246.

Jenkins, S. P. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, 57: 129–136.

Jürges, H. (2007). Unemployment, life satisfaction and retrospective error. *Journal of the Royal Statistical Society - Series A*, 170: 43–61.

Lancaster, T. (1990). *The Econometric Analysis of Transition Data.* Cambridge: Cambridge University Press.

Manzoni, A., Luijkx, R., and Muffels, R. (2011). Explaining differences in labour market transitions between panel and life-course data in West-Germany. *Quality & Quantity*, 45: 241–261.

Mathiowetz, N. A. and Duncan, G. J. (1988). Out of work, out of mind: response errors in retrospective reports of unemployment. *Journal of Business & Economic Statistics*, 6: 221–229.

Mealli, F., and Pudney, S. (1996). Occupational pensions and job mobility in Britain: estimation of a random-effects competing risks model. *Journal of Applied Econometrics*, 11: 293–320.

Mostafa, T., and Wiggins, R. D., (2015). The impact of attrition and non-response in birth cohort studies: a need to incorporate missingness strategies. *Longitudinal and Life Course Studies*, 6: 131–146.

Mroz, T. A., and Savage, T. H. (2006). The long-term effects of youth unemployment. *Journal of Human Resources*, XLI: 259–293.

Peters, H. E. (1988). Retrospective versus panel data in analyzing lifecycle events. *The Journal of Human Resources* 23: 488–513.

Schröder, M. (2011). *Retrospective Data Collection in the Survey of Health, Ageing and Retirement in Europe, SHARELIFE Methodology.* Mannheim: MEA.

Van Den Berg, G. J. (2001). Duration models: specification, identification, and multiple durations. In Heckman, J. J., and Leamer, E. (eds.), *Handbook of Econometrics*, Vol. V, pp. 3381–3460, Amsterdam: North Holland.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd Ed.). Cambridge, MA: MIT Press.

Table 1. Observed spells and exit transition frequencies by gender and age-group

			Number of spells			Destination states				
Gender	Origin	Age	N_T	N_C	N_U	$\mathcal{W}$	$\mathcal{U}$	$\mathcal{O}$	$\mathcal{R}$	N_Y
Men	$\mathcal{S}$	10 – 30	8304	0	8304	75.54	3.97	20.48	–	108094
	$\mathcal{W}$	10 – 44	1387	0	1387	–	15.93	84.07	–	11465
		45 – 70	8327	2753	5574	–	7.48	26.21	66.31	309920
		10 – 70	9714	2753	6961	–	9.17	37.74	53.10	321385
	$\mathcal{U}$	10 – 44	511	0	511	98.63	–	1.37	–	2021
		45 – 70	465	120	345	47.54	–	10.14	42.32	2238
		10 – 70	976	120	856	78.04	–	4.91	17.06	4259
	$\mathcal{O}$	10 – 44	2642	0	2642	99.85	0.15	–	–	8808
		45 – 70	1728	323	1405	9.61	0.28	–	90.11	14411
		10 – 70	4370	323	4047	68.52	0.20	–	31.28	23219
Women	$\mathcal{S}$	10 – 30	9260	0	9260	63.01	2.62	34.36	–	111700
	$\mathcal{W}$	10 – 44	4951	0	4951	–	8.93	91.07	–	41711
		45 – 70	6569	2401	4168	–	9.38	38.39	52.23	185579
		10 – 70	11520	2401	9119	–	9.13	66.99	23.87	227290
	$\mathcal{U}$	10 – 44	573	0	573	96.34	–	3.66	–	2705
		45 – 70	518	155	363	57.58	–	10.74	31.68	3494
		10 – 70	1091	155	936	81.30	–	6.41	12.29	6199
	$\mathcal{O}$	10 – 44	4317	0	4317	99.91	0.09	–	–	29072
		45 – 70	5034	3369	1665	36.70	0.66	–	62.64	145353
		10 – 70	9351	3369	5982	82.31	0.25	–	17.44	174425

Notes. Age denotes the relevant age-group at the time of the exit transitions. Under the columns "Number of spells", N_T denotes the total number of spells for the origin states $\{\mathcal{S}, \mathcal{W}, \mathcal{U}, \mathcal{O}\}$, N_C the number of right-censored spells, and $N_U = N_T - N_C$ the number of uncensored spells (i.e. the exit transitions ending in the destination states $\{\mathcal{W}, \mathcal{U}, \mathcal{O}, \mathcal{R}\}$). Under the columns "Destination states", $\mathcal{W}$, $\mathcal{U}$, $\mathcal{O}$ and $\mathcal{R}$ denote the relative frequencies of the exit transitions ending in the admissible destination states. Here, the symbol "–" means inadmissible transitions. N_Y denotes the total number of year/spell observations. For the origin state $\mathcal{S}$, N_Y is computed by assuming school-entry age equal to 5 for all respondents.

Table 2. Top-20 transition sequences by gender

Men				Women			
Sequence	N_I	%	Cum.	Sequence	N_I	%	Cum.
$\mathcal{SWR}$	2208	26.59	26.59	$\mathcal{SO}$	1477	15.95	15.95
$\mathcal{SW}$	1800	21.68	48.27	$\mathcal{SW}$	1058	11.43	27.38
$\mathcal{SWOR}$	834	10.04	58.31	$\mathcal{SWO}$	954	10.30	37.68
$\mathcal{SOWR}$	779	9.38	67.69	$\mathcal{SWR}$	876	9.46	47.14
$\mathcal{SOW}$	428	5.15	72.84	$\mathcal{SWOW}$	587	6.34	53.48
$\mathcal{SWOWR}$	369	4.44	77.29	$\mathcal{SWOWR}$	540	5.83	59.31
$\mathcal{SWOW}$	243	2.93	80.21	$\mathcal{SOWO}$	410	4.43	63.74
$\mathcal{SOWOR}$	202	2.43	82.65	$\mathcal{SOWR}$	400	4.32	68.06
$\mathcal{SUWR}$	174	2.10	84.74	$\mathcal{SWOR}$	363	3.92	71.98
$\mathcal{SWO}$	152	1.83	86.57	$\mathcal{SWOWOR}$	291	3.14	75.12
$\mathcal{SWOWOR}$	126	1.52	88.09	$\mathcal{SWOWO}$	264	2.85	77.97
$\mathcal{SWUR}$	83	1.00	89.09	$\mathcal{SOW}$	253	2.73	80.70
$\mathcal{SO}$	82	0.99	90.08	$\mathcal{SOWOR}$	165	1.78	82.48
$\mathcal{SWUW}$	81	0.98	91.05	$\mathcal{SWOWOW}$	118	1.27	83.76
$\mathcal{SUW}$	78	0.94	91.99	$\mathcal{SOWOWR}$	89	0.96	84.72
$\mathcal{SWU}$	65	0.78	92.77	$\mathcal{SWOWOWR}$	86	0.93	85.65
$\mathcal{SWUWR}$	43	0.52	93.29	$\mathcal{SWUW}$	80	0.86	86.51
$\mathcal{SOWOWR}$	42	0.51	93.80	$\mathcal{SUW}$	72	0.78	87.29
$\mathcal{SOWO}$	30	0.36	94.16	$\mathcal{SOWOW}$	70	0.76	88.05
$\mathcal{SWOWOWR}$	29	0.35	94.51	$\mathcal{SOWOWO}$	69	0.75	88.79

Notes. Transition sequences of men and women are ordered on the basis of their relevance. N_I denotes the number of individuals in each sequence, '%' the relative frequency, and 'Cum.' the cumulative relative frequencies.

