

# Life-cycle worker flows in a dual labor market

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## Abstract

This paper studies the life cycle of worker flows in a dual labor market, divided between open-ended, permanent jobs with firing restrictions and fixed-term, temporary jobs. Using French Employment Survey data, we estimate age profiles of transition probabilities between unemployment, permanent and temporary employment conditional on education levels. Transition probabilities from unemployment to temporary and permanent employment have a declining profile over the life cycle for high-education workers but are flat for low-educated workers. The same holds for the transition probability from temporary to permanent employment (TP). We show that a search-and-matching model with heterogeneous workers and jobs, information frictions with Bayesian learning about worker ability, and match-specific unemployment risk can account for these facts. Calibration to French data indicates that Bayesian learning is more prevalent in explaining the life-cycle patterns of worker flows for highly educated individuals. In contrast, unemployment-risk match heterogeneity is the key driver of the variation for the low-education group. These group-specific mechanisms imply that firing costs account for most of the large unemployment differential between low and high-education young workers.

**JEL Codes:** E24, J63, J64.

**Keywords:** Dual labor market, Employment protection legislation, Life-cycle, Worker flows, Search frictions.

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# 1 Introduction

Reforms of employment protection legislation have arguably been the primary policy response to the high unemployment rate in European countries in the post-oil-shock era (see, e.g., [Boeri \(2011\)](#)). A large literature provides evidence that these reforms, in most cases focused on easing the regulation of temporary contracts, resulted in dual labor markets segmented between permanent jobs with strict firing restrictions and temporary jobs (e.g., [Blanchard and Landier \(2002\)](#), [Cahuc and Postel-Vinay \(2002\)](#), [Alonso-Borrego et al. \(2005\)](#), [Boeri and Garibaldi \(2007\)](#), [Bentolila et al. \(2012\)](#), [Cahuc et al. \(2016\)](#)). A key question, with important implications for the life-cycle dynamics of employment and earnings and the formation of human capital, is whether temporary jobs are stepping stones towards stable, protected permanent contracts, or “dead ends” leading to higher unemployment risk and unstable employment prospects (e.g., [Booth et al. \(2002\)](#), [Faccini \(2014\)](#), and [García-Pérez et al. \(2019\)](#)). However, most of the existing macro-search literature studying labor-market duality has relied on models with representative agents; as a result, relatively little is known about the implications of permanent and temporary jobs for life-cycle outcomes in the presence of search frictions. This paper intends to fill this gap.

This paper consists of two main parts. First, using French employment survey data, we provide new estimates of the life-cycle profile of worker flows in a dual labor market, with a distinction between permanent and temporary employment. Based on these estimates, we propose a stock-flow decomposition to gauge the contribution of life-cycle heterogeneity in flows in and out of permanent and temporary employment to the life-cycle variation in (i) the employment rate and (ii) the incidence of temporary employment. Second, we build a novel life-cycle equilibrium search-and-matching model with information frictions about workers’ ability and heterogeneity in match-specific separation risk as the two main ingredients, which intends to account for the empirical age profiles of worker flows. We then use this model to assess the contribution of (i) information frictions and (ii) separation-risk match heterogeneity in accounting for the empirical life-cycle variation in outcomes. In these two pieces of analysis, we distinguish between education groups (dropout and secondary vs. tertiary education) as these feature stark differences in the prevalence of temporary jobs in French data.

Our empirical analysis shows that worker flows are highly heterogeneous across age and education groups. Transition probabilities from unemployment to temporary (UT) and to permanent employment (UP) have a declining profile over the life cycle for high-education workers but a flat profile for low-education workers. The same holds for the transition probability from temporary to permanent employment (TP). We extend the life-cycle decomposition of [Choi et al. \(2015\)](#) to a framework with a distinction between permanent

and temporary employment to gauge the contribution of the age variation in worker flows to the life-cycle difference in the stocks. Our decomposition indicates that the age profile of the probability of exiting permanent employment (into nonemployment, PN), is the first-order factor shaping the life-cycle employment rate and explaining the low employment probability of young individuals, for both the low and high-education group. The temporary employment to nonemployment probability (TN) is the second main factor explaining the low youth employment rate of these two groups.

We complement this analysis by developing a quantitative search equilibrium model providing a theoretical framework to rationalize these empirical life-cycle patterns. This model features heterogeneous workers and jobs, information frictions, and match-specific separation risk. In this framework, workers accumulate human capital on the job but have heterogeneous skill-accumulation abilities. This ability is unobserved to all agents in the economy, and the human capital accumulation process is subject to idiosyncratic shocks: the agents cannot tell if skill formation is the result of the true ability level or the idiosyncratic shocks. Instead, the agents use the publicly observed realized skill levels as a signal for true abilities and update their beliefs accordingly. In addition, jobs can be either *generic* or *complex*: generic jobs have technology of production where output is independent of skills; in complex jobs, the output depends positively on skills. In other words, highly skilled workers have a comparative advantage in complex jobs. Lastly, jobs feature heterogeneity in separation risk drawn at the beginning of potential matches, independently of skills. In this framework, where permanent contracts have relatively high firing costs, temporary contracts are valuable due to two distinct motives: (i) learning about individuals’ ability (and accumulating skills), a “screening” motive; (ii) adjusting in the face of a high separation risk, a “churning” motives. These two motives have distinctly different implications for life-cycle employment outcomes, as screening is expected to be associated with a lower mismatch of skills to jobs—implying a role for temporary contracts as stepping stones toward stable employment and better life-cycle outcomes. In contrast, churning is expected to be associated with job instability, potentially detrimental to life-cycle earnings.

We calibrate the model to fit estimates of life-cycle transition probabilities from our empirical analysis, for the low and high-education groups. The model fits the age profiles closely for low-educated individuals and reasonably well for those with high education. The model is consistent with the qualitative patterns observed in our worker-flow estimates. We use the calibrated model to assess the importance of the “screening” and “churning” motives in explaining the life-cycle variation in worker flows. Specifically, we show that the discrepancy between the profile of UP transition across education groups can be mostly explained by information frictions and learning (the “screening” interpretation). In particular, learning plays

a significant role in explaining the declining profile of the UP transition for the high-education group. In contrast, the separation-risk heterogeneity channel (the “churning” interpretation) is the main factor shaping the worker-flow profiles of the low-educated individuals.

The intuition for these results is as follows. Our calibration implies a high return to skills for the highly educated relative to the low education workers. In other words, for the highly educated, complex jobs and skills have a high degree of complementarity. As such, for these workers, since information frictions are dissipated on the job through Bayesian learning, the matching value associated with the acquisition of information regarding skill processes is high. As a result, the screening motive is predominant for young workers. This implies relatively high transitions into employment and from temporary to permanent employment, as seen in the data. Since the value from information acquisition is lower for the low-education group, the screening motive is less important and life-cycle transitions are primarily shaped by heterogeneity in separation risk: the churning motive dominates for this group.

We study the implications of these heterogeneous mechanisms for the effect of employment protection on employment by age and education group. Removing firing costs substantially reduces the unemployment rate of workers with low education, but has a very mild effect on outcomes of the high-education group. Further, we find that most of the (large) unemployment differential between education groups is caused by the different effects of firing costs across these two groups, especially for the youth. Since, for the high-education group, temporary contracts are used for screening workers’ ability, these allow for mitigating the costs of employment protection—acting as stepping stones towards stable employment. It follows that the effect of firing costs on unemployment is low. For the low-education group, for which separation risk of matches is high and churning is highly prevalent, temporary contracts do not increase workers’ transitions to stable employment and only partially mitigate the negative effects of employment protection. The latter implies that the employment effect of firing costs is high for this group.

This paper connects the literature analyzing life-cycle outcomes in frictional labor markets (e.g., [Chéron et al. \(2013\)](#), [Bagger et al. \(2014\)](#), [Menzio et al. \(2016\)](#), [Lalé and Tarasonis \(2018\)](#), [Jung and Kuhn \(2019\)](#), [Kuhn and Ploj \(2020\)](#), [Cajner et al. \(2020\)](#)) and the body of work that studies the effect of dual employment protection legislation in search-and-matching models (e.g., [Blanchard and Landier \(2002\)](#), [Cahuc and Postel-Vinay \(2002\)](#), [Berton and Garibaldi \(2012\)](#), [Bentolila et al. \(2012\)](#), [Faccini \(2014\)](#), [Cahuc et al. \(2016\)](#), [Tejada \(2017\)](#), [Cahuc et al. \(2020\)](#), and [Créchet \(2023\)](#)). Our paper’s contribution is to build a life-cycle model to study worker flows in a dual labor market with search frictions. We also propose a novel empirical analysis of workers flows over the life cycle distinguishing between permanent and temporary employment. In addition, the paper is related to the body of work studying

the implications of information frictions in the labor market and Bayesian learning for the employment and earnings dynamics (e.g., Jovanovic (1979), Altonji and Pierret (2001), Lange (2007), Kaymak (2014), Papageorgiou (2014), Gervais et al. (2016), Gorrry, Gorrry, and Trachter (2019), Guvenen et al. (2020)). We contribute to this literature by examining the interaction between learning and the dynamics of temporary employment, which is highly prevalent for the youth in OECD countries.

**Outline.** The rest of the paper is organized as follows. Section 2 studies empirical patterns of worker flows over the life cycle. Section 3 presents the model. Section 4 provides a quantitative analysis. Section 5 concludes.

## 2 Empirical analysis

### 2.1 Data

We use the French Continuous Employment Survey (*Enquête emploi en continu*, EEC) for 2003-2018. The EEC is a nationally representative household survey of the French population, conducted by the French national institute (INSEE). The EEC provides detailed socio-demographic and labor market information for individuals in a sample of households. In particular, the data has information on educational attainment, individuals’ labor-force status (employed, unemployed, out of the labor force), and the type of employment contract (permanent or temporary). Since 2003, the survey has been called “continuous” due to respondents’ information being collected for each calendar week of the year. The EEC follows a rotating panel design—a household is part of the survey for up to six consecutive quarters with one-sixth of the sampled dwellings replaced every quarter—allowing to potentially follow individuals in the sampled households over several consecutive quarters. Since 2009, around 73,000 dwellings have been surveyed in each quarter.

We rely on restricted-use research files from the National Archive of Data from Official Statistics (*Archives de Données Issues de la Statistique Publique*, ADISP). A key advantage of the restricted-use files is the availability of household and individual identifiers, allowing for tracking individuals over consecutive quarters. Using the longitudinal dimension of the data, we estimate quarterly transition probabilities by identifying events of a change in workers’ labor market status.

We restrict the sample to individuals between ages 20 to 50 who are non-military and non-institutionalized, living in metropolitan (mainland) France. By considering this age range, we reduce the influence of schooling and retirement decisions on transition profiles,

which is outside the scope of our analysis. Since we are interested in worker flows, we have also restricted our sample to individuals who have participated in at least two consecutive interviews, with labor market information available from the previous quarter. Our resulting sample consists of 1,821,333 observations for 342,116 individuals covering 2003-2018.

## 2.2 Age profiles of transition probabilities

The estimation of our age profiles of transition probabilities proceeds as follows. First, we exploit the continuous and rotating design of the EEC to estimate quarterly worker flows between permanent and temporary employment, and non-employment (unemployment and non-participation) by age. Second, we run an OLS regression of these worker flow estimates on a full set of age (by year) and time (month  $\times$  year) dummies. Finally, we take OLS predicted values averaged by age to get life-cycle profiles. We condition these estimates on education levels, dividing our sample into dropout and secondary-education individuals (referred to as the low-education group) and tertiary-education individuals (referred to as the high-education group).

More specifically, let  $s_{i,t}^j = 1$  if individual  $i$  has labor force status indexed by  $j \in \{I, U, P, T, O\}$  at date  $t$ , and zero otherwise, where the index  $I$  refers to individuals who are out of the labor force,  $U$  is for unemployment,  $P$  and  $T$  are for permanent and temporary employment, and  $O$  is for another status (detailed below). In our baseline definition, we classify open-ended and apprenticeship contracts into permanent employment ( $P$ ). Temporary-agency contracts (*contrat d'intérim*), fixed-term contracts (*contrats à durée déterminée*), are into the temporary-employment ( $T$ ) category. The remaining status (self-employed and entrepreneurs) are classified into the  $O$  category (along with those with no information about the contract type, 0.02% of the sample).<sup>1</sup>

Using our EEC sample for 2003-2018, we first compute the following quarterly transition probabilities

$$\pi_{t,a}^{jk} = \frac{\sum_{i \in \iota(t,a)} \omega_i \mathcal{I}(s_{i,t-3}^j = 1 \text{ and } s_{i,t}^k = 1)}{\sum_{i \in \iota(t,a)} \omega_i \mathcal{I}(s_{i,t-3}^j = 1)}, \quad (1)$$

for each monthly date  $t$  in our sample period and each age  $a = 20, \dots, 50$  (and for each education group), where  $\iota(t, a)$  is the set of indexes for individuals of age  $a$  appearing in the sample at  $t$ . The variable  $\omega_{i,t}$  represents the survey weight of individual  $i$  at time  $t$ , and  $\mathcal{I}(\cdot)$

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<sup>1</sup>Finally, for those individuals counted as interns or in subsidized contracts (*contrats aidés*) but for whom the relevant contract information is missing are imputed as being a temporary job, which is the dominant category (more than 80% of individuals with an internship or subsidized contract). These observations for which the information is imputed represent less than 0.1% of the total number of observations.

is the indicator function taking the value of one if the expression is true (zero otherwise). Hence,  $\pi_{t,a}^{jk}$  simply estimates the fraction of individuals in state  $j$  at time  $t$  among those who were in state  $k$  in the previous quarter and aged  $a$  at time  $t$ .

Next, we run the set of OLS regressions

$$\pi_{t,a}^{jk} = \gamma_t^{jk} + \beta_a^{jk} + \varepsilon_{t,a}^{jk} \quad (2)$$

for all transitions  $j, k \in \{I, U, P, T, O\}$ , where the observation weight for cell  $t, a$  is the associated individual weighted count;  $\gamma_t^{jk}$  and  $\beta_a^{jk}$  are coefficients for time and age-effects respectively, and  $\varepsilon_{t,a}^{jk}$  is an error term. Then, we compute averages of the predicted values for each age and each transitions. Once again, we condition on education. We take these as estimates of age-specific quarterly transition probabilities. Finally, we report smoothed age profiles and 95% confidence intervals using local polynomials with an Epanechnikov kernel function. Our results for transitions between unemployment and permanent and temporary employment are shown in figure 1, for the two education groups. In the appendix, we show transitions in and out of participation.

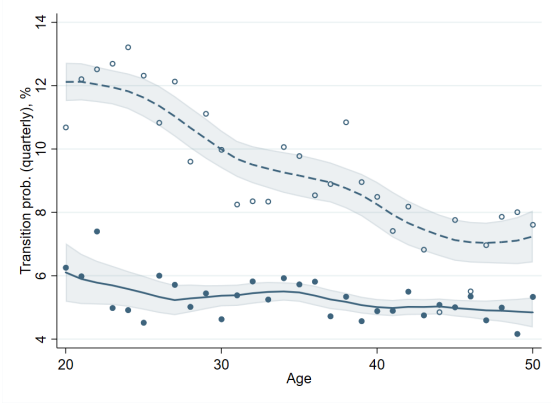
**Empirical findings.** Transition probabilities display significant variation by age and education. First, job-finding rates, measured by UP and UT transitions rates, exhibit a decreasing profile for highly educated workers, but a much flatter profile for low-educated individuals. The UP profile is significantly higher for the high-education group. Second, separation rates (TU and PU) decline for both education groups; however, the decline in the TU rate is much stronger for the highly educated. Third, transitions from temporary to permanent employment (TP) are declining by age for the highly educated but are flat for individuals with low education. Lastly, the estimates suggest significant moves from temporary to permanent employment, especially for the youth and the highly educated.

## 2.3 Markov Chain Analysis

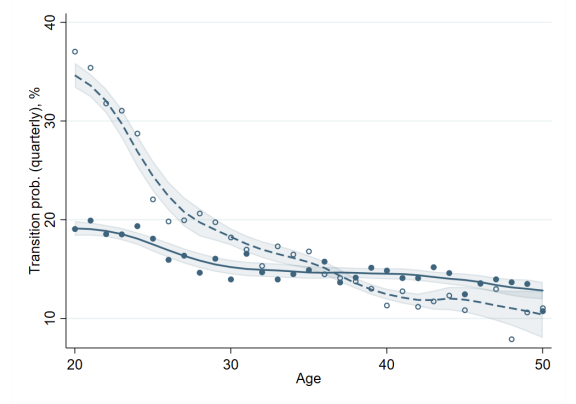
In this section, we extend the method of [Choi et al. \(2015\)](#), decomposing age differences in unemployment into contributions from differences in transition rates, to a framework with a distinction between permanent and temporary employment. With our estimates for transition probabilities computed above, we construct, by education group  $e$ , an age-specific Markov transition matrix  $\Gamma_{a,e}$ . Starting from initial conditions on the distribution of workers among labor force statuses at a starting age  $a_0$ , we compute the implied labor market status as

$$S_{a,e} = \left( \prod_{a'=1}^{a-1} (\Gamma_{a',e})^4 \right) S_{a_0,e}, \quad (3)$$

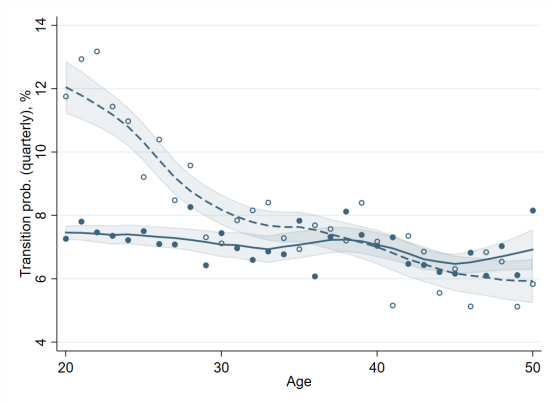
Figure 1: Age profiles of quarterly transition probabilities, by education group



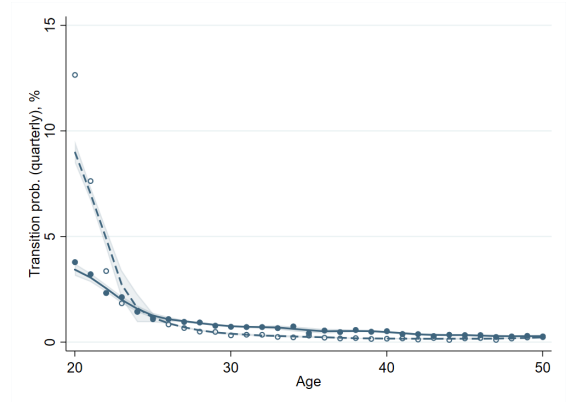
(a) UP



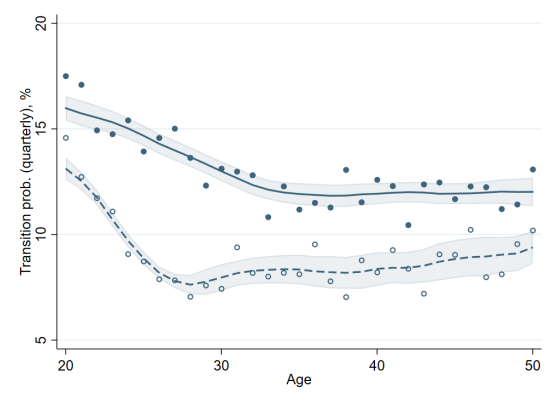
(b) UT



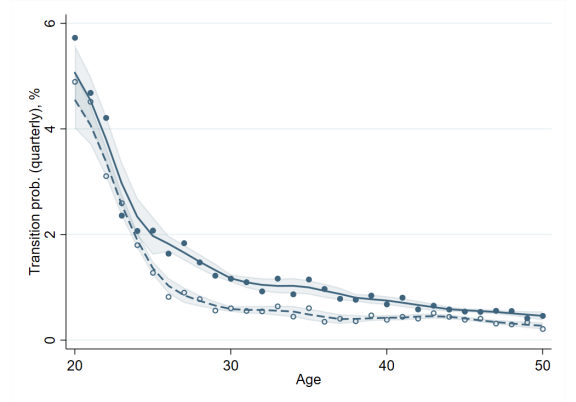
(c) TP



(d) PT



(e) TU



(f) PU

Notes: quarterly transition probabilities by age between unemployment ( $U$ ), non-employment ( $N$ ), employment ( $E$ ) and temporary ( $T$ ), and permanent employment ( $P$ ), computed using *Enquête emploi continu* (EEC) data for 2004-2018. The dots indicate estimated mean transition probabilities by age, and lines represent a point estimate of a local polynomial model with Epanechnikov kernel with 95% confidence interval. The plain lines and dots are for dropout and secondary-education individuals. The dashed lines and empty dots are for the tertiary-education individuals. See text for more details.



where  $S_{a,e}$  represents the vector for the distribution of individual of age  $a$  (expressed in years) in education group  $e$  into labor status N,T,P, where N denotes non-employment.  $\Gamma_{a,e}$  represents the quarterly transition probability matrix for age  $a$  and education  $e$ .  $a_{0,e}$  represents the initial age for the different education groups and equals 20 in our sample. Notice that the age-specific transition matrix is taken at power four since our transition probabilities are quarterly. Using (3), we can obtain life cycle profiles of employment and employment share of temporary jobs that are implied by the estimated transition probability matrix. We compare the computed lifetime sequences of employment and employment share of temporary jobs to the actual lifetime profiles obtained from the data in figure 2. In each subfigure, we display the value of R-squared of the linear regression between the actual profile and the implied one. The estimated transition by the Markov chain does well in replicating the actual profile; the associated R-squared is always above 95 percent.

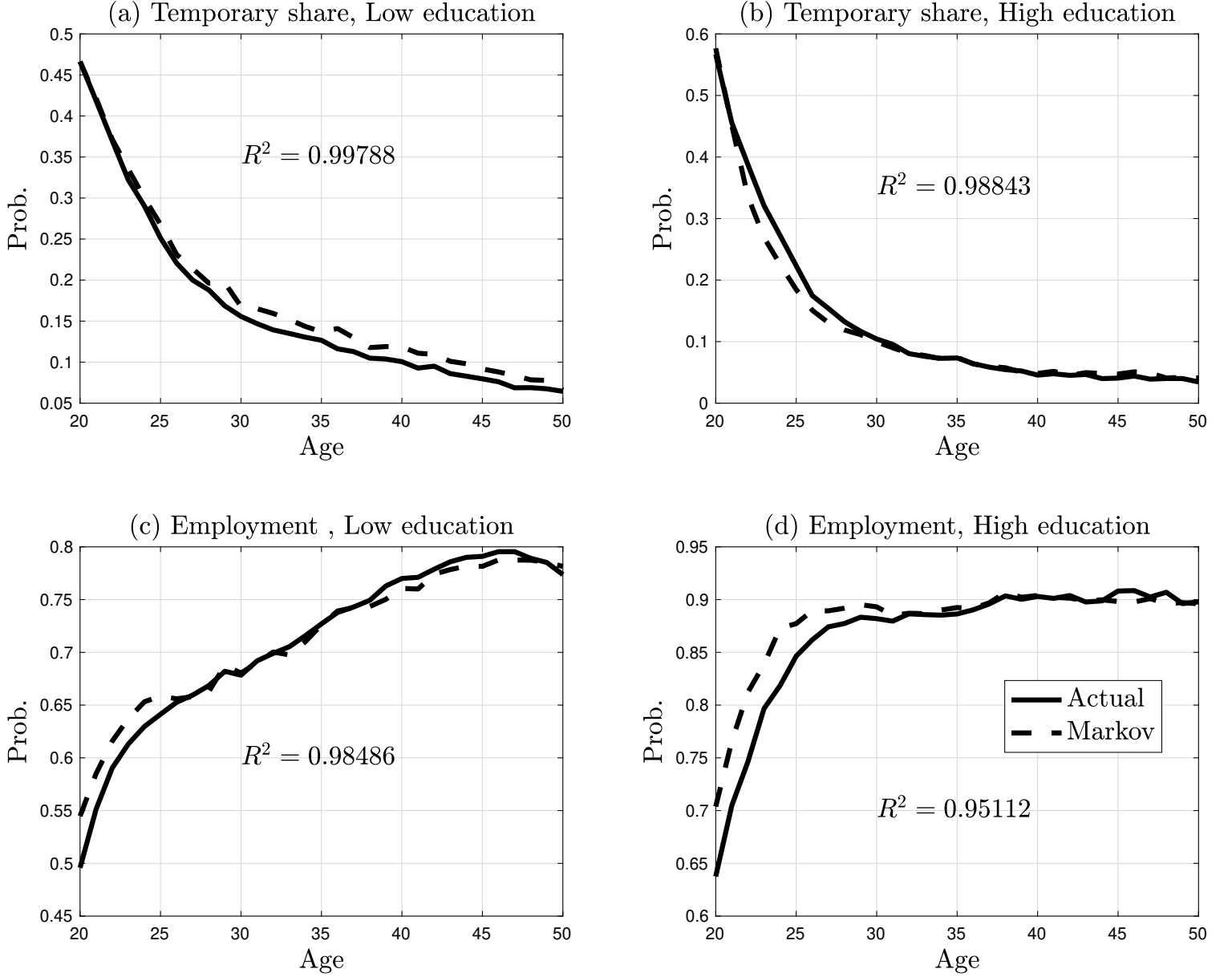
## 2.4 Decomposition

We perform a set of decomposition exercises using the above transition matrices. We consider two cases. One that distinguishes between the unemployment state (U) and inactivity (I), along with the employment states (T and P); and another that combines U and I into a non-employment (N) state. For ease of presentation, we present the analysis for three states (N, T, P). The findings with four states are presented in Appendix A. They are qualitatively similar to the three states' results.

We use the “*all but one change*” (AB1C) method for the decomposition proposed by Choi et al. (2015). This involves the following steps: (i) fixing the value of the transition rate for which the contribution is to be assessed to its average sample value across ages; (ii) creating a counterfactual transition matrix with this alternative transition probability, by adjusting the element on the associated diagonal to keep the transition matrix well-defined; (iii) and computing the counterfactual implied age profiles distributions. Figures 3 and 4 show the alternative employment profiles for both high and low-education group workers. Figures A1 and A2 in appendix A present the results for the temporary employment share. To understand the graphs, notice that the first subfigure in Figure 3, depicts a hypothetical life-cycle employment rate if the job-finding rate into a temporary contract (NT) was fixed at the life-cycle average for all ages, instead of being age specific. Here, whenever there is a significant difference between the two lines (that is, the  $1 - R^2$  is high), the particular transition probability contributes to the shape of the life-cycle profile in either employment rate or temporary employment share. The same applies to the other subfigures.

Results from Figures 3 and 4 indicate that the employment exit probability from a

Figure 2: Markov chain implied employment and temporary job share



Notes: actual and Markov-chain implied age profiles by age and education, for the employment share of temporary jobs (Panels (a) and (b)) and for the employment rate (Panels (c) and (d)). The actual profiles are computed using French continuous employment survey data for 2003-2018 (see subsection 2.1 for details). The implied profiles are computed using transition matrices 3, combined with initial (age-20) stocks in the data. The figure also report  $R^2$  statistics associated with actual and implied data.

permanent job, PN, is the most important contributor in explaining the employment rate variation by age, for individuals with low education. However, for those with high education, job separations from temporary contract, TN and moves from permanent to temporary employment, PT, also matter significantly. More specifically, the PN transition is the primary factor accounting for high employment rates among workers aged 30 and above, irrespective of education. Moreover, the probability of transitioning from a temporary job to non-employment, TN, plays a significant role in explaining the low employment rates among highly educated young workers, specifically those under the age of 30. Fixing this probability at its average value across the life-cycle results in an overall increase in the employment rate over the life cycle. In particular, for individuals with a high level of education, fixing the TN probability at its average level raises the employment rate by approximately 6% at the age of 25.

These findings suggest that labor market duality has different implications for age-specific employment dynamics across skill groups and for youth employment. Furthermore, the decomposition process helps identify the specific flows that need to be carefully modeled in order to replicate the observed evolution of employment over the life cycle. In the next section, we explore further the sources of employment variation by age and education (and the implications of these sources for the effect of employment protection) with a theoretical model.

## 3 Model

### 3.1 Environment

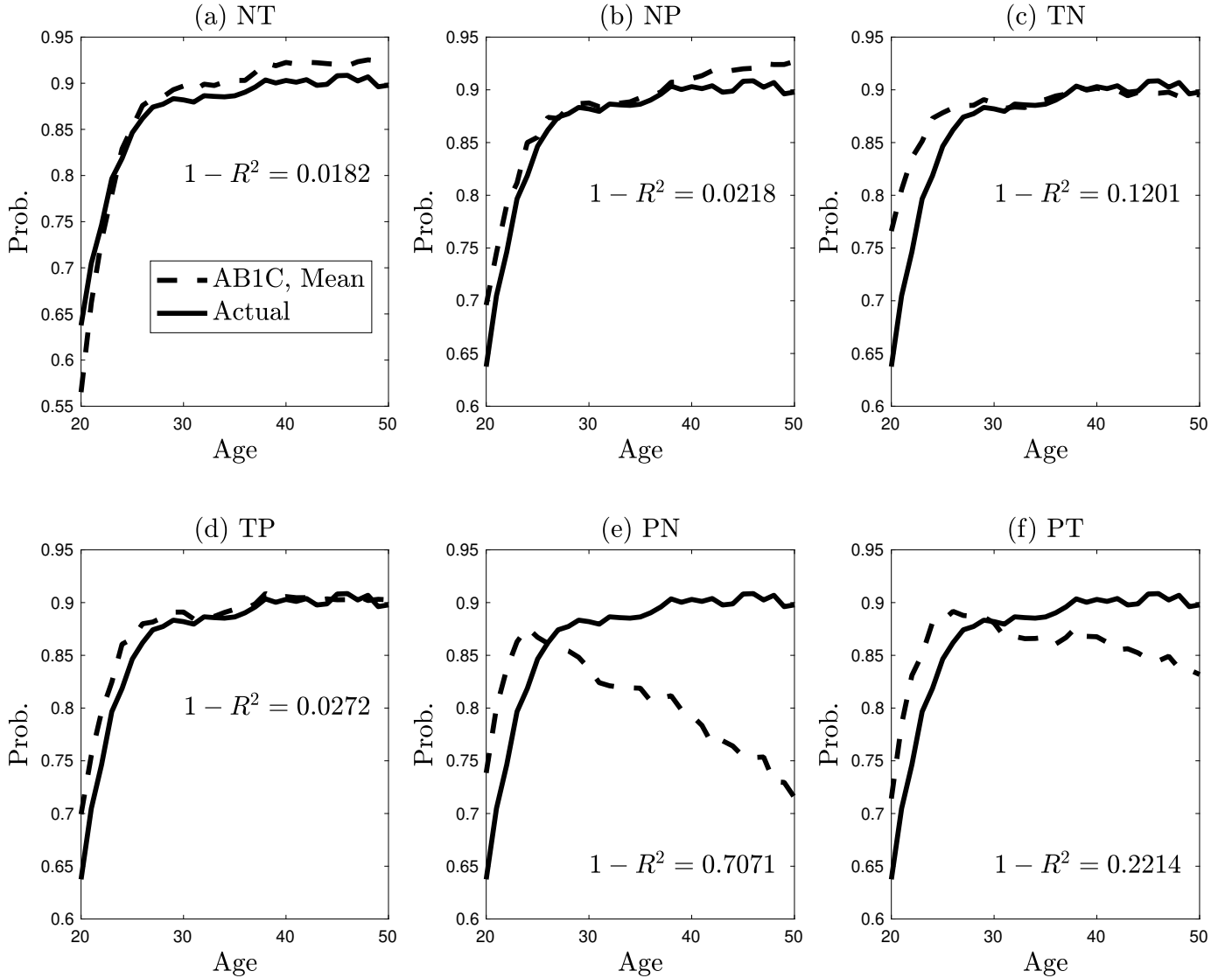
We present a search-and-matching model with heterogeneous workers and jobs. This model features uncertainty and Bayesian learning about worker ability and match-specific unemployment risk.