Table 3. Starting age and duration in years of compulsory education

Region	Country	Years	Entry age	Min exit age	Min Duration
Germanic	AT	up to 1961	6	14	8
		since 1962	6	15	9
	DE*	up to 1963	6	14	8
		since 1964	6	15	9
	NL	up to 1941	6	13	7
		1942 - 1946	6	14	8
		1947 - 1949	6	13	7
		1950 - 1967	6	15	9
		since 1968	6	16	10
Nordic	DK	up to 1957	7	11	7
		1958 - 1970	7	14	7
	SE	up to 1948	7	13	6
		1949 - 1961	7	14	7
		since 1962	7	16	9
French	BE *	up to 1952	6	14	8
		since 1953	6	15	9
	FR	up to 1935	6	13	7
		1936 -1958	6	14	8
		since 1959	6	16	10
Southern	IT	up to 1962	6	11	5
	IT	since 1963	6	14	8
	ES	up to 1969	6	12	6
	GR	up to 1975	6	12	6

Notes. The symbol '*' means that there is some variation within the country.

Table 4. Eligibility for old-age pension schemes between 1972-2008

		Men		Women	
Region	Country	Period	Age	Period	Age
Germanic	AT	1972 – 2008	65	1972 – 2008	60
	CH	1972 – 2008	65	1972 – 1974	63
				1975 – 2003	62
				2004	63
				2005 – 2008	64
	DE	1972 – 2008	65	1972 – 2008	65
	NL	1972 – 2008	65	1972 – 2008	65
Nordic	DK	1972 – 2003	67	1972 – 2003	67
		2004 – 2008	65	2004 – 2008	65
	SE	1972 – 1994	67	1972 – 1994	67
		1995 – 2007	65	1995 – 2007	65
		2008	61	2008	61
French	BE	1972 – 2008	65	1972 – 1998	60
				1998 – 2003	61
				2004	63
				2005 – 2008	64
	FR	1972 – 1994	65	1972 – 1994	65
		1995 – 2008	60	1995 – 2008	60
Southern	ES	1972 – 2008	65	1972 – 2008	65
	GR	1972 – 1974	65	1972 – 1974	60
		1975 – 1998	62	1975 – 1998	57
		1999 – 2008	65	1999 – 2008	60
	IT	1972 – 1993	60	1972 – 1993	55
		1994 – 1995	61	1994 – 1995	56
		1996	62	1996	57
		1997 – 1998	63	1997 – 1998	58
		1999	64	1999	59
		2000 – 2008	65	2000 – 2008	60

Table 5. Eligibility for early retirement pension schemes between 1972-2008

		Men			Women		
Region	Country	Period	Age	N_W	Period	Age	N_W
Germanic	AT	1972 – 2000	60	15	1972 – 2000	55	15
		2001 – 2004	61	15	2001 – 2004	56	15
		2005 – 2008	62	15	2005 – 2007	57	15
					2008	57	37
	CH	1972 – 2006	62	15	1972 – 1997	59	15
		2007 – 2008	63	15	1998 – 2004	60	15
					2005 – 2006	61	15
					2007 – 2008	62	15
	DE	1972 – 2008	63	35	1972 – 2008	60	35
	NL	1972 – 1995	60	10	1972 – 1995	60	10
		1996 – 2008	62	35	1996 – 2008	62	35
Nordic	DK*	1972 – 1976	–	–	1972 – 1976	–	–
		1977 – 1991	60	15	1977 – 1991	60	15
		1992 – 1993	60	15	1992 – 1993	60	15
			55†	15		55†	15
		1994 – 1995	61	15	1994 – 1995	61	15
			60	25		60	25
			50†	15		50†	15
		1996 – 2000	61	15	1996 – 2000	61	15
			60	25		60	25
		2001 – 2008	60	25	2001 – 2008	60	25
	SE	1972 – 1997	60	15	1972 – 1997	60	15
		1998 – 2008	61	15	1998 – 2008	61	15
French	BE	1972 – 1997	60	15	1972 – 1986	55	15
					1987 – 1997	60	15
		1998	60	20	1998	60	20
		1999	60	24	1999	60	24
		2000	60	26	2000	60	26
		2001	60	28	2001	60	28
		2002	60	30	2002	60	30
		2003	60	32	2003	60	32
		2004	60	34	2004	60	34
		2005 – 2008	60	35	2005 – 2008	60	35
	FR	1972 – 1994	60	15	1972 – 1994	60	15
		1995 – 2007	–	–	1995 – 2007	–	–
		2008	56	32	2008	56	32

Table 5. Eligibility for early retirement pension schemes between 1972-2008 (continued)

		Men			Women		
Region	Country	Period	Age	N_W	Period	Age	N_W
Southern	ES	$1972-1982$	64	15	$1972-1982$	64	15
		$1983-1993$	60	15	$1983-1993$	60	15
		$1994-2001$	61	15	$1994-2001$	61	15
		$2002-2007$	61	30	$2002-2007$	61	30
		2008	60	15	2008	60	15
	GR	$1972-2007$	60	15	$1972-2008$	55	15
		2008	58	15			
	IT	$1972-1995$	45	35	$1972-1995$	45	35
		$1996-1997$	52	35	$1996-1997$	52	35
		1998	54	35	1998	54	35
		$1999-2000$	55	35	$1999-2000$	55	35
		2001	56	35	2001	56	35
		$2002-2007$	57	35	$2002-2007$	57	35
		2008	58	35	2008	58	35

Notes. N_W denotes the years of work required for eligibility. The early retirement pension scheme of DK ...(check). † means... (check). TO BE COMPLETED

Table 6. Cross-validation estimates of the average duration of spells

		Predicted		Observed		Ratio	
Gender	Spell	N_T	τ	N_T	τ	N_T	τ
Men	$\mathcal{W}$	2422	33.12	2420	33.12	1.00	1.00
	$\mathcal{U}$	243	4.59	244	4.35	1.00	1.05
	$\mathcal{O}$	1073	5.42	1087	5.32	0.99	1.02
Women	$\mathcal{W}$	2956	19.29	2877	19.72	1.03	0.98
	$\mathcal{U}$	277	6.11	273	5.61	1.01	1.09
	$\mathcal{O}$	2386	18.20	2334	18.64	1.02	0.98

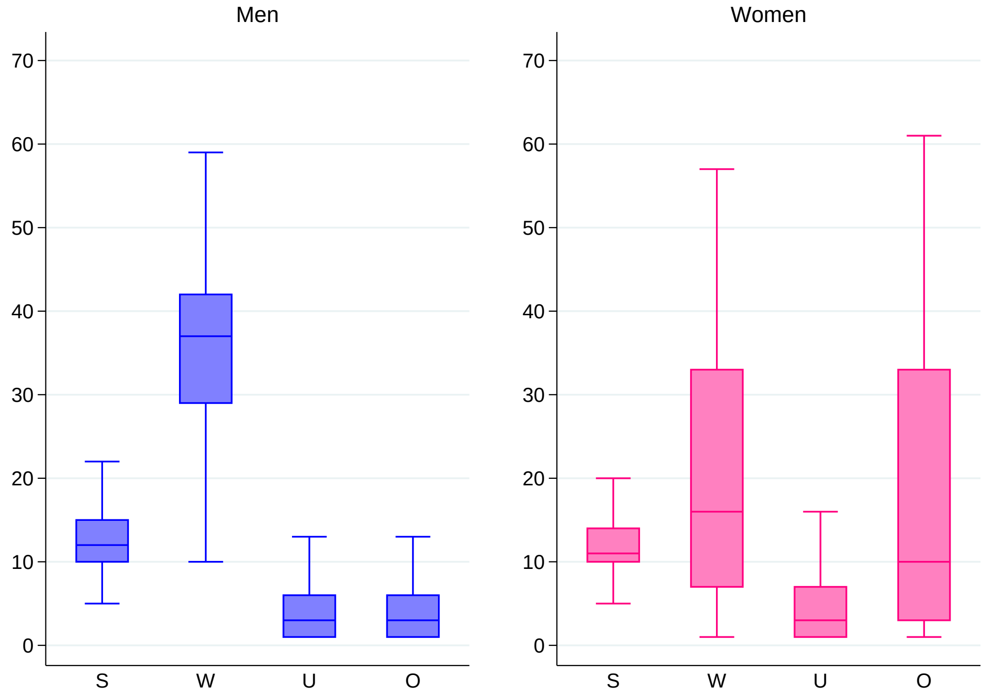
Notes. Out-of-sample predictions are computed by 200 replications of the Monte Carlo algorithm in Section 5.1 using 75% of the original respondents in each country as training sample and the remaining 25% as validation sample. N_T and τ denote, respectively, the average number and the average duration of spells across both replications and individuals. Ratio is the ratio between predicted and observed statistics.