Time is discrete, goes to infinity, and is indexed by  $t = 0, 1, \dots$ . The economy is populated by a large number of risk-neutral workers and firms. The population of workers is constant and normalized to  $L = 1$ , and the population of firms, denoted by  $M > 0$  is determined in equilibrium. In each period, a worker has a probability  $\xi$  of exiting the population (dying) and being replaced by a newborn worker.

**Skills.** Workers have skill level denoted by  $x_t \in \mathbb{R}_+$ . A newborn worker has skill normalized to one. A worker employed at time  $t$  accumulates skills following the process

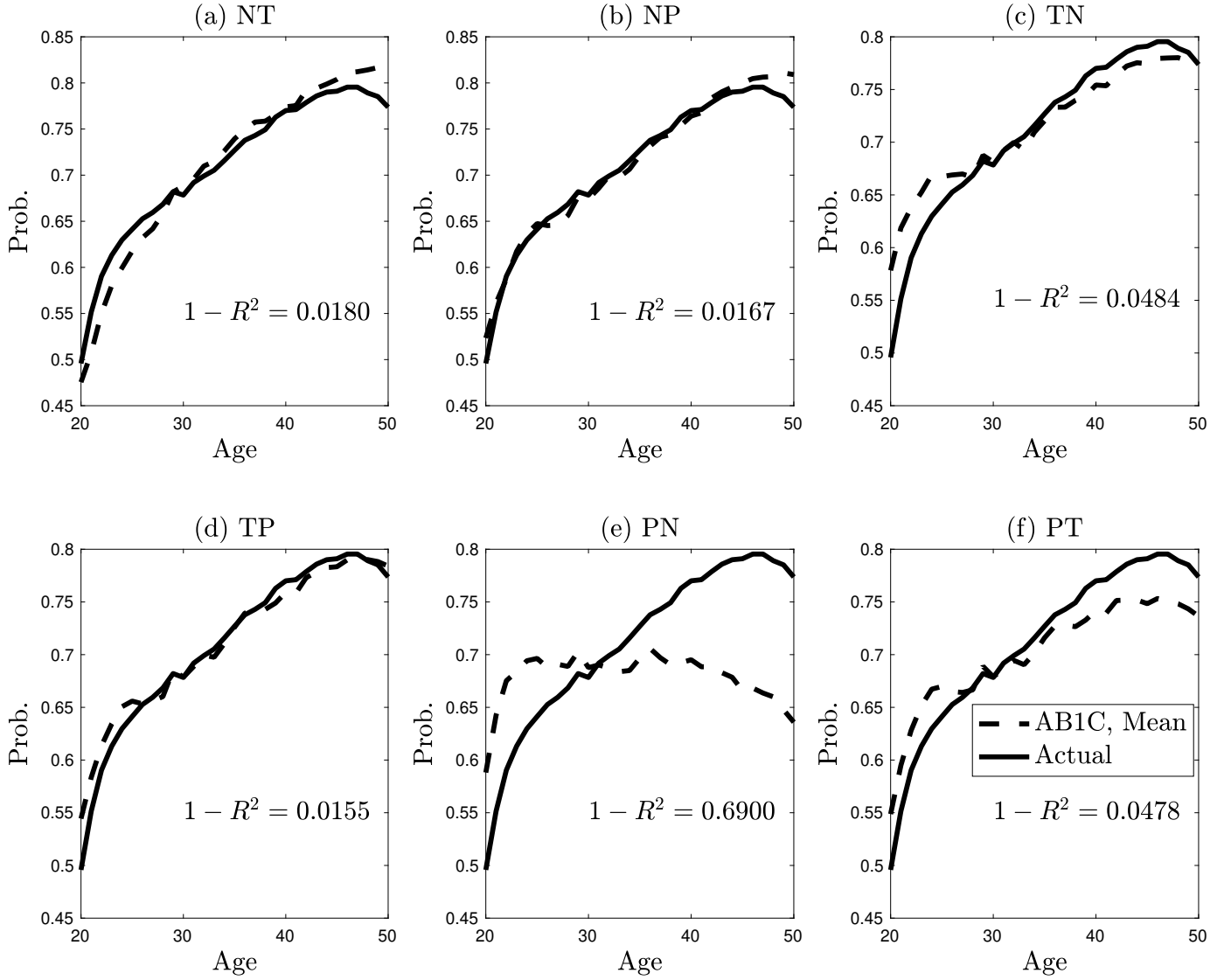
$$\ln x_{t+1} = A + \alpha \ln x_t + \varepsilon_{t+1} \tag{4}$$

Figure 3: AB1C flow decomposition of employment by age: high education



Notes: baseline and counterfactual (AB1C) Markov-chain implied age profiles for employment rates, for the high-education sample. Each panel presents a counterfactual profile, where one transition rate is held equal to its average over age groups. The panels also present actual age profiles for employment rates (presented in Figure 2). For instance the first panel, “NT” presents the age profile by counterfactually holding the NT rate constant and equal to its average. The  $R^2$  coefficients are computed by regressing the counterfactual AB1C on the actual employment rate.

Figure 4: AB1C flow decomposition of employment by age: low education



Notes: baseline and counterfactual (AB1C) Markov-chain implied age profiles for employment rates, for the low-education sample. See notes of Figure 3 for details.

where  $A \in \{\underline{A}, \overline{A}\}$ ,  $0 \leq \underline{A} \leq \overline{A}$  denotes the skill-acquisition ability of the worker.  $\varepsilon_t$  is i.i.d., normally distributed with mean zero and variance  $\sigma_\varepsilon^2$ , and  $\alpha \in (0, 1)$ . We assume that the process for skill dynamics differs between employment and unemployment: an unemployed worker faces the following skills process

$$\ln x_{t+1} = A_0 + \alpha \ln x_t + \varepsilon_{t+1}, \quad (5)$$

where  $A_0 \leq 0$ , meaning that on average, skill depreciates when the worker is unemployed. The skill acquisition probability  $A$  is drawn at the worker's birth. A fraction  $\pi$  of workers are born with skill  $A = \overline{A}$ , and the remaining fraction has  $A = \underline{A}$ . The ability  $A$  of worker is *not* observed by any agents in the economy, nor the realization of the disturbance term in (4). However, the skill level  $x_t$  is observable and can be relied upon as a signal informative about the true ability level  $A$ . Hence, there is uncertainty regarding the precise role of ability in driving the skill dynamics versus the role of the disturbance terms in (4). As such, the agents use the realized skill levels implied by (4) and (5) as signals for forming and updating Bayesian beliefs regarding the distribution of the true, unobserved worker's ability. At a time  $t$ , these beliefs are represented by a probability  $\tilde{\pi}_t$  that the worker has high ability  $\overline{A}$ .

Conditional on prior beliefs at time  $t$  described by  $\tilde{\pi}_t$  and on the current (log) skill level  $x_t$ , the next period ( $t + 1$ ) posterior beliefs are updated based on the realized skill level following:

$$\tilde{\pi}_{t+1} = \frac{\tilde{\pi}_t f(\ln x_{t+1} - \alpha \ln x_t - \overline{A})}{\tilde{\pi}_t f(\ln x_{t+1} - \alpha \ln x_t - \overline{A}) + (1 - \tilde{\pi}_t) f(\ln x_{t+1} - \alpha \ln x_t - \underline{A})}, \quad (6)$$

where  $f$  is the probability density function of a normal distribution with mean 0 and variance  $\sigma_\varepsilon^2$ . Moreover, the initial beliefs for a worker born at time  $t_0$  are described by distribution parameters equal to their population counterparts:

$$\tilde{\pi}_{t_0} = \pi \quad (7)$$

for all  $t_0 \geq 0$ .

**Jobs.** Workers with varying skill levels choose jobs based on the specific skill they possess, and these jobs are further distinguished by the extent to which they utilize this skill ("task complexity"). Hence, jobs are heterogeneous and have type indexed by  $j \in \{0, 1\}$ . There are *generic* ( $j = 0$ ) and *complex* ( $j = 1$ ) jobs. The output produced at time  $t$  by a match in a complex job depends on the worker's skill level  $x_t$ , whereas the output produced by a generic job is independent of skills. The output of a worker-firm match in a complex job is given by

$$y_t = \zeta x_t^\rho, \quad (8)$$

where  $\zeta > 0$  and  $\rho \in (0, 1)$ . The output produced by a match in a generic job is equal to  $\bar{y}$ . We assume that  $\bar{y} > 0 = \ln(x_{t_0})$  for any birth date  $t_0$ . Low-skill workers have a comparative advantage in generic jobs, whereas the highly skilled have a comparative advantage in complex jobs.

Moreover, a match has a probability of separation  $\delta$ . This probability is assumed heterogeneous across matches. Job type  $j$  and the probability  $\delta$  are stochastically drawn at the beginning of potential matches between workers and firms upon meeting in the labor market, as explained in more detail below.

**Search frictions.** Workers are either unemployed or employed, and firms have jobs that are either vacant or occupied. An unemployed worker receives period utility  $b > 0$ . The per-period cost of posting a vacancy is  $c > 0$ . There is a search on the job; thus, unemployed and employed workers search for jobs. The labor market tightness is denoted  $\theta_t = v_t/(u_t + sn_t)$ , where  $v_t > 0$  is the mass of vacant jobs,  $u_t$  is the mass of unemployed workers, and  $n_t$  the mass of employed workers;  $s > 0$  is the search intensity of employed workers relative to the unemployed. We denote by  $n_{s,t} = u_t + sn_t$  the effective mass of job seekers.

There is a standard Cobb-Douglas matching function  $m(n_s, v) = \chi n_s^\eta v^{1-\eta}$ , with  $\chi > 0$  the efficiency of matching and  $\eta \in (0, 1)$  the elasticity of matching with respect to the effective mass of job seekers. Matching is random. The contact rate of an unemployed worker is  $sp(\theta) = \chi\theta^{1-\eta}$ , whereas for a vacancy it is  $q(\theta) = \chi\theta^{-\eta}$ . Each worker-firm pair brought together via the matching technology draws a job type  $j = 0, 1$  and a separation risk  $\delta \in [0, 1]$ . The probability of drawing a job of type  $j = 0, 1$  is  $\gamma_j$ . We assume a probability  $\bar{\gamma}$  of drawing a complex job,  $\gamma_1 = \bar{\gamma}$ .

The exogenous probability of separation is drawn from a distribution with c.d.f.  $G_\delta(\cdot|j)$ , dependent on the job type. Based on these elements and the worker's current unemployment or employment status and job type, the agents evaluate if it is mutually beneficial to form a match, and matching takes place accordingly.

**Bargaining.** As in [Postel-Vinay and Robin \(2002\)](#), we assume full bargaining power to the firm combined with sequential auctions and Bertrand competition between employers or firms. Hence, in the absence of an outside offer received by workers, firms extract the entire surplus of their match, but workers can use outside offers to trigger wage renegotiation and increase their share of the surplus. Wages are renegotiated following [Lise and Postel-Vinay \(2020\)](#). Workers' surplus share is endogenous and is a result of competition between firms.

This assumption allows us to introduce on-the-job search at a modest computational cost. Hence, the model features a job ladder with heterogeneous risk of unemployment. We show

that this job ladder feature and Bayesian learning about the ability of worker are the keys to explaining the empirical facts we highlight regarding transition rates. Essentially and as it will become clear later, assuming full bargaining power to the firm implies that competition between firms only affects the distribution of the surplus between agents. As a result, the surplus functions are independent of the search on the job outcomes. This simplifies the computation of surplus functions dramatically, even in the presence of rich state space (see [Lise and Postel-Vinay \(2020\)](#)).

**Labor market institutions.** Firms can either offer a temporary or a permanent contract. We denote by  $TC$ , a temporary contract and  $PC$  a permanent contract. A permanent contract incurs firing costs of  $F$ , whereas a temporary contract has no firing costs. Temporary contracts are governed by regulations, and restrictions on these contracts are captured by a tax  $\tau$  on the output of a match in a temporary job. Both  $F$  and  $\tau$  represent deadweight losses that capture the effects of employment protection legislation (EPL). Alternatively,  $\tau$  can be interpreted as a reduced-form approach for capturing contractual frictions that are inherent to temporary jobs, which helps accounting for the coexistence of permanent and temporary jobs as observed in the data. Rationalizing this coexistence is beyond the scope of this paper <sup>2</sup>. Additionally, temporary contracts have a stochastic maximum duration. With probability  $\phi$ , the contract will come to an end and must be converted into a permanent contract. Existing legislation only permits the conversion of a temporary contract into a permanent one.

**Timing.** The timing of events for each worker type is as follows.

*Unemployed worker.*

- (i) Exits the labor market with probability  $\xi$  or stays with the complement probability.
- (ii) If stays, observes the new skill level  $x_t$  implied by process (5).
- (iii) Searches and receives an offer with probability  $sp(\theta)$ .
- (iv) If receives an offer, draws a job type  $j = 0, 1$  and an exogenous separation probability  $\delta$ .
- (v) Based on skill, belief, the job type, and the probability of separation, the agents evaluate the surplus in a PC and a TC jobs and decide whether they form a match or not and the type of contract.

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<sup>2</sup>See [Cahuc et al. \(2016\)](#), [Créchet \(2023\)](#), for papers that rationalize coexistence of permanent and temporary contracts.



- (vi) If there is no offer or the surplus is not high enough to make matching mutually profitable, the agent stays unemployed.

*Permanent worker.*

- (i) Exits the labor market with probability  $\xi$ , stays otherwise.
- (ii) Updates skill and belief according to (4) and (6).
- (iii) Receives exogenous separation shock with probability  $\delta$  or stay otherwise.
- (iv) If stays, he receives an outside offer with probability  $sp(\theta)$ , and draws a job type  $j'$  and a probability of separation  $\delta'$  for the new potential match.
- (v) In the case of an offer, compares the current surplus with the outside surplus. leaves the current match for the outside match if this is profitable, and chooses the best contract type.
- (vi) If there is no transition to an outside match, the worker stays employed if the surplus in the current match associated with the current skill and belief from stage (ii) is positive; otherwise, the worker returns to unemployment.

*Temporary worker.*

- (i) Exits the labor market with probability  $\xi$ , and stays otherwise.
- (ii) Updates skill and belief.
- (iii) Receives exogenous separation shock with probability  $\delta$  or stay otherwise.
- (iv) With probability  $1 - \phi$ , the agents are free to choose between a TC and PC contracts and choose the contract type yielding the more surplus; with the complement probability, the agents are required to convert the T into a P.
- (v) Receives a potential outside offer and evaluates the current and outside surplus; continues the match or separates for a new match or unemployment.

### 3.2 Value functions

We consider a steady-state recursive equilibrium of the labor market and drop time subscript. For extra clarity, let the dying probability  $\xi = 0$  for the ease of the model's presentation. We denote by  $a$  and  $a'$  the current and next-period value of a variable  $a$ .

Let  $\omega = (p, x) \in \Omega \equiv [0, 1] \times \mathbb{R}_+$  be a vector describing the worker's state: the belief for the distribution of the skill-acquisition ability and the current skill level. Moreover, denote by  $S_P : \Omega \times \{0, 1\} \times [0, 1] \rightarrow \mathbb{R}_+$  and  $S_T : \Omega \times \{0, 1\} \times [0, 1] \rightarrow \mathbb{R}_+$  the total worker-firm surplus functions in a permanent and a temporary contract, respectively. Let  $U$  be the worker's lifetime discounted utility value of unemployment.

As typically assumed in the literature (see [Cahuc and Postel-Vinay \(2002\)](#), [Faccini \(2014\)](#)), firing costs impact the firm's outside option during an ongoing match (i.e., in periods after the match's initial date) but not at the hiring stage. As such, this introduces a distinction between an ongoing and a hiring stage in a permanent contract. We use  $S_P$  to denote the surplus function in the continuation stage. Hence, the surplus at the hiring stage is  $S_P - F$ . Thus, the surplus from a new match being formed at the hiring stage is lower than that from a continuing or ongoing match because the employer only incurs firing costs once the worker has been dismissed. At the time of the first encounter between the worker and the employer, a disagreement cannot cause firing costs since no contract is yet signed. By the same logic, in the stage where the agents consider converting the temporary contract into a permanent contract (called the *conversion* stage), the surplus function is  $S_P - F$ .

From the assumptions that the firm has complete bargaining power and that non-work income  $b$  is independent of skills, it follows that the worker's discounted utility value of unemployment over their lifetime is simply:

$$U(p) = \frac{b}{1 - \beta}, \quad (9)$$

for all  $p \in [0, 1]$ .

In addition, define

$$S_0(\omega, j, \delta) \equiv \max(S_P(\omega, j, \delta) - F, S_T(\omega, j, \delta), 0), \quad (10)$$

for all  $\omega \in \Omega$ ,  $j \in \{0, 1\}$ ,  $\delta \in [0, 1]$ , which is the maximized surplus of a potential match upon contact between a firm with a vacancy and an unemployed worker in state  $\omega$ , conditional on drawing job characteristics  $(j, \delta)$ .

As previously mentioned, wage renegotiation takes place as in [Postel-Vinay and Robin \(2002\)](#) or [Lise and Postel-Vinay \(2020\)](#), but with adjustments made to account for the presence

of both permanent and temporary contracts. Importantly, we assume that in the case of renegotiation, the worker can use the threat represented by firing costs to negotiate wages up to the point where the firm is indifferent between paying firing costs and keeping the worker. Hence, the employer's willingness to pay in a permanent job is the wage such that the profit of the active job equals the value of a vacant position net of firing costs.<sup>3</sup>

We denote by  $\nu \in [0, 1]$  the surplus share of a worker in a given match. Due to assumption of firms having full bargaining power, workers hired from unemployment have  $\nu = 0$ . In subsequent periods, they can use outside offers to trigger competition between employers and improve their surplus, implying that  $\nu \geq 0$  in general. Let begin by assuming a worker in a permanent contract and in state  $(\omega, j, \delta)$ . Conditional on receiving an outside offer from a vacancy with job characteristics  $(j', \delta')$ , the worker moves to the new job if  $S_0(\omega, j', \delta') > S_P(\omega, j, \delta)$ , and otherwise stays with the same employer (assuming  $S_P(\omega, j, \delta) \geq 0$ ). Conditional on staying, the worker receives an updated surplus share given by<sup>4</sup>

$$\nu' = \mathcal{I}(\nu S_P(\omega, j, \delta) > S_0(\omega, j', \delta'))\nu + \mathcal{I}(\nu S_P(\omega, j, \delta) \leq S_0(\omega, j', \delta')) \frac{S_0(\omega, j', \delta')}{S_P(\omega, j, \delta)}, \quad (11)$$

for all job types for current and outside firms  $(j, \delta)$  and  $(j', \delta')$  and for all current  $\nu \in [0, 1]$ . In the case of job-to-job move, the worker surplus share in the new match is:

$$\nu' = \frac{S_P(\omega, j, \delta)}{S_0(\omega, j', \delta')}. \quad (12)$$

As a result, the worker expected surplus, conditional on receiving an outside offer (with probability  $sp(\theta)$ ), reads:

$$\Delta_{W,P}(\omega, j, \delta, \nu) = \sum \gamma_j \int \min \left\{ \max(\nu S_P(\omega, j, \delta), S_0(\omega, j', \delta'), 0), \max(S_P(\omega, j, \delta), 0) \right\} dG_\delta(\delta'|j'), \quad (13)$$

for all  $\omega, j, \delta$ ; the expected surplus of the firm conditional on an outside offer is

$$\Delta_{J,P}(\omega, j, \delta, \nu) = \sum \gamma_j \int \max \left\{ \min(S_P(\omega, j, \delta) - S_0(\omega, j', \delta'), (1 - \nu)S_P(\omega, j', \delta')), 0 \right\} dG_\delta(\delta'|j'). \quad (14)$$

It is easy to see that  $\Delta_{W,P}(\omega, j, \delta, \nu) + \Delta_{J,P}(\omega, j, \delta, \nu) = \max(S_P(\omega, j, \delta), 0)$  for all  $\nu \in [0, 1]$ . Hence, there is no gain in match surplus resulting from searching on the job. However, from

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<sup>3</sup>We abstract from transfers between workers and firms upon separations (i.e., severance payments). See [Postel-Vinay and Turon \(2014\)](#) for a case where such transfers are allowed.

<sup>4</sup>See appendix A for sequences that give the result

the worker's perspective, there is a gain. The worker receives the total surplus of the current match. This follows from the assumption of zero bargaining power to the worker, implying that the worker's gains and the firm's losses offset each other. Hence, the total surplus of a permanent job can be expressed as:

$$S_P(\omega, j, \delta) = y_j - b + (1 - \beta) F + \beta(1 - \delta) \int \max \{S_P(\omega', j, \delta), 0\} dH_x(x'|\omega), \quad (15)$$

such that the next-period worker's state vector  $\omega' = (p', x')$  has belief  $p'$  updated following:

$$p' = \frac{pf(\ln x' - \alpha \ln x - \bar{A})}{pf(\ln x' - \alpha \ln x - \bar{A}) + (1 - p)f(\ln x' - \alpha \ln x - \underline{A})}, \quad (16)$$

for all  $p \in [0, 1]$  and all  $x \geq 0$ . The next-period skill  $x'$  follows the normal mixture distribution with density:

$$h(x'|x, p) = \frac{1}{x'\sigma\sqrt{2\pi}} \left\{ p \exp \left[ -\frac{1}{2} \frac{(\ln x' - \alpha \ln x - \bar{A})^2}{\sigma^2} \right] + (1 - p) \exp \left[ -\frac{1}{2} \frac{(\ln x' - \alpha \ln x - \underline{A})^2}{\sigma^2} \right] \right\}, \quad (17)$$

and associated c.d.f.  $H(\cdot|x, p)$ .

Hence, the surplus function (15) has a current-period value given by the match current output net of the annuity value of unemployment and firing costs. An exogenous separation occurs with probability  $\delta$ . The next-period expectation for the discounted total lifetime value is taken over the distribution of next-period skills  $x'$  implied by the current skill level  $x$  and by the current beliefs regarding the distribution of the skill-acquisition ability,  $p$ . This distribution is described by (17). Moreover, the agents internalize that their next-period beliefs  $p'$  will be updated based on the realization of  $x'$  and given the current state, following (16).

Worker's gains and employer's losses from on-the-job search do not show up in the equation for the total surplus since, as discussed above, they offset each other. With full bargaining power to the employer, on-the-job search outcomes only affect the distribution of the surplus over time, leaving the total surplus unchanged. Here, we can interpret the job-to-job move as if the worker stays in the same match but extracts the entire surplus.

Similarly, the worker-firm match surplus in a temporary job is

$$\begin{aligned} S_T(\omega, j, \delta) &= (1 - \tau)y_j - b \\ &\quad + \beta(1 - \delta)(1 - \phi) \int \max \{S_T(\omega', y, \delta), S_P(\omega', y, \delta) - F, 0\} dH_x(x'|\omega) \\ &\quad + \beta(1 - \delta)\phi \int \max \{S_P(\omega', y, \delta) - F, 0\} dH_x(x'|\omega), \end{aligned} \quad (18)$$

such that (16) to (17) are satisfied. With probability  $\phi$ , the agents must convert the temporary contract into a permanent one or terminate the match. With the complement probability  $1 - \phi$ , the agents are allowed to continue into a temporary job, convert the contract into permanent or endogenously dissolve the match.

Since unemployment income is independent of skill, the surplus in a generic job is independent of skill following the assumption of zero bargaining power to the worker. As such, the surplus of a generic ( $j = 0$ ) permanent job satisfies

$$S_P(0, \delta) = \bar{y} - b - (1 - \beta)F + \beta(1 - \delta) \max(S_P(0, \delta), 0), \quad (19)$$

for all  $\delta \in [0, 1]$ , independently of the worker type. In a temporary job, we have

$$S_T(0, \delta) = \bar{y} - b + \beta(1 - \delta) \left[ (1 - \phi) \max(S_T(0, \delta), S_P(0, \delta) - F, 0) + \phi \max(S_P(0, \delta) - F, 0) \right]. \quad (20)$$

In steady-state, the equilibrium surplus in a permanent job is

$$S_P(0, \delta) = \frac{\bar{y} - b + (1 - \beta)F}{1 - \beta(1 - \delta)}, \quad (21)$$

for all  $\delta \in (0, 1)$ , independently of the worker's state  $\omega$ . Moreover, in equilibrium, a temporary job that has been formed upon meeting between the worker and the firm in the match must have a higher surplus than in a P job. Otherwise, the T match would not have been formed in the first place. Hence, the surplus in a T solves

$$S_T(0, \delta) = \frac{\bar{y} - b + \beta\phi(1 - \delta) \max(S_P(0, \delta) - F, 0)}{1 - \beta(1 - \delta)(1 - \phi)}, \quad (22)$$

for all  $\delta \in (0, 1)$ .

### 3.3 Wages

To derive the equilibrium wage functions, it is useful to denote by  $W_{P,i}(\omega, y, \delta; \nu)$  the value function of a worker in a permanent contract receiving surplus share  $\nu \in [0, 1]$ , resulting from past renegotiation triggered by previous outside offers. The index  $i$  indicates whether the state is taken to be in the hiring/conversion stage ( $i = 0$ ) or in the continuation stage ( $i = 1$ ). Notice that

$$W_{P,i}(\omega, j, \delta; \nu) - U = \nu(S_P(\omega, y, \delta; \nu) + \mathcal{I}(i = 1)F). \quad (23)$$

Further, the worker's surplus, after making use of (13), can be written as

$$W_{P,i}(\omega, j, \delta; \nu) - U = w_{P,i}(\omega, j, \delta; \nu) - b + \beta(1 - \delta) \\ \times \int \left[ (1 - sp(\theta))\nu \max(S_P(\omega', j, \delta), 0) + sp(\theta)\Delta_{W,P}(\omega', j, \delta; \nu) \right] dH_x(x'|\omega), \quad (24)$$

for all  $i, \omega, y, \delta, \nu$ , where  $w_{P,i}(\omega, y, \delta; \nu)$  denotes the wage. From the perspective of the worker, the surplus gains in the eventuality of a contact with an outside firm,  $\Delta_{W,P}$ , show up in expectations regarding the next-period surplus. With probability  $1 - sp(\theta)$ , there is no outside offer, and the surplus share of the worker remains unchanged.

We have, for a worker in a temporary contract

$$W_T(\omega, j, \delta, \nu) - U = w_{P,i}(\omega, j, \delta; \nu) - b + \beta(1 - \delta) \\ \times \int \left\{ (1 - \phi) \left[ (1 - sp(\theta))\nu \max(S_T(\omega', j, \delta, \nu), S_P(\omega', j, \delta, \nu) - F, 0) + sp(\theta)\Delta_{W,T}(\omega', j, \delta, \nu) \right] \right. \\ \left. + \phi \left[ (1 - sp(\theta))\nu \max(S_P(\omega', j, \delta; \nu) - F, 0) + sp(\theta)\Delta_{W,P,0}(\omega', j, \delta, \nu) \right] \right\} dH_x(x'|\omega), \quad (25)$$

where

$$\Delta_{W,T}(\omega, j, \delta; \nu) = \\ \int \int \min \left\{ \max(\nu S_T(\omega, j, \delta), S_0(\omega, j', \delta'), 0), \max(S_T(\omega, j, \delta), S_P(\omega, j, \delta) - F, 0) \right\} \\ \times dG_\delta(\delta'|j') dG_j(j'),$$

and

$$\Delta_{W,P,0}(\omega, j, \delta; \nu) = \\ \int \int \min \left\{ \max(\nu(S_P(\omega, j, \delta) - F), S_0(\omega, j', \delta'), 0), \max(S_P(\omega, j, \delta) - F, 0) \right\} \\ \times dG_\delta(\delta'|j') dG_j(j')$$

represent the expected surplus of the worker, conditional on the state and on a contact with an outside firm, in a TC and in PC (at the conversion stage) respectively.

Using (15) and (24) the wage in a PC can be written as

$$w_{P,i}(\omega, j, \delta, \nu) = \nu y_j + (1 - \nu)b + \nu(\mathcal{I}(i = 1) - \beta)F \\ - sp(\theta) \int \left( \Delta_{W,P}(\omega', j, \delta; \nu) - \nu \max(S_P(\omega', j, \delta; \nu), 0) \right) dH_x(x'|p), \quad (26)$$

for  $i = 0, 1$ , and the wage in a temporary contract is written as, using (18) and (25)

$$\begin{aligned}
w_T(\omega, j, \delta; \nu) &= \nu y_j + (1 - \nu)b \\
&- sp(\theta)(1 - \phi) \int \left( \Delta_{W,T}(\omega', j, \delta; \nu) - \nu \max(S_T(\omega', j, \delta; \nu), S_P(\omega', j, \delta; \nu) - F, 0) \right) dH_x(x'|\omega) \\
&- sp(\theta)\phi \int \left( \Delta_{W,P,0}(\omega', j, \delta; \nu) - \nu \max(S_P(\omega', j, \delta; \nu) - F, 0) \right) dH_x(x'|\omega), \tag{27}
\end{aligned}$$

for all  $\omega, j, \delta$ , and  $\nu$ . Worker collects a fraction  $\nu$  of the match output net of the expected gains from renegotiation due to on-the-job search, and a fraction  $1 - \nu$  of the annuity value of unemployment. In the case of a permanent contract, the worker also collects a fraction  $\nu$  of the annuity value of firing costs at the continuation stage ( $i = 1$ ), and the same fraction of the discounted firing costs.

### 3.4 Equilibrium

We assume free entry of firms, which in equilibrium implies zero expected profits from vacancy posting. Let  $u(a)$  and  $n(a)$  denote the measures at age  $a$  of unemployed and employed workers respectively. Free entry yields the following equation

$$\begin{aligned}
\frac{c}{\beta q(\theta)} &= \beta \sum_a \left\{ \underbrace{\frac{u(a)}{u + sn} E \left[ \max(S_0(\omega', j', \delta', 0), 0) \right]}_{\text{meeting with an unemployed worker}} + \right. \\
&\quad \left. \underbrace{s \frac{n(a)}{u + sn} E \left[ \mathcal{I}_{(S_0(\omega, j', \delta', \nu') > S_0(\omega', j'', \delta'', \nu))} (1 - \nu') \max(S_0(\omega', j', \delta', \nu'), 0) \right]}_{\text{meeting with an employed worker}} \right\} \tag{28}
\end{aligned}$$

The expectations are taken with respect to the distribution of worker states and job characteristics in the pool of employed and unemployed job searchers of age  $a$ , and with respect to . Primes ( $'$ ) denotes state variables associated with the own firm's potential match; double primes ( $''$ ) denote state variable of with an existing job, to which an employed worker is matched. An equilibrium definition is as follows.

**Definition.** A stationary labor market equilibrium is a list of functions  $\{S_0, S_P, S_T, \nu, w_P, w_T\}$ , labor market stocks  $\{u(a), n(a)\}$  for all age  $a \geq 0$ , and a labor market tightness  $\theta$ , and cross-sectional distributions of workers' skills, beliefs and job characteristics such that: (i)  $S_0, S_P$ , and  $S_T$  satisfy (10), (15), (18), (21), and (22);  $\nu$  follows (11) and (12);  $w_P$  and  $w_T$  solve (24) and (25); (ii) the labor market tightness  $\theta$  solves (28) given  $S_0, S_P, S_T$ , the labor market stocks and distributions; (iii) the labor market stocks and distributions are constant over time.

## 4 Calibration

This section describes the calibration strategy. We calibrate the model for the two education groups. Some parameters are assigned to standard values and are assumed to be the same across education groups. The parameters governing the distribution of unemployment risk, skill and beliefs, the composition of job type, and some institutional factors are separately calibrated to match salient features of workers' life cycle in high and low-education groups.