Table 7. Cross-validation estimates of average transition probabilities

Origin	Age	Type	Men N_U	Men $\mathcal{W}$	Men $\mathcal{U}$	Men $\mathcal{O}$	Men $\mathcal{R}$	Women N_U	Women $\mathcal{W}$	Women $\mathcal{U}$	Women $\mathcal{O}$	Women $\mathcal{R}$
$\mathcal{S}$	$10-30$	Pre.	2071	0.76	0.04	0.20	–	2311	0.63	0.03	0.34	–
		Obs.	2071	0.76	0.04	0.21	–	2311	0.63	0.03	0.34	–
		Rat.	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	–
$\mathcal{W}$	$10-44$	Pre.	344	–	0.15	0.85	–	1303	–	0.09	0.91	–
		Obs.	343	–	0.16	0.84	–	1237	–	0.09	0.91	–
		Rat.	1.00	–	0.96	1.01	–	1.05	–	1.01	1.00	–
	$45-70$	Pre.	1353	–	0.08	0.26	0.66	1018	–	0.09	0.39	0.52
		Obs.	1389	–	0.08	0.26	0.66	1041	–	0.09	0.38	0.52
		Rat.	0.97	–	1.02	0.98	1.00	0.98	–	0.98	1.01	0.99
$\mathcal{U}$	$10-44$	Pre.	125	0.99	–	0.01	–	147	0.97	–	0.03	–
		Obs.	127	0.99	–	0.01	–	144	0.96	–	0.04	–
		Rat.	0.98	1.00	–	1.02	–	1.02	1.00	–	0.94	–
	$45-70$	Pre.	88	0.51	–	0.09	0.40	88	0.62	–	0.10	0.28
		Obs.	87	0.48	–	0.10	0.42	91	0.58	–	0.11	0.32
		Rat.	1.01	1.07	–	0.88	0.95	0.97	1.07	–	0.95	0.88
$\mathcal{O}$	$10-44$	Pre.	656	1.00	0.00	–	–	1132	1.00	0.00	–	–
		Obs.	657	1.00	0.00	–	–	1079	1.00	0.00	–	–
		Rat.	1.00	1.00	1.03	–	–	1.05	1.00	1.11	–	–
	$45-70$	Pre.	316	0.11	0.00	–	0.89	406	0.42	0.01	–	0.57
		Obs.	350	0.10	0.00	–	0.90	415	0.37	0.01	–	0.63
		Rat.	0.90	1.12	0.97	–	0.99	0.98	1.15	1.17	–	0.91

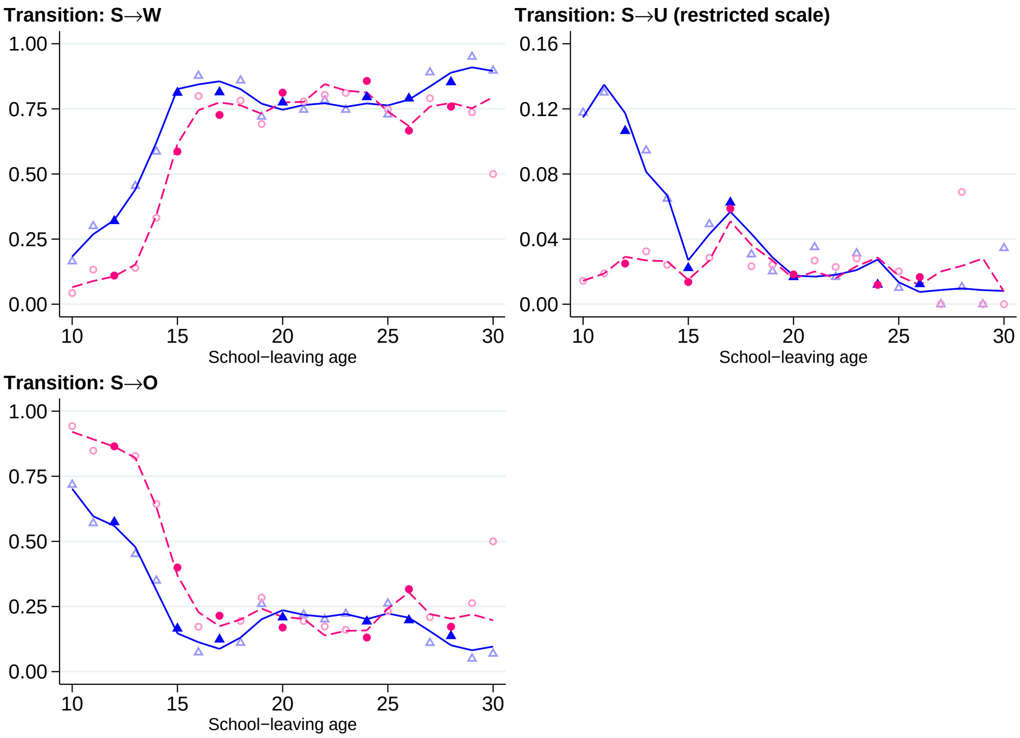
Notes. Out-of-sample predictions are computed by 200 replications of the Monte Carlo algorithm in Section 5.1 using 75% of the original respondents in each country as training sample and the remaining 25% as validation sample. N_U denotes the number of labour market transitions from the origin state reported in each row of the table to the destination states reported in its columns. The symbol "–" means inadmissible transitions. "Rat." is the ratio between predicted ("Pre.") and observed ("Obs.") statistics.

Figure 1. Boxplots of observed spell length by gender and type of spell



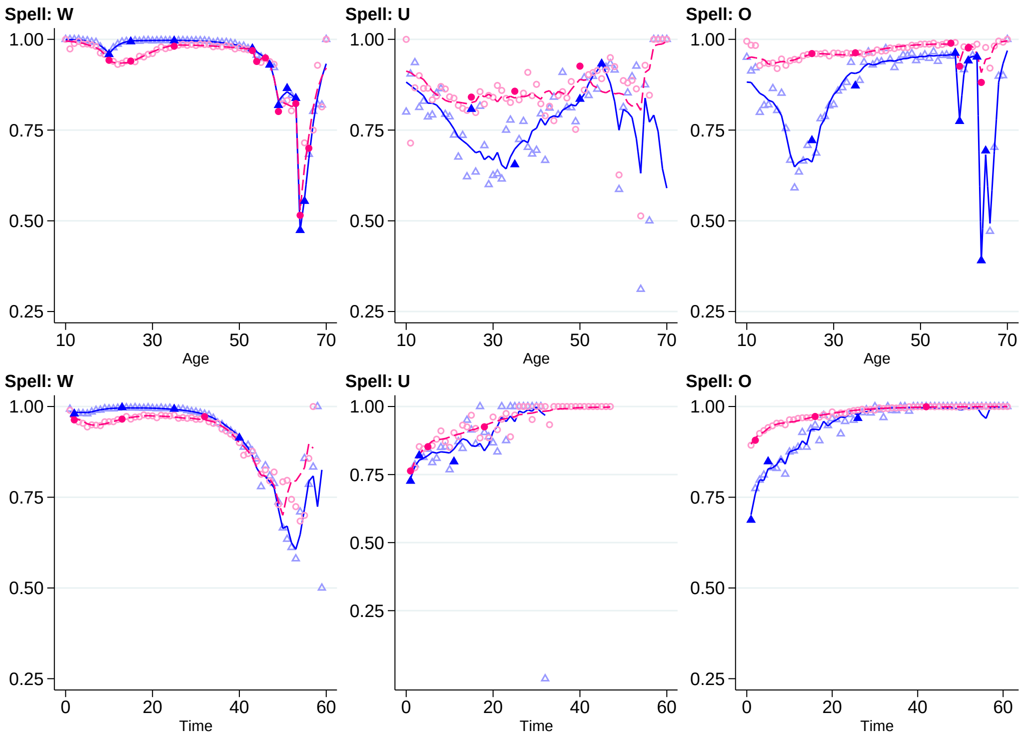
Notes. The length of $\mathcal{S}$ is computed by assuming school-entry age equal to 5 for all respondents.