### 4.1 Preset parameters

The time unit is set to a quarter, and the working-life duration equals 38 years. Taken together, these imply an exogenous dying probability of  $\xi = 0.0065$ . We set  $\beta = 0.9902$  (a 4% annual discount rate). The elasticity of matching is set to  $\eta = 0.5$ , a conventional value. The matching efficiency  $\chi$  is part of the internal calibration procedure described below. Hence, a value for the firms' search costs  $c$  will be backed out to satisfy the free-entry condition, using the calibrated value for  $\chi$  and the normalization of labor tightness value  $\theta = 1$ . On average, when a worker is not employed, the log-skill  $x$  depreciates and drifts down toward a low level of ability  $A_0$ , which we normalize to 0. We calibrate the parameter for the duration restriction  $\phi$  to 0.1175. This value matches two years of an expected duration of a temporary contract before conversion to a permanent contract. This is consistent with legislation in many countries for the maximum duration of these contracts. The process of skill dynamics is governed by the persistence parameter  $\alpha$ . We set  $\alpha$  to 0.9702 in line with Santos and Rauh (2022), which approximates mean earnings profile from a standard Mincer regression of log wages, controlling for education. We assume that initial belief about ability is uniform across ability level. Hence, we set the probability of having high ability belief initially to  $p_0 = 0.5$ . The preset parameters are reported in Table 1.

### 4.2 Internally calibrated parameters

The following remaining parameters are separately calibrated to match salient features of workers' life cycles in high- and low-education groups using a simulation-based method. Those are the matching efficiency  $\chi$ , the non-work income  $b$ , the firing cost  $F$ , the employed worker relative search intensity on the job  $s$ , the proportion of complex job  $\bar{\gamma}$ , the high and low level of potential ability ( $A_h, A_l$ ), the variance of disturbance embed in skill learning  $\sigma_\epsilon$ , the shape parameters for job separation distribution with respect to job type, and the elasticity  $\rho$  of output with respect to skill  $x$  in the complex job. We assume that the job separation  $\delta$  is drawn from a beta distribution with shapes  $(\lambda_1, \lambda_2)$ .



Table 1: Preset parameter values

Parameter	Description	Value
$\beta$	Discount rate	0.9902
$\xi$	Exogenous dying probability	0.0066
$\bar{y}$	Output for generic job	1.4286
$\eta$	Elasticity of matching function	0.5
$\phi$	Expected max duration of TC	0.1175
$\alpha$	AR1 skill dynamics persistence, employment	0.9702
$p_0$	Proportion having high ability beliefs $A_h$	0.5
$A_0$	Ability in skill process from unemployment	0

The calibration of the parameters mentioned above minimizes the sum of the relative differences (in absolute values) of a set of simulated moments and their empirical counterparts. We target the following transition rates, computed from 2003-2018 EEC data: the age profiles of the UP, UT, PT, PU, TP, and TU. We also target the unemployment age profile and the age profile of the share of employment in a temporary contract.

### 4.3 Model fit

The estimated parameters are reported in Table 2, and the model fit to the data is displayed in Figures 5, 6, and 7. Figure 5 plots the unemployment rate and the share of temporary employment in the model along with its empirical counterpart. Panel (a) presents results for low low-education group and panel (b) reports results for the high-education group.

We observe that the model fits the data well, capturing the decline in the unemployment rate and a share of temporary contract jobs as workers age. Figure 6 plots the transition rates for the low-education group. The model closely matches the transition profiles. It replicates the flat profile observed in the data for UP, UT, and TP transition rates throughout the life cycle, as well as the associated levels. In addition, the model replicates the declining profile for job separation rate as measured by PU and TU as workers age, although, in the model, the separation rate from temporary jobs to unemployment slightly decreases at the end of the careers. This can be attributed to an absence of participation margin in the analysis: in the data, transitions from employment to inactivity are relatively high for the oldest workers (e.g., Choi et al. (2015), Lalé and Tarasonis (2018)), a pattern that could be reproduced in the presence of a distinction between unemployment and non-participation. Nonetheless,

Table 2: Benchmark values of estimated parameters

Parameter	Description	Value	
		Low-educ.	High-educ.
$b$	Non work utility	0.9629	0.9517
$F$	Firing cost	1.9727	1.8942
$\chi$	Matching efficiency	0.3216	0.3450
$s$	Employed search intensity	0.5	0.5
$\rho$	Complex job output function parameter	0.0249	0.3442
$\lambda_{1,g}$	Shape 1 for generic job sepa. distribution	0.3267	1.8047
$\lambda_{2,g}$	Shape 2 for generic job sepa. distribution	1.1875	1.5121
$\lambda_{1,c}$	Shape 1 for complex job sepa. distribution	2	0.1745
$\lambda_{2,c}$	Shape 2 for complex job sepa. distribution	7.1283	2.7585
$\bar{\gamma}$	Proportion of complex job	0.6745	0.4305
$\sigma_\varepsilon$	Standard deviation for skill disturbance	0.0181	0.1852
$\underline{A}$	Low level of ability belief	0.0076	0.0011
$\bar{A}$	High level of ability belief	0.0387	0.0251

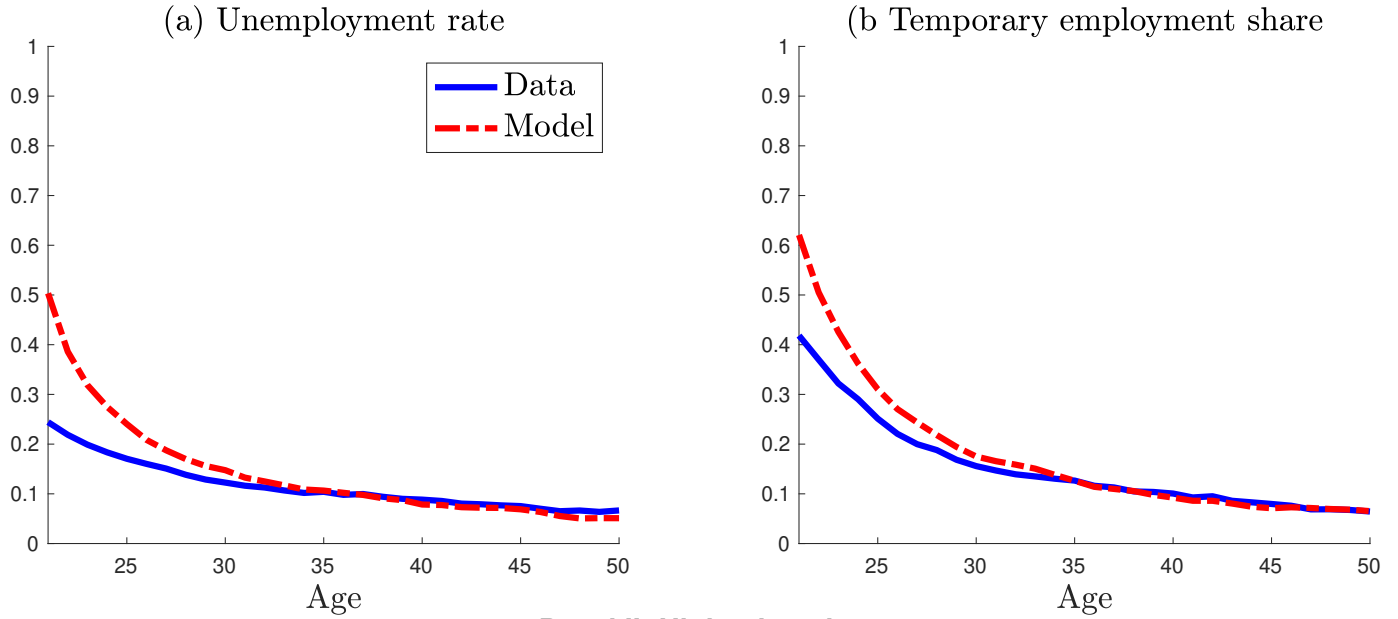
the model replicates the age profile of the PU transition quite well, which, according to the empirical decomposition of section 2 is the main factor associated with life-cycle employment variation.

Figure 7 plots the transition rates for the high education group. The model fits fairly well the empirical targets. It captures the main qualitative feature of the data, such as the declining shapes of transition profiles. The transition UP, PU, PT, and TU are well matched but the model has difficulties with fitting the empirical level of UT and TP. Here again, an important result is that the model fits closely the age profile of PU and PT transition rates for high-education individuals, which are the most important contributors in explaining total employment rate dynamics over the life cycle for high-education groups (decomposition of section 2).

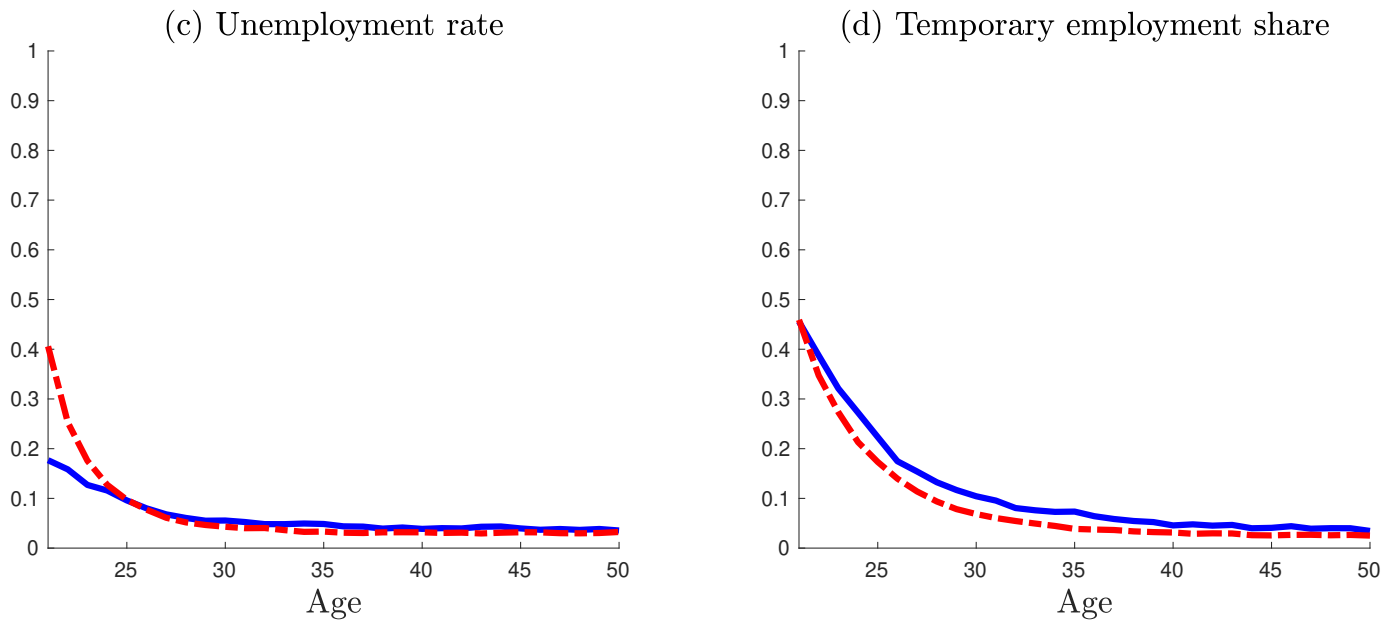
In the following, we explore the role of learning versus idiosyncratic unemployment risk in fitting the observed transition rates.

Figure 5: Target unemployment and temporary employment share profiles - Model vs. Data

**Panel I: Low education**



**Panel II: High education**



Notes: age profiles for the unemployment rate and the employment share of temporary jobs in the data and as predicted by the model. The empirical profiles are estimated using French Employment Survey data, according to the procedure in section 2. The theoretical profiles are based on simulations of the calibrated model (Tables 1 and 2).

## 4.4 Model Mechanisms

What mechanisms explain the life-cycle properties of worker flows across education groups in the model? We zoom into the main two channels present in the model: learning about worker ability, and idiosyncratic, match-specific unemployment risk.

We investigate the contribution of the learning channel to the model fit of the job-finding rate (UP) for low-education versus high-education workers. We compare the life-cycle profiles of the benchmark model with those of a counterfactual model where we alternatively switch off the learning and the idiosyncratic unemployment risk  $\delta$ . More precisely, to eliminate the learning in the model, we let the standard deviation of the disturbance be approximately zero  $\sigma_\varepsilon \approx 0$ . This reduction diminishes the noise in the worker’s ability signal reflected in screening and match formation decisions. With noise close to zero, the ability of the worker is essentially revealed upon contact, eliminating the need for screening and learning. To eliminate the idiosyncratic unemployment risk, we substantially increase the second shape parameter of the beta distribution for job separation draws to induce the variance of match separation risk to be approximately zero. By doing so, we remove the individual variation in unemployment risk experienced by workers. To isolate the effects of removing each channel separately, we keep the remaining model parameters unchanged from the baseline case, except for the vacancy cost  $c$ . We then recalibrate the model to match the labor market tightness  $\theta = 1$ , consistent with the benchmark case. The results of these counterfactuals are presented in Figure 8.

Panel (a) of Figure 8 depicts a scatter plot comparing the UP transition between the benchmark model and the model with only the learning mechanism, for high-education individuals. Panel (b) presents the case of the model shutting down unemployment-risk heterogeneity. Panels (c) and (d) do the same but for the low-education workers. The figures show that the learning model yields higher R-squared compared to the model focusing solely on the unemployment risk channel. This suggests that learning plays a crucial role in explaining the declining profile of the UP transition for higher education. Conversely, the unemployment risk channel appears to be an important factor in generating a flat profile for low-educated individuals.

The underlying intuition is as follows. The calibration implies a high complementarity between skills and job complexity for the high-ability workers. Hence, highly educated individuals have a strong comparative advantage in complex jobs. These complex jobs involve tasks that necessitate abilities that are not directly observable. Consequently, high-education individuals sort into jobs where their true ability needs to be screened, giving rise to a learning process that fades away over the life cycle. The fraction of high-education workers with a

higher probability of ability revelation increases with age. Hence, for older workers with higher education, the probability of finding a job is lower, as they may be perceived as having lower abilities based on their observed characteristics while they are unemployed.

Since learning and churning have different implications for employment ([Blanchard and Landier \(2002\)](#), [Faccini \(2014\)](#)), the potential costs of employment protection is expected to differ across age and education groups. In the next section, we explore these distributional effects.

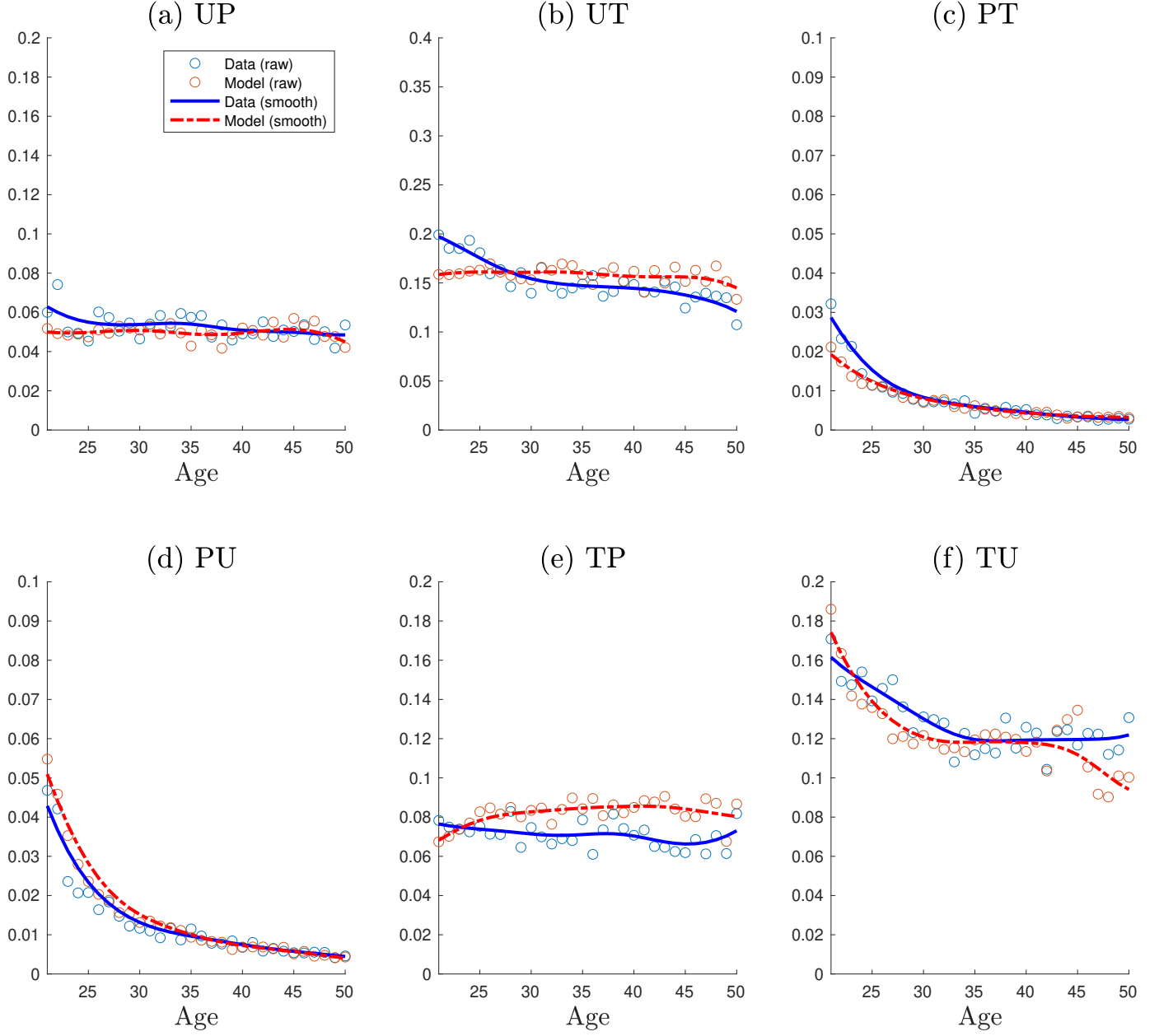
## 4.5 The distribution of the costs of (dual) employment protection across age and education groups

What are the model’s implications for the distribution of the costs of employment protection across education and age groups? The calibrated model suggests that distinctly different mechanisms shape the life-cycle employment dynamics across education groups: information frictions and learning versus heterogeneity in separation risk. How do these different channels interact with employment protection? The answer holds significance for the distribution of potential gains associated with employment protection reforms.

As is well known, the effect of firing costs on employment is ambiguous. On the one hand, this policy induces a higher probability of retention in response to adverse shocks, increasing employment. On the other hand, firing costs deter job creation and the formation of new matches, with a negative effect on employment. In addition to these effects, it is well known as well that firing costs combined with temporary contracts (with an exogenous restriction on duration) result in inefficient turnover increasing employment separation rates (e.g., [Blanchard and Landier \(2002\)](#), [Cahuc and Postel-Vinay \(2002\)](#), [Boeri and Garibaldi \(2007\)](#)). We expect this inefficiency to be more severe for the low-education group, for which heterogeneity in separation risks is a key driver of employment dynamics. Finally, as discussed by [Faccini \(2014\)](#), considering information frictions about the quality of matches mitigates inefficiencies due to excess turnover, as temporary contracts can be used as a screening device offsetting firing costs. The latter is expected to apply to the high-education group, for which learning about skills has a key role in accounting for life-cycle outcomes. In other words, we expect that the costs associated with (dual) employment protection will be disproportionately borne by individuals with lower education, as turnover inefficiencies are presumably more severe for this group.

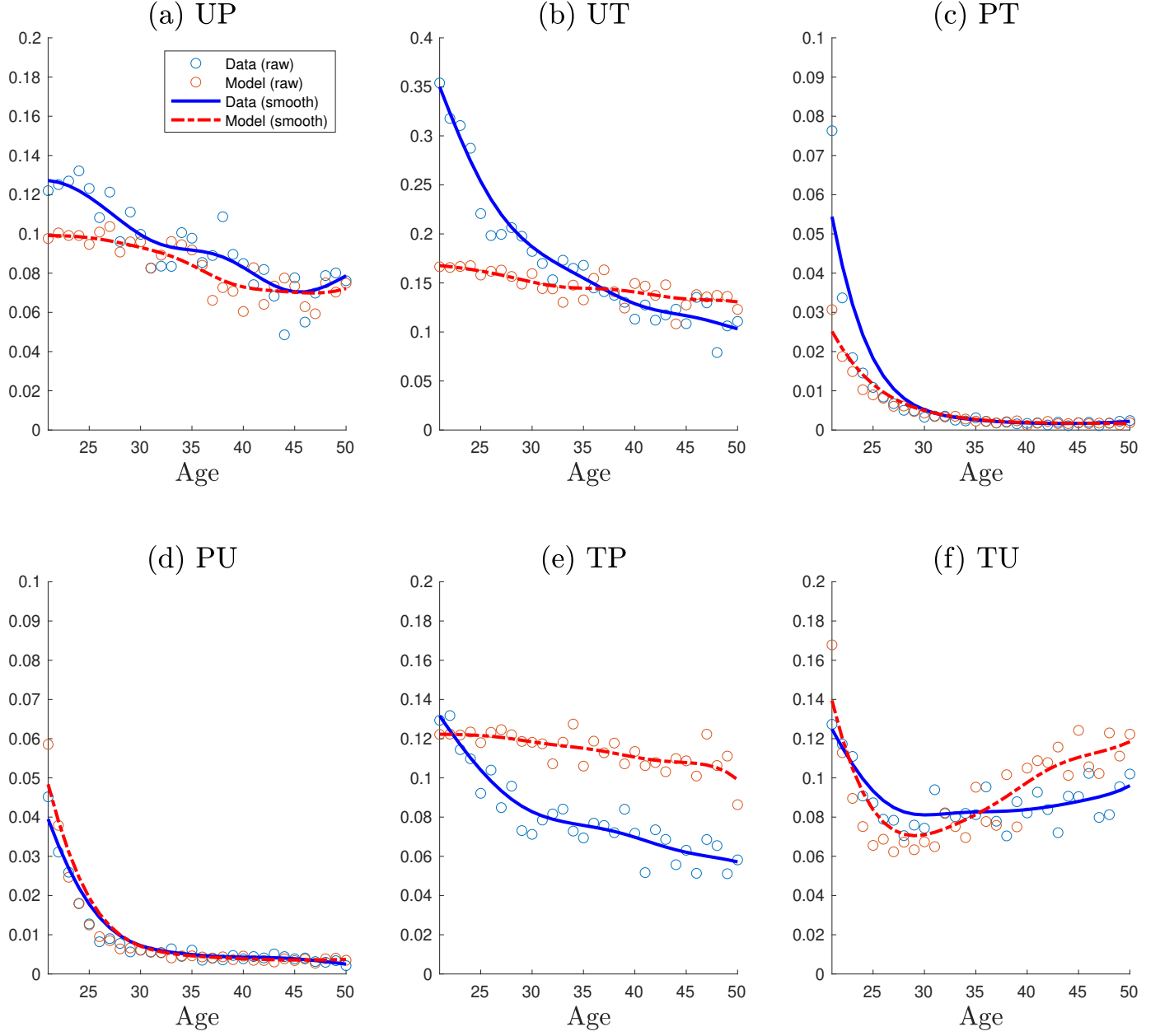
We conduct an experiment comparing the benchmark with a counterfactual economy without firing cost ( $F = 0$ ). In this counterfactual economy, there is no distinction between permanent and temporary jobs and no inefficiencies from excess turnover due to employment

Figure 6: Target transition profiles - Low education



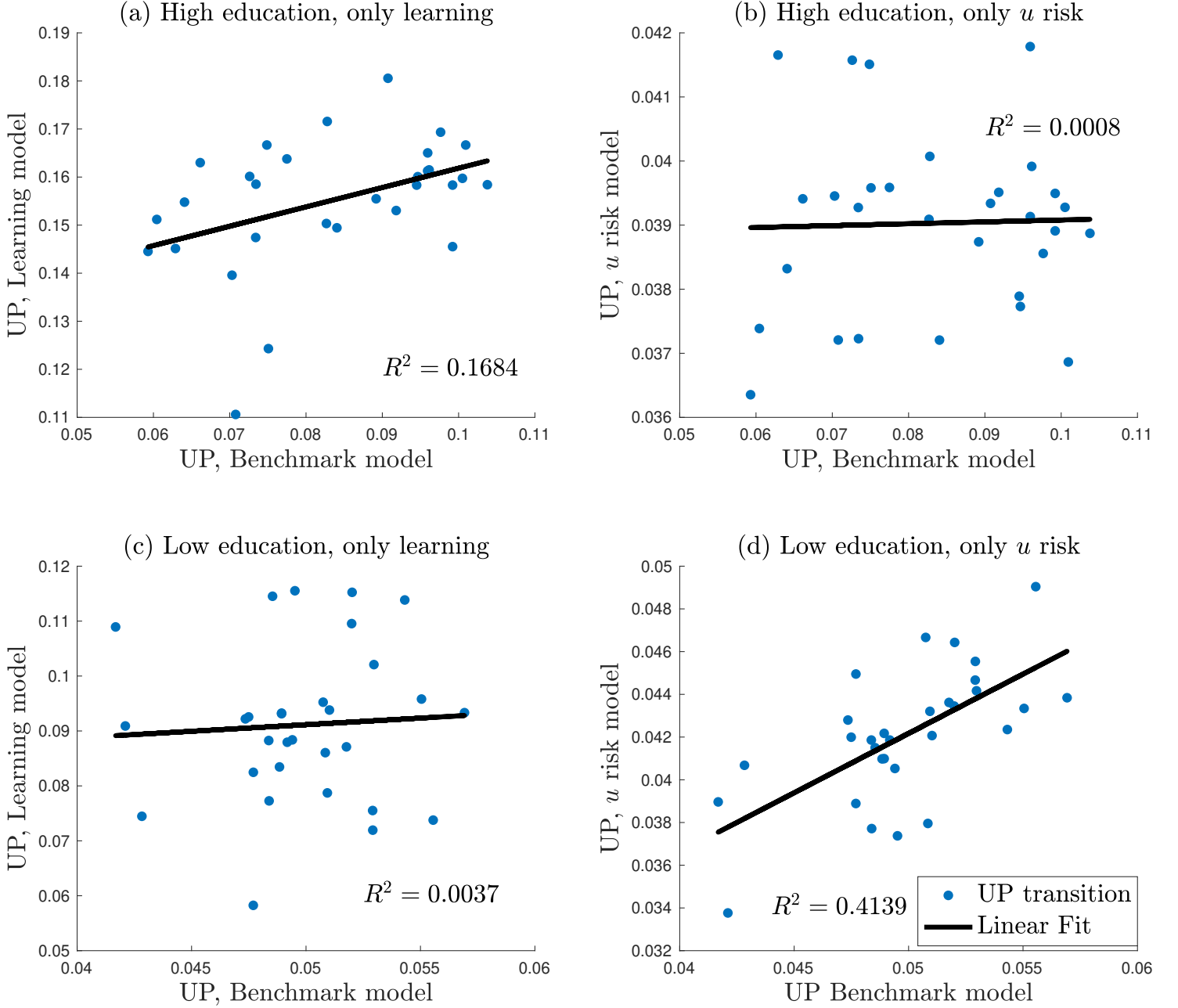
Notes: age profiles of quarterly transition probabilities in the data and the model, for the low-education group. The empirical profiles are estimated using French Employment Survey data, according to the procedure in section 2. The theoretical profiles are based on simulations of the calibrated model (Tables 1 and 2).

Figure 7: Target transition profiles - High education



Notes: age profiles of quarterly transition probabilities in the data and the model, for the high-education group. The empirical profiles are estimated using French Employment Survey data, according to the procedure in section 2. The theoretical profiles are based on simulations of the calibrated model (Tables 1 and 2).

Figure 8: The role of learning versus idiosyncratic unemployment risk in shaping UP transition probabilities

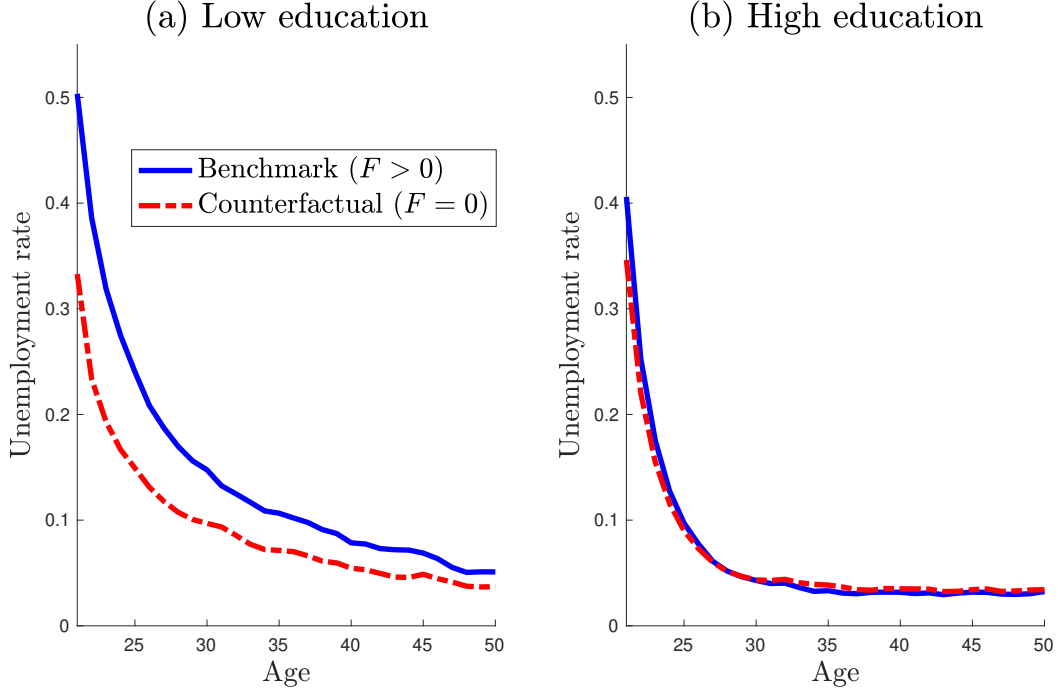


Notes: UP denotes the transition probability from unemployment to permanent contract employment. The Benchmark model refers to UP profile based on simulations of the calibrated model (Tables 1). The “ $u$ -risk” and “Learning” models refer to counterfactual eliminating respectively learning and unemployment risk heterogeneity from the benchmark model. Eliminating learning removes the noise in the worker’s ability signal while eliminating  $u$ -risk heterogeneity makes the distribution of match separation probabilities degenerate. Each subfigure compares the counterfactual model’s predicted power to the benchmark for UP transition by education group. A lower  $R^2$  indicates a minor role for the remaining channel in capturing the UP variation for the specified education group.



protection. The experiment focuses on the effect on the unemployment rate by age and education group, as implied by the calibrated model.

Figure 9: The effect of firing costs on the unemployment rate by age and education



Notes: theoretical age profiles of the unemployment rate from simulations of the calibrated model (see Tables 1). The counterfactual sets firing costs to zero ( $F = 0$ ).

Figure 9 shows the results. Removing firing costs implies a substantial decline in the unemployment rate for the low-education group (Panel (a)). The magnitude of this effect is high for all age groups but especially so the youth and it fades away with age. The unemployment rate is barely changed for the high-education group (Panel (b)). Further, the results show that for all age groups, the unemployment gap between education groups is closed by around a half when firing costs are eliminated. For the youth, firing costs account for the major part of the gap.

These results suggest inefficiencies from excess turnover of an important severity for the low education group, temporary contracts are “dead-ends” reducing employment stability in the presence of firing costs. For the highly educated, the presence of temporary contracts appears to mitigate the negative employment effects of firing costs, and, as such, could be interpreted as stepping stones towards stable, protected employment.