Figure 2. Observed and estimated age-profiles of the initial transition probabilities for men and women



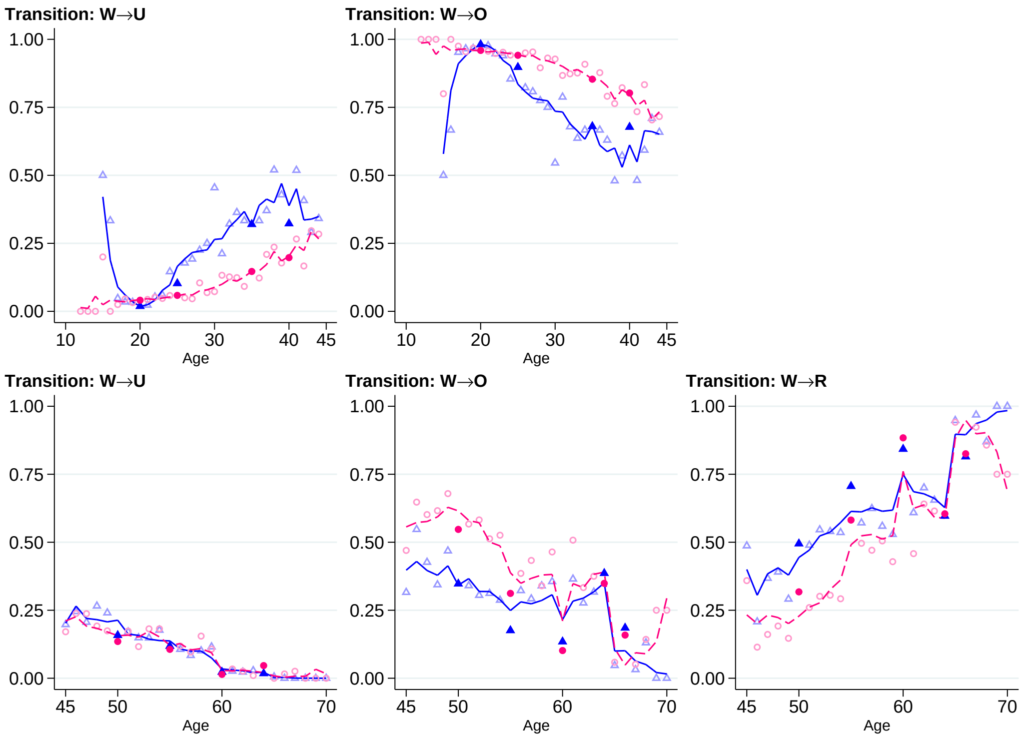
Notes. The three panels refer to the exit transitions from school: $\mathcal{S} \to \mathcal{W}$, $\mathcal{S} \to \mathcal{U}$ and $\mathcal{S} \to \mathcal{O}$. Solid-blue lines and dashed-pink lines denote the estimated age-profiles of the initial transition probabilities for men and women, respectively, circles and triangles their observed age-profiles, full-circles and full-triangles the knots of their linear age-splines. The age-profiles for $\mathcal{S} \to \mathcal{U}$ appear on a restricted scale to improve the visualization of the results.

Figure 3. Observed and estimated age-profiles (upper panels) and time-profiles (bottom panels) of the instantaneous survival probabilities for men and women



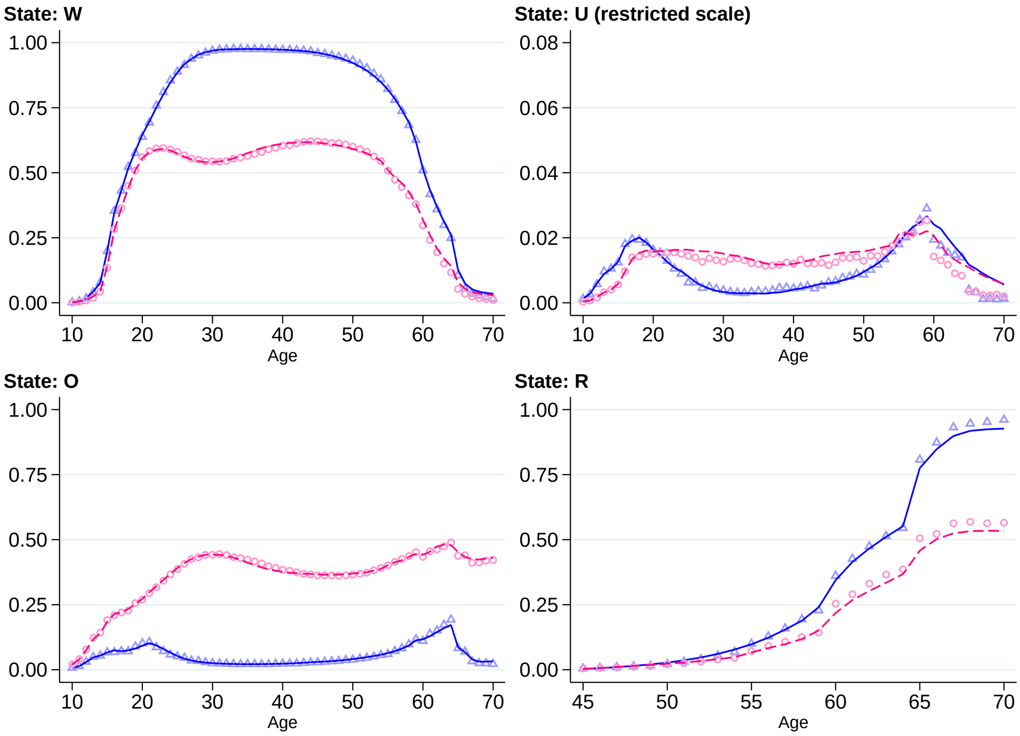
Notes. Upper panels show the age-profiles of the instantaneous survival probabilities for $\mathcal{W}$, $\mathcal{U}$ and $\mathcal{O}$ spells, while bottom panels show the underlying time-profiles. Solid-blue lines and dashed-pink lines denote the estimated profiles for men and women, respectively, circles and triangles their observed profiles, full-circles and full-triangles the knots of their linear age-splines (upper panels) or their restricted cubic splines in the time index t (bottom panels).