Our analysis shows that the effect of dual employment protection is highly heterogeneous across education groups. This heterogeneous impact is an implication of the stark difference

in the mechanisms at play between groups and that are plausibly driving the employment dynamics: screening and learning for the highly educated and heterogeneity in match-specific unemployment risk for the low education group. Further, the results indicates that examining the heterogeneous sources of workers reallocation across age and education is key to assess the aggregate effects of employment protection.

## 5 Conclusion

This paper studies the life cycle of worker flows in a dual labor market divided between permanent and temporary jobs. The age profiles of worker flows differ substantially across education groups. We build a life-cycle model of a dual labor market to account for these facts. We show that two theoretical ingredients allow for matching the empirical worker-flow patterns: (i) information frictions and Bayesian learning about workers' skills and (ii) heterogeneity in match-specific separation risks. Calibration to French labor-force survey data suggests that the prevalence of these two channels differ across education groups: learning (i) is a key driver to the employment dynamics of the highly educated, whereas heterogeneity in separation risk (ii) is key to explaining age profiles for the low-education group.

We finally explore the model's implications for the distribution of the costs of employment protection across age and education groups. Firing costs combined with temporary contracts induce substantial negative employment effects for low-education workers due to heterogeneity in separation risk implying large excess turnover. The same effect has a very low magnitude on the employment of the highly educated, for whom learning is highly prevalent and results in temporary contracts being used as a screening device mitigating the negative effect of firing costs. The results suggest sharp heterogeneity in the impact of employment protection. Our model provides a framework to examine the implications of this heterogeneity for the life-cycle dynamics of earnings and aggregate outcomes.

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# A Appendix

## A.1 Proofs

### 1. Updated value of worker surplus share (expression 11) & 12

The result holds for any type of contract. Hence, for simplicity, we abstract for any contract subscript and unnecessary notation. Consider a type- $\omega$  worker employed at a type- $(j, \delta)$  firm and assume that the worker receives an outside offer from a firm of type  $(j', \delta')$ . Bertrand competition between the type- $(j, \delta)$  and type- $(j', \delta')$  employers implies that the worker ends up in the match that has higher total value, that is, they stay in their initial job if  $S(\omega, j, \delta) \geq S_0(\omega, j', \delta')$  and moves to the type- $(j', \delta')$  job otherwise. Following, [Lise and Postel-Vinay \(2020\)](#), the new contract, regardless of the moving decision, worths:

$$W' = \min \{S + U, \max (S_0 + U, W)\} \quad (29)$$

where,  $W$  is the worker value in the current match, and for the ease of presentation, we denote  $S(\omega, j, \delta)$  by  $S$  and  $S_0(\omega, j', \delta')$  by  $S_0$ . Worker surplus share in the new contract reads:

$$W' - U = \min \{S, \max (S_0, \nu S)\} \quad (30)$$

where  $\nu$  is the current surplus share. Let  $\tilde{S}$  be the surplus in the new contract. We have  $\tilde{S} = S\mathcal{I}(S \geq S_0) + S_0\mathcal{I}(S < S_0)$ . Denote by  $\nu'$ , the updated surplus share. Thus, we have:

$$\nu' \tilde{S} = \min \{S, \max (S_0, \nu S)\} \quad (31)$$

that is:

$$\nu' = \min \left\{ \frac{S}{\tilde{S}}, \max \left( \frac{S_0}{\tilde{S}}, \nu \frac{S}{\tilde{S}} \right) \right\} \quad (32)$$

If the worker stays, that is  $S \geq S_0$ , then:

$$\nu' = \min \left\{ 1, \max \left( \frac{S_0}{S}, \nu \right) \right\} \quad (33)$$

If the worker moves, that is  $S < S_0$ , then:

$$\nu' = \min \left\{ \frac{S}{S_0}, \max \left( 1, \nu \frac{S}{S_0} \right) \right\} \quad (34)$$

which imply that:

$$\nu' = \nu \mathcal{I}(\nu S > S_0) + \frac{S_0}{S} \mathcal{I}(\nu S \leq S_0), \quad \text{if stay} \quad (35)$$

$$\nu' = \frac{S}{S_0}, \quad \text{if move} \quad (36)$$

## A.2 Markov chain analysis (4 states)

We perform the same exercise with four states where we depict the non-employment into inactivity and unemployment. Hence we compute the contribution of the age variation of each transition probability between states  $I, U, T, P$  in the age variation of the employment stock and the employment share of temporary jobs. Here,

$$S_{a,e} = \begin{pmatrix} I_{a,e} \\ U_{a,e} \\ T_{a,e} \\ P_{a,e} \end{pmatrix} \quad (37)$$

represents the vector for the distribution of individual of age  $a$  in education group  $e$  into status  $I, U, T, P$ . Each element of this vector represents a probability of having a given labor-market status conditional on age  $a$  and education group  $e$ . Moreover, let

$$\Gamma_{a,e} = \begin{pmatrix} II_{a,e} & IU_{a,e} & IT_{a,e} & IP_{a,e} \\ UI_{a,e} & UU_{a,e} & UT_{a,e} & UP_{a,e} \\ TI_{a,e} & TU_{a,e} & TT_{a,e} & TP_{a,e} \\ PI_{a,e} & PU_{a,e} & PT_{a,e} & PP_{a,e} \end{pmatrix} \quad (38)$$

represents the quarterly transition probability matrix for age  $a$  and education  $e$ . We have

$$S_{a,e} = \left( \prod_{a'=1}^{a-1} (\Gamma_{a',e})^4 \right) S_{a_0(e),e}, \quad (39)$$

where  $a_0(e)$  represents the initial age in our sample for the different education groups. Notice that the age-specific transition matrix is taken at the power 4, since our transition probabilities are quarterly. Using (39), we can compute the life cycle path of  $E_a$ ,  $T_a$ , and  $P_a$  that is implied by the estimated transition probability matrix, for a given initial state vector,  $S_{a_0(e)}$ . We could also compute the contribution to  $U_a$ , but for consistency and comparative purposes, we only present the results for  $E_a$  and  $T_a$ , as we did for the 3-state analysis in the main text. Figures A3–A7 show the findings.

## A.3 Supplementary Tables and Figures

Figure A1: AB1C Decomposition of the importance of Flows: temporary employment share, High education (3 states)

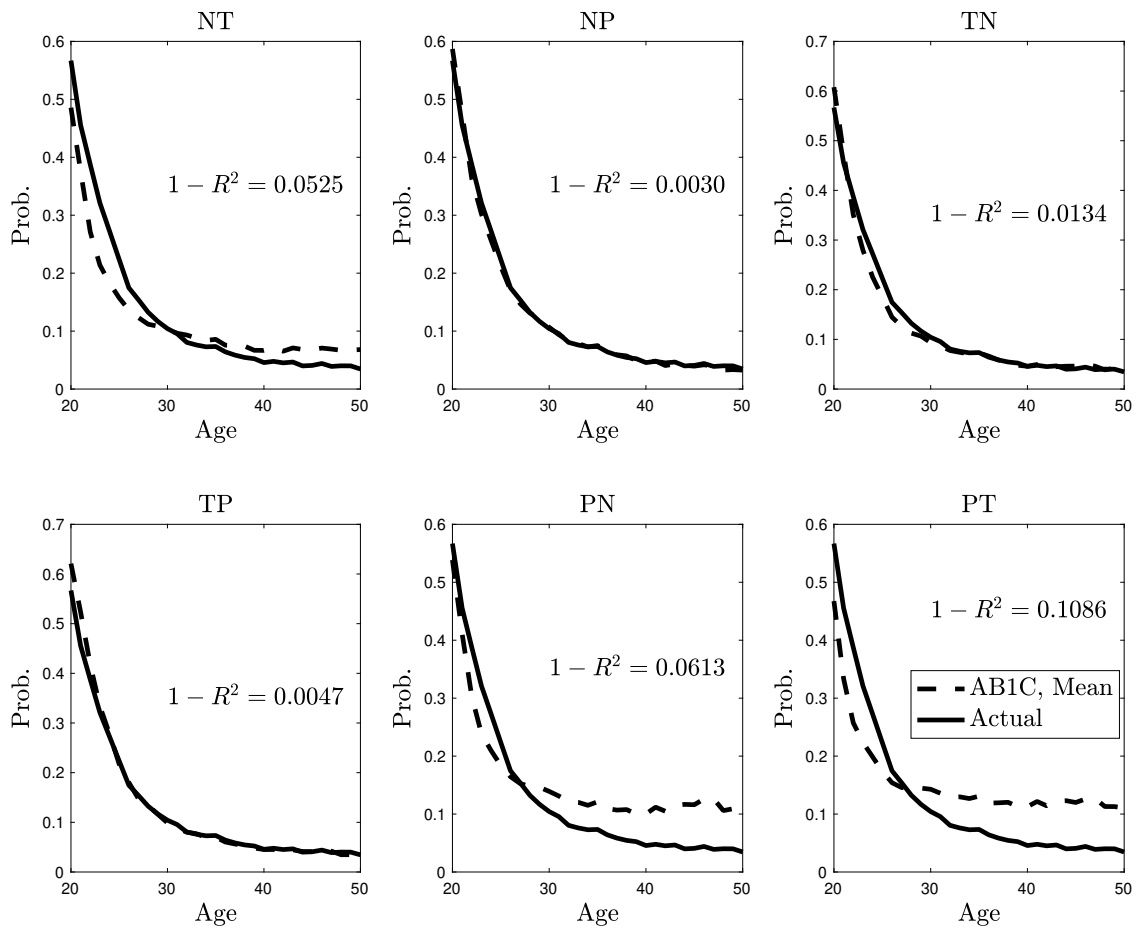




Figure A2: AB1C Decomposition of the importance of Flows: temporary employment share, Low education (3 states)

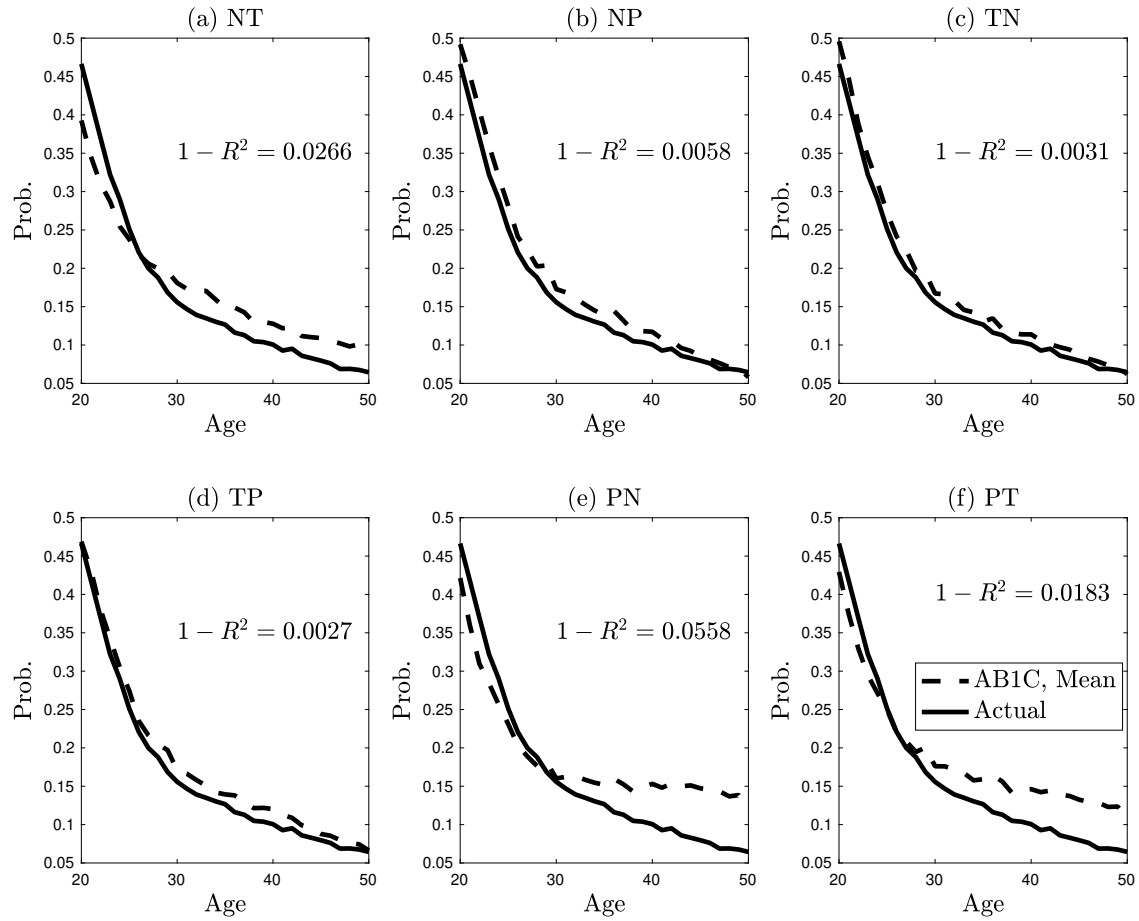


Figure A3: Markov chain simulated employment and temporary job share (4 states)