Figure 4. Observed and estimated age-profiles of exit transition probabilities from work for men and women



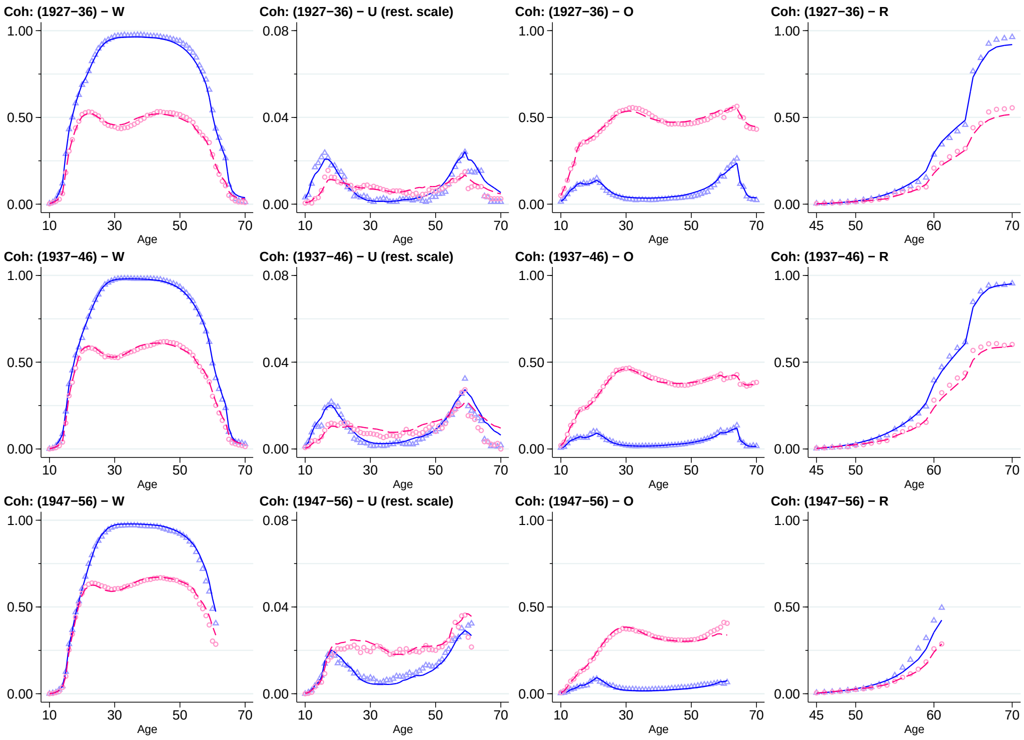
Notes. Upper panels refer to transitions occurring in the $10-44$ age range, while bottom panels refer to transitions occurring in the $45-70$ age range. Solid-blue lines and dashed-pink lines denote the estimated profiles for men and women, respectively, circles and triangles their observed profiles, full-circles and full-triangles the knots of their linear age-splines.

Figure 5. Observed and predicted age-profiles of binary indicators for labour market states of men and women



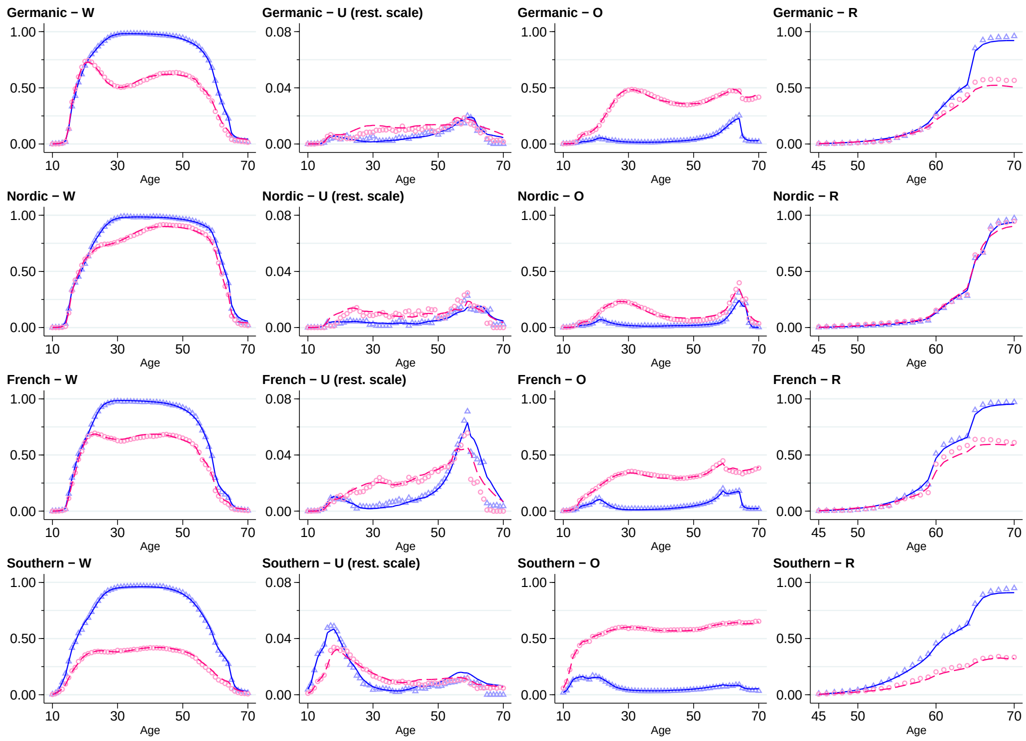
Notes. Out-of-sample predictions are computed by 200 replications of the Monte Carlo algorithm in Section 5.1 using 75% of the original respondents in each country as training sample and the remaining 25% as validation sample. Solid-blue lines and dashed-pink lines denote the predicted age-profiles for men and women, respectively, while circles and triangles their observed age-profiles. The age-profiles for $\mathcal{U}$ appears on a restricted scale to improve the visualization of the results.

Figure 6. Observed and predicted age-profiles of binary indicators for labour market states of men and women by cohort



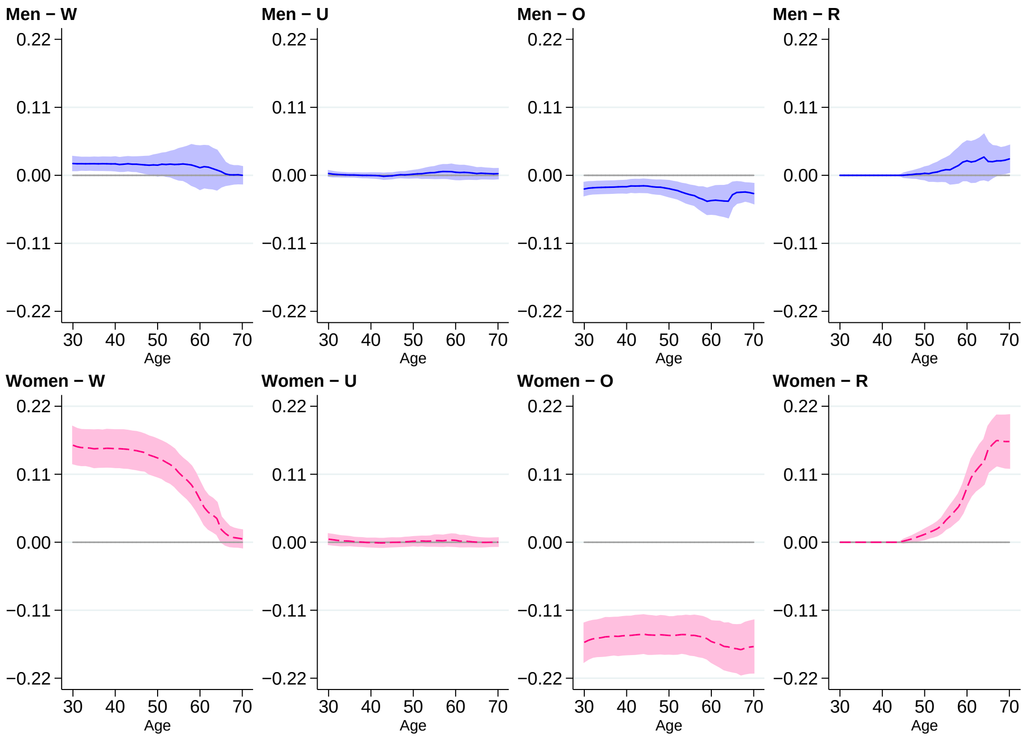
Notes. Out-of-sample predictions are computed by 200 replications of the Monte Carlo algorithm in Section 5.1 using 75% of the original respondents in each country as training sample and the remaining 25% as validation sample. Solid-blue lines and dashed-pink lines denote the predicted age-profiles for men and women, respectively, while circles and triangles their observed age-profiles. The age-profiles for $\mathcal{U}$ appears on a restricted scale to improve the visualization of the results.

Figure 7. Observed and predicted age-profiles of binary indicators for labour market states of men and women by macro-region



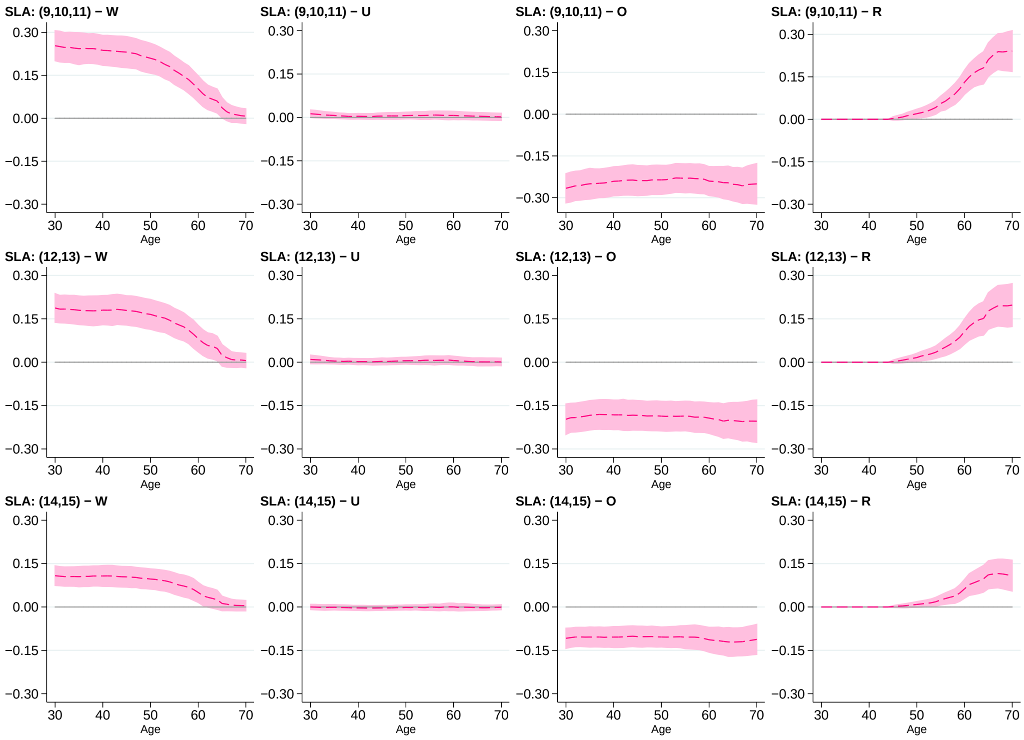
Notes. Out-of-sample predictions are computed by 200 replications of the Monte Carlo algorithm in Section 5.1 using 75% of the original respondents in each country as training sample and the remaining 25% as validation sample. Solid-blue lines and dashed-pink lines denote the predicted age-profiles for men and women, respectively, while circles and triangles their observed age-profiles. The age-profiles for $\mathcal{U}$ appears on a restricted scale to improve the visualization of the results.

Figure 8. Simulated age-profiles of the education reform on compulsory school for people with low education by gender and labour market state



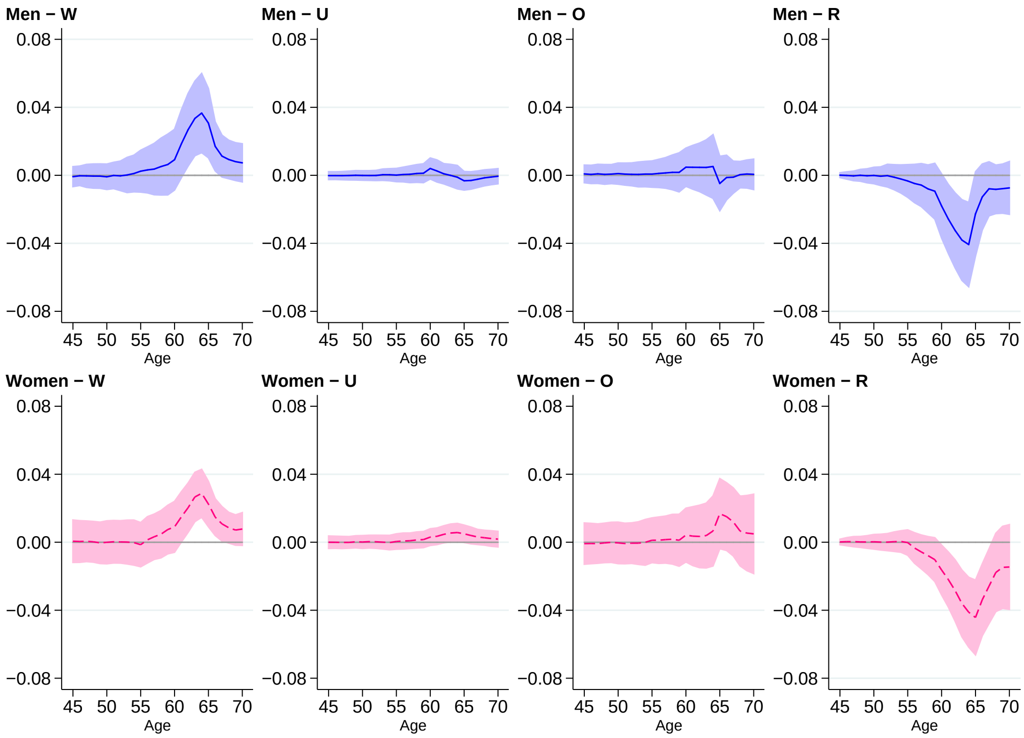
Notes. This education reform increases compulsory school-leaving age from 9-15 years to 16 years and assigns middle education to individuals with low education. The baseline scenario is represented by the observed schooling choices. In each panel, we plot the age-profile of the difference between the proportions of individuals (men in the upper panels and women in the bottom panels) in a given labour market state which result from the reform and baseline scenarios, respectively. Simulation results are based on averages over 30 independent replications of the Monte Carlo algorithm which predicts individual labour market careers under the reform and baseline scenarios. Shaded areas denote 95% symmetric confidence bands based on stratified nonparametric bootstrap with 200 replications (see Section 6).

Figure 9. Simulated age-profiles of the education reform on compulsory school for women with low education by school-leaving-age group and labour market state



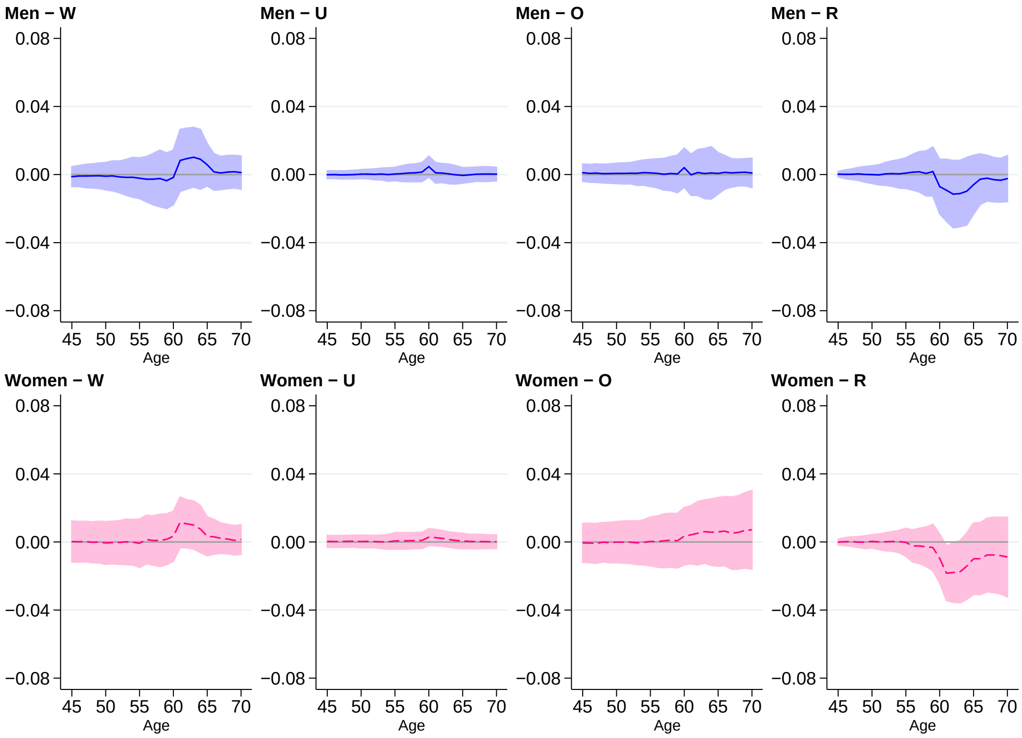
Notes. Reform and baseline scenarios are the same as Figure 8. In this case, we classify women with low education in three school-leaving-age (SLA) groups: SLA= $(9, 10, 11)$ upper panels, SLA= $(12, 13)$ central panels, SLA= $(14, 15)$ bottom panels. For each SLA group, we plot the age-profile of the difference between the proportions of women in a given labour market state which result from the reform and baseline scenarios, respectively. Simulation results are based on averages over 30 independent replications of the Monte Carlo algorithm which predicts individual labour market careers under the reform and baseline scenarios. Shaded areas denote 95% symmetric confidence bands based on stratified nonparametric bootstrap with 200 replications (see Section 6).

Figure 10. Simulated age-profiles of the pension reform on the abolition of ERP by gender and labour market state



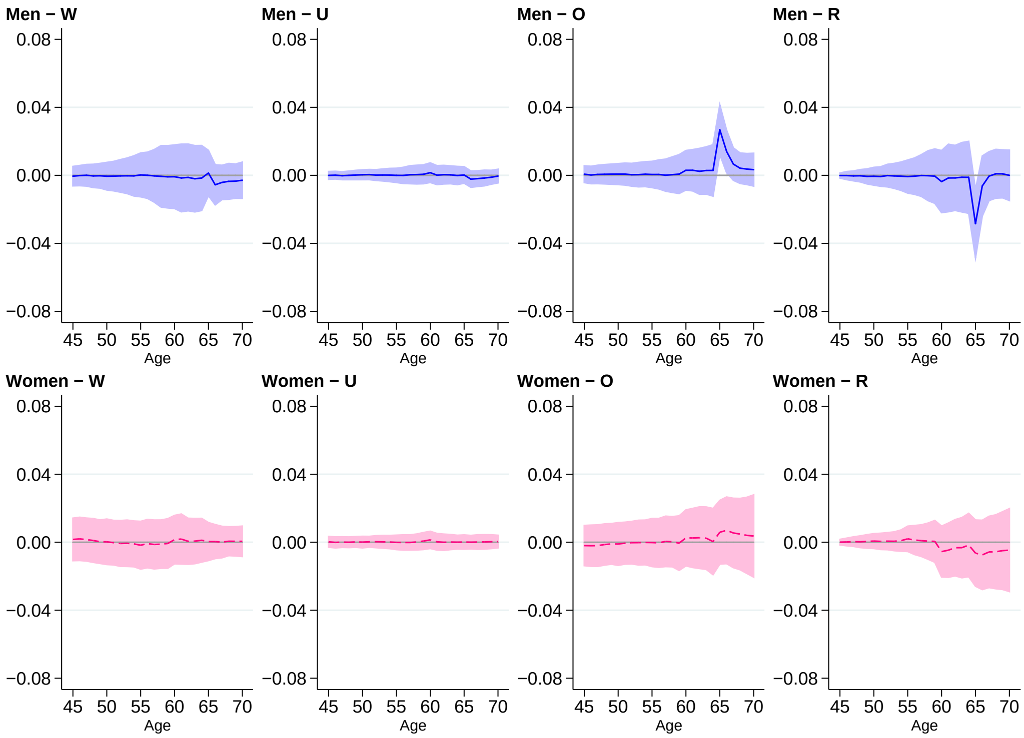
Notes. This pension reform considers the abolition of ERP by setting its eligibility dummy equal to zero until the age when the individual becomes eligible for OAP. The baseline scenario is represented by the OAP/ERP age-eligibility rules in Tables 4 and 5. In each panel, we plot the age-profile of the difference between the proportions of individuals (men in the upper panels and women in the bottom panels) in a given labour market state which result from the reform and baseline scenarios, respectively. Simulation results are based on averages over 30 independent replications of the Monte Carlo algorithm which predicts individual labour market careers under the reform and baseline scenarios. Shaded areas denote 95% symmetric confidence bands based on stratified nonparametric bootstrap with 200 replications (see Section 6).

Figure 11. Simulated age-profiles of the pension reform on a one-year increase in ERP age-eligibility by gender and labour market state



Notes. This pension reform considers a one-year increase in ERP age-eligibility, against the baseline scenario represented by the ERP age-eligibility rules in Table 5. In each panel, we plot the age-profile of the difference between the proportions of individuals (men in the upper panels and women in the bottom panels) in a given labour market state which result from the reform and baseline scenarios, respectively. Simulation results are based on averages over 30 independent replications of the Monte Carlo algorithm which predicts individual labour market careers under the reform and baseline scenarios. Shaded areas denote 95% symmetric confidence bands based on stratified nonparametric bootstrap with 200 replications (see Section 6).

Figure 12. Simulated age-profiles of the pension reform on a one-year increase in OAP age-eligibility by gender and labour market state



Notes. This pension reform considers a one-year increase in OAP age-eligibility, against the baseline scenario represented by the OAP age-eligibility rules in Table 4. In each panel, we plot the age-profile of the difference between the proportions of individuals (men in the upper panels and women in the bottom panels) in a given labour market state which result from the reform and baseline scenarios, respectively. Simulation results are based on averages over 30 independent replications of the Monte Carlo algorithm which predicts individual labour market careers under the reform and baseline scenarios. Shaded areas denote 95% symmetric confidence bands based on stratified nonparametric bootstrap with 200 replications (see Section 6).

Appendix A: Empirical specification of the TPM

In this appendix, we provide additional information on the empirical specification of the three building blocks of our transition probability model.

Initial transitions from school. Here, due to the small numbers of exit transitions from school to unemployment, namely 330 for men and 243 for women, we restrict the coefficients of $\alpha_{\mathcal{U}}$ associated with the last age-spline component, six country dummies (AT, DE, SE, NL, DK, and CH) and their interactions with the cohort dummies to be zero.

Discrete time duration distributions. Several socio-demographic characteristics in X_{jt} are similar to the explanatory variables $X_{\mathcal{S}}$ employed for the initial transition probabilities, but now measured at different points in time rather than at school-leaving age. The common socio-demographic characteristics include an intercept, a linear spline in current age with state and gender-specific lists of predetermined knots (between 3 and 10 knots in the $20-66$ age range), current family composition variables (a time-varying dummy for being married, a time-invariant indicator for total number of children, and - only for women - a time-varying dummy for having new natural children in the last three years), and a set of time-invariant dummies for socio-economic conditions at 10 years of age, educational attainments, cohorts and macro-regions (defined as in Section 4.1). As additional socio-demographic characteristics, X_{jt} also includes interaction terms between the age-spline components and the macro-region dummies, additional controls for disability and health problems (a time-invariant dummy for ever left job because of disability and a time-varying variable for the number of chronic illness conditions), and time-varying eligibility dummies for early retirement pension and old-age pension. The duration models for $\mathcal{U}$ and $\mathcal{O}$ spells are relatively more parsimonious than those for $\mathcal{W}$ spells due to their considerably lower sample size. In addition to the above socio-demographic characteristics, the model for $\mathcal{W}$-women includes a set of four (instead of two) cohort dummies (1937-41, 1942-46, 1947-51 and 1952-56) and their interactions with the macro-region dummies. In the model for $\mathcal{W}$-men, we also replace the macro-region dummies and their interactions with the cohort dummies with a full set of dummies and interaction terms at the country level. The history variables H_{jt} include two time-invariant dummies for the three states of origin in the transition before the start of the current spell in state j (i.e. $q \in \mathcal{Q} = \{\mathcal{S}, \mathcal{W}, \mathcal{U}, \mathcal{O}\}$ with $q \neq j$ and $q = \mathcal{S}$ as base category which is absorbed in the intercept) and six time-varying variables measuring, respectively, the fractions of active live, last ten years, and last 5 years spent in state

$q \neq j$. In the models for $\mathcal{U}$ and $\mathcal{O}$ spells, we restrict the coefficients of β_j associated with some of the time-varying history variables to be zero in order to avoid collinearity problems. For each type of spell, we approximate the unknown function $g_j(t, Z_{jt}; \gamma_j)$ by a restricted cubic spline in t with $3-4$ knots at Harrell's (2001) recommended percentiles, plus interactions between the t-spline components and some of the socio-demographic characteristics X_{jt} (e.g. cohort, macro-region, education attainments, family composition and health condition variables). Such approximations do not contain additional interactions between the t-spline components and the history variables H_{jt} because of convergence problems encountered in estimating the underlying elements of γ_j. After setting these coefficients equal to zero, this approach gives us a set of flexible parametric models which admit nonmonotonic forms of duration dependence and variation of duration dependence across population groups. In addition, since $\eta_j(t, Z_{jt}; \theta_j)$ is in fact a linear predictor, the free coefficients of $\theta_j = (\beta_j^\top, \gamma_j^\top)^\top$ can be easily estimated by maximum likelihood.

Exit transition probabilities. All these models are estimated by maximum likelihood, separately for men and women. The explanatory variables V_j are similar to those used in the other two modules of our TPM, but we now impose a number of restrictions on the coefficients of (4) and (5) due to the smaller sample size available in each model. First, the transitions $\mathcal{U} \to \mathcal{O}$ and $\mathcal{O} \to \mathcal{U}$ are so rare (less than 35 observations in each model) that we have to estimate $\pi_{\mathcal{UO}}^{10-44}$, $\pi_{\mathcal{OU}}^{10-44}$, $\pi_{\mathcal{UO}}^{45-70}$ and $\pi_{\mathcal{OU}}^{45-70}$ through a set of constant probability models. Second, we restrict the linear predictors of $\pi_{\mathcal{UR}}^{45-70}$ and $\pi_{\mathcal{OR}}^{45-70}$ to depend on respondent's age linearly.[5] More flexible age effects are allowed only for the exit transitions from $\mathcal{W}$. Specifically, we use a linear age-spline with 4 knots at 20, 25, 35 and 40 years in the linear predictor of $\pi_{\mathcal{WU}}^{10-44}$ and a linear age-spline with 5 knots at 50, 55, 60, 64 and 66 years of age in the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$.[6] Third, we restrict the way in which the other socio-demographic characteristics affect the various exit transition probabilities of men and women. For example, family composition variables (if married and total number of children) do not enter the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ for men, the dummy for having new natural children in the last three years enters only the linear predictor of $\pi_{\mathcal{WU}}^{10-44}$ for women, the number of chronic illness conditions enters only the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$, pension eligibility indicators enter only the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$, $\pi_{\mathcal{WR}}^{45-70}$, $\pi_{\mathcal{UR}}^{45-70}$, and $\pi_{\mathcal{OR}}^{45-70}$, and interaction terms between cohort and macro-region dummies enter only the linear predictors of $\pi_{\mathcal{WR}}^{45-70}$ (for

[5] For women, the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ also includes interactions between age and macro-region dummies.

[6] In the linear predictor of $\pi_{\mathcal{WU}}^{45-70}$, we always restrict the coefficient of $\psi_{\mathcal{WU}}$ corresponding to the last age-spline component to be zero.

both men and women) and $\pi_{\mathcal{OR}}^{45-70}$ (only for women). Fourth, the subset of history variables is also more parsimonious with respect to those employed in the duration models. Specifically, we include only the fraction of active life spent in $\mathcal{W}$ in the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ for women, the fractions of active life spent in $\mathcal{U}$ and $\mathcal{O}$ in the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$, the fraction of last ten years spent in $\mathcal{U}$ in the linear predictors of $\pi_{\mathcal{WU}}^{10-44}$, $\pi_{\mathcal{WU}}^{45-70}$ (only for men) and $\pi_{\mathcal{WR}}^{45-70}$, and the fraction of last ten years spent in $\mathcal{O}$ in the linear predictors of $\pi_{\mathcal{WU}}^{10-44}$ and $\pi_{\mathcal{WR}}^{45-70}$. Fifth, we model the dependence of the exit transition probabilities from the duration of the spell just ended by approximating the unknown functions $p_j(\tau_j;\varphi_j)$ and $p_j(\tau_j;\varphi_{jk})$ through restricted cubic splines with $3-4$ knots at Harrell's (2001) recommended percentiles. The only exceptions are $\pi_{\mathcal{UO}}^{10-44}$, $\pi_{\mathcal{OU}}^{10-44}$, $\pi_{\mathcal{UO}}^{45-70}$ and $\pi_{\mathcal{OU}}^{45-70}$ which are kept constant, $\pi_{\mathcal{UR}}^{45-70}$ whose linear predictors for men and women depend on $\tau_{\mathcal{U}}$ linearly, and $\pi_{\mathcal{OR}}^{45-70}$ whose linear predictor for men is quadratic in $\tau_{\mathcal{O}}$. With regard to socio-demographic characteristics, we assume that family composition variables (if married and total number of children) do not enter the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ for men, the dummy for having new natural children in the last three years enters only the linear predictor of $\pi_{\mathcal{WU}}^{10-44}$ for women, the number of chronic illness conditions enters only the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$, pension eligibility indicators enter only the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$, $\pi_{\mathcal{WR}}^{45-70}$, $\pi_{\mathcal{UR}}^{45-70}$, and $\pi_{\mathcal{OR}}^{45-70}$, and interaction terms between cohort and macro-region dummies enter only the linear predictors of $\pi_{\mathcal{WR}}^{45-70}$ (both men and women) and $\pi_{\mathcal{OR}}^{45-70}$ (only women). With regard to history variables, we assume instead that the fraction of active life spent in $\mathcal{W}$ enters only the linear predictor of $\pi_{\mathcal{OR}}^{45-70}$ for women, the fractions of active life spent in $\mathcal{U}$ and $\mathcal{O}$ enter only the linear predictors of $\pi_{\mathcal{WU}}^{45-70}$ and $\pi_{\mathcal{WR}}^{45-70}$, the fraction of last ten years spent in $\mathcal{U}$ enters only the linear predictors of $\pi_{\mathcal{WU}}^{10-44}$, $\pi_{\mathcal{WU}}^{45-70}$ (only for men) and $\pi_{\mathcal{WR}}^{45-70}$, and the fraction of last ten years spent in $\mathcal{O}$ enters only the linear predictors of $\pi_{\mathcal{WU}}^{10-44}$ and $\pi_{\mathcal{WR}}^{45-70}$.