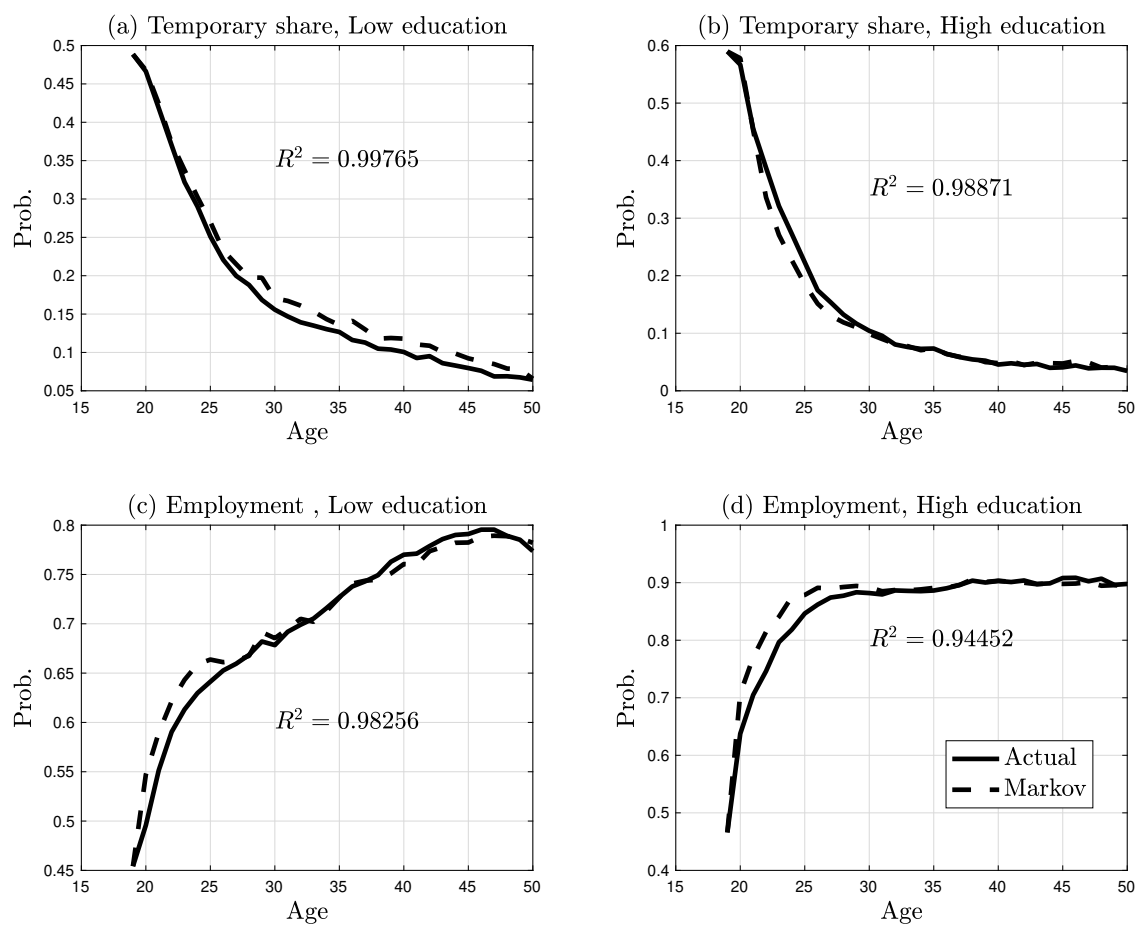
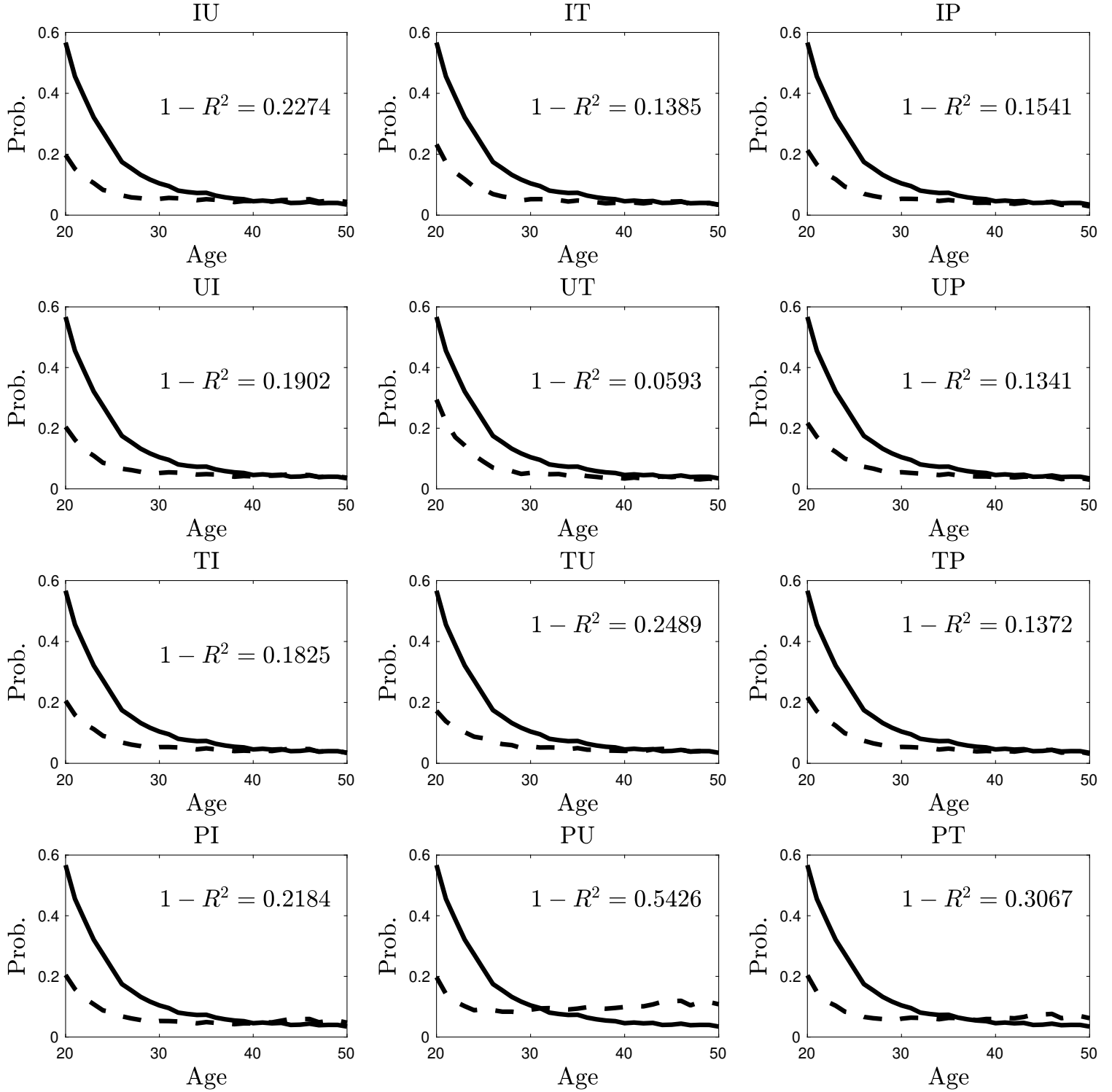
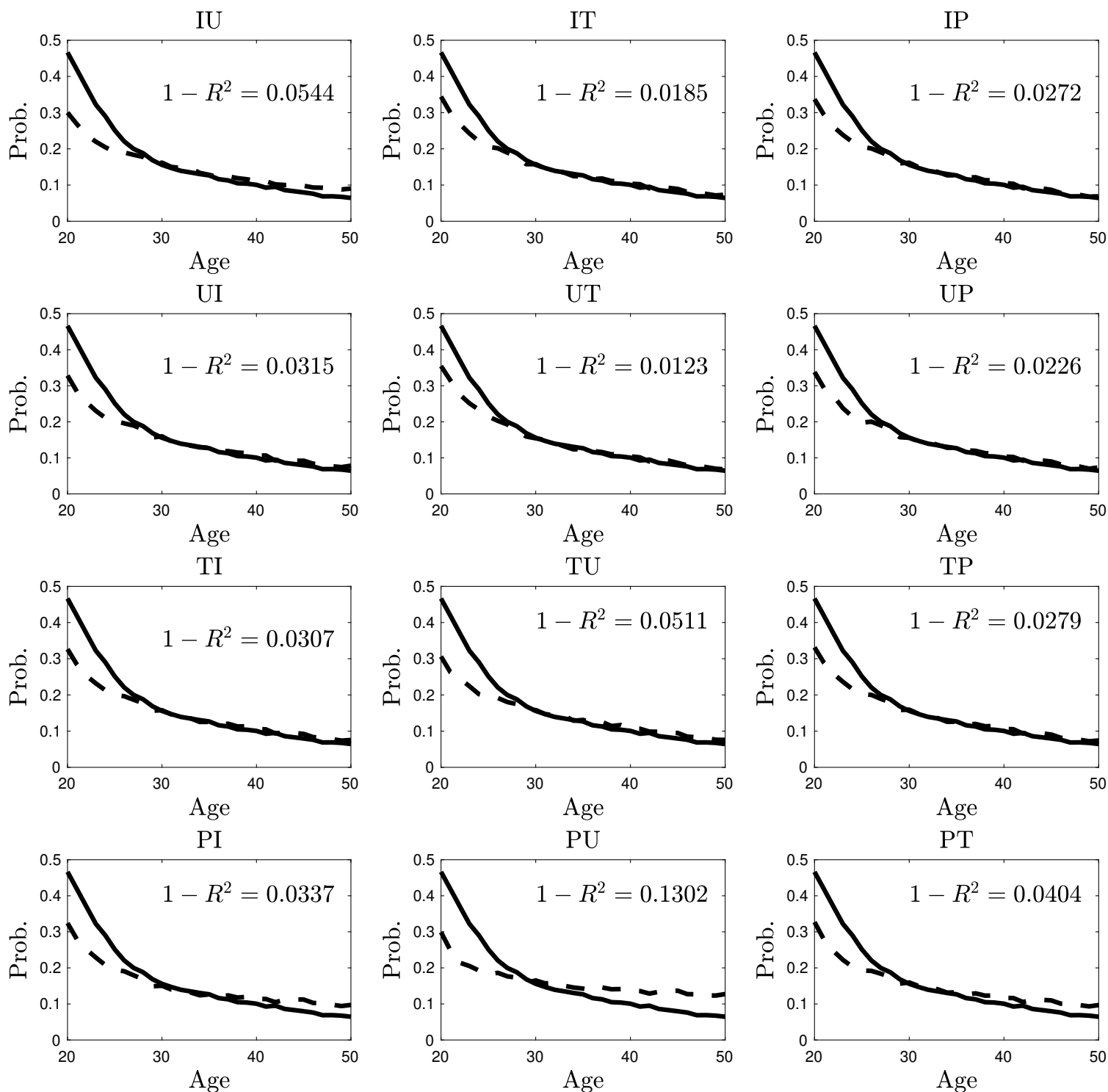


Figure A4: AB1C Decomposition of the importance of Flows: temporary employment share, High education (4 states)



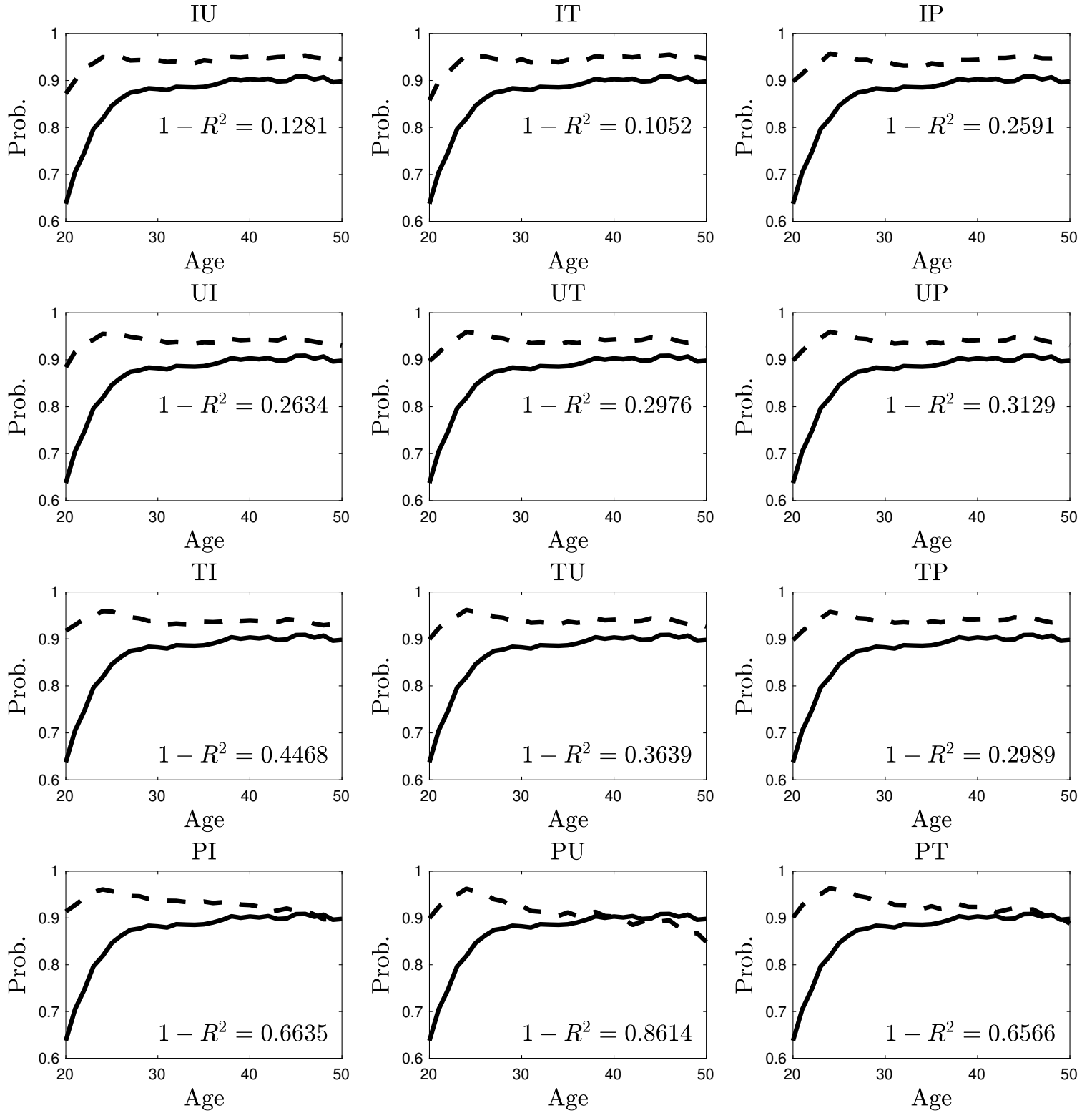
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure A5: AB1C Decomposition of the importance of Flows: temporary employment share, Low education (4 states)



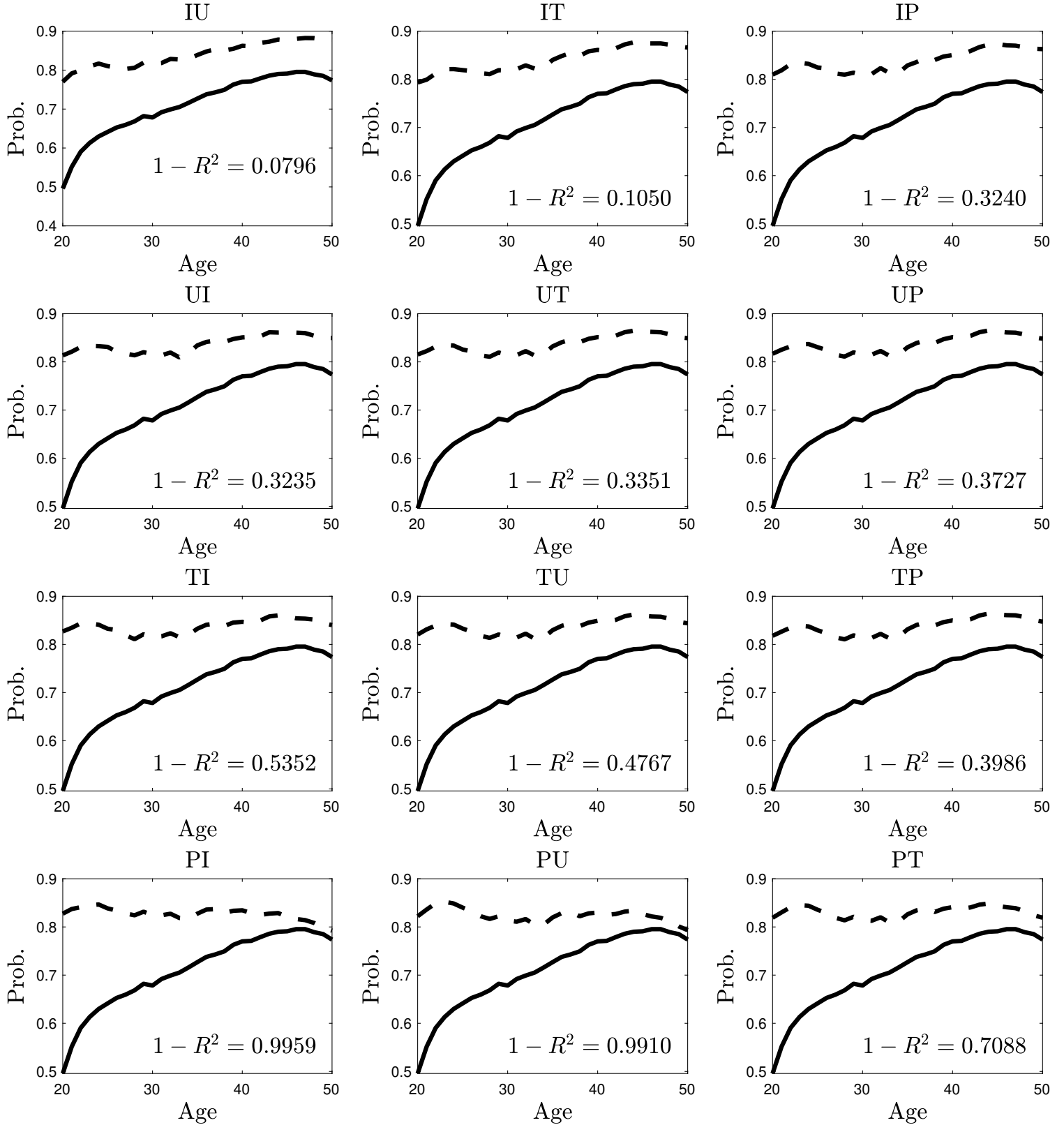
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure A6: AB1C Decomposition of the importance of Flows: employment-High education (4 states)



Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure A7: AB1C Decomposition of the importance of Flows: employment- low education (4 states)



Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov