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 stable, permanent jobs with high firing restrictions and temporary jobs. Using longitudinal data from the French Employment Survey, we estimate that the transition probabilities from unemployment to temporary (UT) and permanent (UP) employment 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 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. Bayesian learning is more prevalent in explaining life-cycle heterogeneity in worker flows for high-educated individuals. In contrast, unemployment-risk heterogeneity is the key driver of this variation for the low-educated.

JEL Codes: E24, J63, J64.

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

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1 Introduction

Employment protection legislation (EPL) reforms have arguably been the primary policy response to the persistently high unemployment rate in European countries in the post-oil-shock era (see, e.g., Boeri (2011)). A significant literature has provided evidence that these reforms, in most cases focused on easing the regulation of temporary contracts, generated the formation of 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 the temporary jobs are "dead ends" leading to higher unemployment risk and unstable employment prospects for individuals, or stepping stone towards stable, protected permanent contracts (e.g., Booth et al. (2002), Faccini (2014), and García-Pérez et al. (2019)). However, most of the existing macro-search literature has been relying on models with representative agents, and, as a result, relatively little is known about the implications of labor-market duality and search frictions for the formation of life-cycle labor-market outcomes. This paper intends to fill this gap.

Our study 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—for both low and high-education groups of individuals, featuring very different age employment profiles. 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 life-cycle equilibrium search-and-matching model with information frictions about workers' ability and heterogeneity in job separation risk as the two main ingredients, which intends to account for the empirical age profiles of worker flows. We use this model to assess the contribution of these two ingredients to the life-cycle variation of worker flows.

Our empirical analysis shows that worker flows are highly heterogeneous across age and education groups. We show that the transition probabilities from unemployment to temporary (UT) and permanent (UP) employment 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). Our stock-flow decomposition, based on Choi et al. (2015), 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; further, the age profile of the temporary employment exit probability (TN) is an important contributor of the employment life-cycle dynamics for highly educated individuals. Specifically, setting the TN probability at its average life-cycle level results in an approximately 6% rise in the employment rate at the age of 25 for this education group.

We complement this analysis by developing a quantitative general equilibrium model that provides a theoretical framework to rationalize these empirical life-cycle patterns. This model features heterogeneous workers and jobs, information frictions, and match-specific unemployment (i.e., employment exit) 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 feature heterogeneity in unemployment risk drawn at the beginning of potential matches, independently of skills. In this framework, where we assume that permanent contracts have relatively high firing costs, temporary contracts can be preferred for two distinct motives: (i) learning about individuals' ability (and accumulating skills), a "screening" motive; (ii) avoiding high expected firing costs associated with high unemployment risk, a "churning" motives.

We calibrate the model to estimates of life-cycle transition probabilities from our empirical analysis for the low and high-education groups taken separately. Our model fits the age profile 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 then 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 explain by a learning view. We find that learning plays a crucial role in explaining the declining profile of the UP transition for high education. Conversely, the unemployment risk channel (churning view) appears to be an important factor in generating a flat profile for low-educated individuals.

The underlying intuition is as follows: Low-educated individuals possess a comparative advantage in generic jobs, where their observable skills are sufficient for employment. On the other hand, high-educated individuals have a 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 unfolds over the life cycle. As a result, the fraction of high-education workers who face a higher probability of immediate ability revelation increases with age. For these older workers, the probability of finding a job is lower since they may be perceived as having lower abilities based on their observed characteristics when they are unemployed, searching for a job.

Related literature. 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 Goensch, Gulyas, and Kospentaris (Goensch et al.)) and the body of work that studies the effect of dual employment protection legislation in labor search models (Blanchard and Landier (2002), Cahuc and Postel-Vinay (2002), Berton and Garibaldi (2012), Bentolila et al. (2012), Faccini (2014), Cahuc et al. (2016), Cahuc et al. (2020), and Crechet (2022)). To the best of our knowledge, our paper is the first to study worker flows over the life cycle in a dual labor market. We contribute to the literature by showing that such worker flows feature substantial heterogeneity across age (and education) groups and that this heterogeneity matters for the life-cycle employment dynamics. We also propose a novel search-and-matching model with a life-cycle component to study labor-market duality.

Structure of the paper. The rest of the paper is organized as follows. Section 2 documents the empirical patterns of worker flows over the life cycle. Section 3 presents the model. Section 4 provides a quantitative analysis, inspecting the model mechanism to replicate the life cycle patterns. Section 5 concludes.

2 Empirical analysis

2.1 Data

We use the French Labor Force Survey (*Enquête emploi en continu*, EEC), for the period 2003-2018. The EEC is a nationally representative 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 and individuals' labor-force status (employed, unemployed, out of the labor force) and on the type of employment contract (permanent or temporary). Since 2003, the survey is said "continuous" in the sense that respondents' information is 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 Data Archive of Issues of Public Statistics (Archives de Données Issues de la Statistique Publique, ADISP). One advantage of the restricted-use files is the availability of household and individual identifiers, allowing us to track individuals over consecutive quarters. Using the longitudinal dimension of the data, we estimate quarterly transition probabilities by identifying events of change in workers' labor market status.

We restrict the sample to individuals between the ages of 20 and 50 who are non-military and non-institutionalized, residing in metropolitan France. 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 by age. Second, we run a simple OLS regression on a full set of age and time dummies. Third, we present the OLS predicted values averaged by age. We also display point estimates and confidence intervals for a local polynomial smoother with Epanechnikov kernel function. 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 I is for 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). The definition of unemployment and non-participation is standard. In our baseline definition, we classify open-ended and apprenticeship contracts into permanent employment (P).[1] 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).[2]

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

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

[1] In the robustness analysis, we propose an alternative classification where the apprentices are counted in T instead of P.

[2] 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.

for each monthly date t in our sample period and each age $a = 20, ..., 50$, 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 $\mathcal{I}(.)$ is the indicator function taking the value of one if the expression is true (zero otherwise). Hence, $\pi^{jk}_{t,a}$ 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.

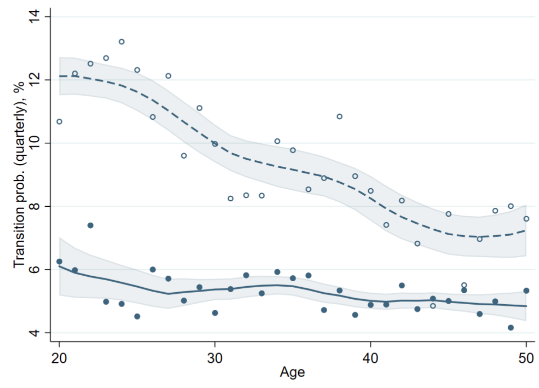
Next, we run a weighted OLS regression on a full set of dummies for age and time fixed-effects

$$\pi^{jk}_{t,a} = \gamma^{jk}_t + \beta^{jk}_a + \varepsilon^{jk}_{t,a} \tag{2}$$

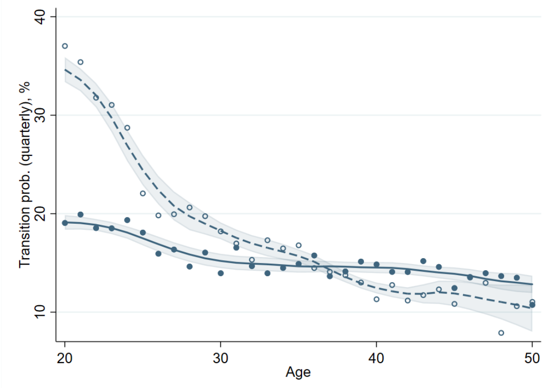
for given j, k, where the observation weight for cell t, a is the individual weighted count for that cell. Then, we compute the mean of the predicted values for each age as our estimates of the age-specific quarterly transition probabilities. Finally, we compute smoothed age profiles and 95% confidence intervals using local polynomials with an Epanechnikov kernel function. Our results for transitions between unemployment and permanent and temporary employment are reported in figure 1. We depict the life-cycle transition profiles by education groups. We consider the primary and secondary-education individuals (referred to as the low-education group) from one side and the tertiary-education individuals (referred to as the high-education group) from the other. In the appendix, we show transitions in and out of participation.

Empirical findings. Transition probabilities display significant variation over the working life of individuals and a marked differentiation among education groups. First, job-finding rates, measured by UP and UT transitions rates, exhibit a decreasing profile for highly educated workers, but a flat profile for low-educated individuals. Unsurprisingly, highly educated unemployed workers are more likely to secure permanent contracts compared to their low-educated counterparts. This pattern holds for jobs with temporary contracts before the late 30s and reverses thereafter. A reason behind this is that highly educated individuals who are over 38 years old and working in temporary jobs may have lower abilities. As a result, they are more likely to compete for temporary jobs that require less education, where low-educated individuals have a comparative advantage.

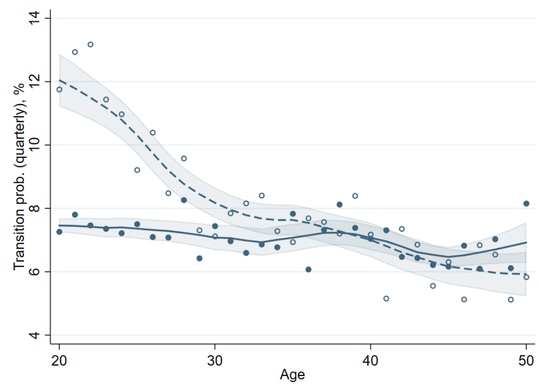
Figure 1: Age profiles of quarterly transition probabilities, by education group



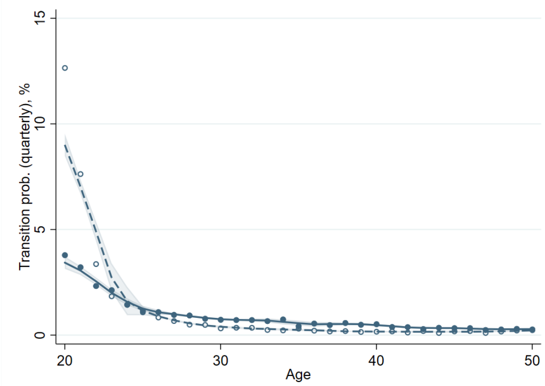
(a) UP



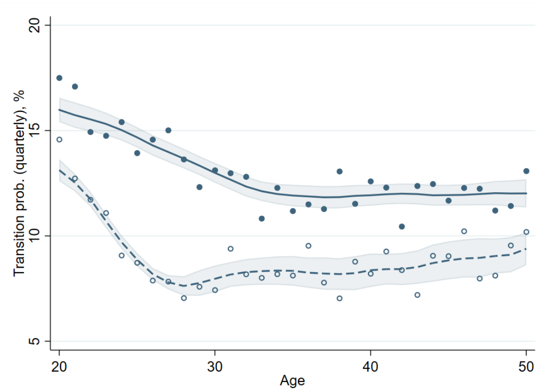
(b) UT



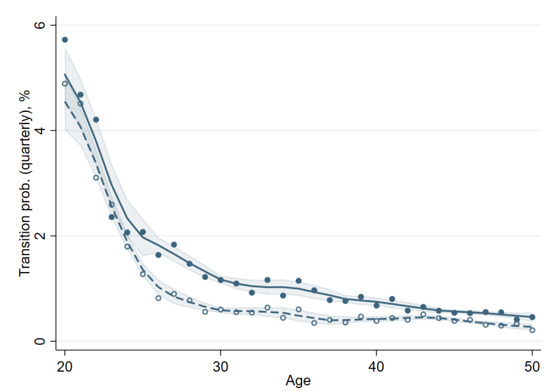
(c) TP



(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.

Second, separation rates, measured by TU and PU, decrease for both education groups. However, TU decreases much more rapidly for highly educated workers. The job separation rate from temporary employment becomes steady, starting at around 28 for high education, whereas it is around 35 for low-educated workers. This suggests a difference in skill accumulation across education groups. Highly educated workers typically have a lower risk of job loss, which enhances skill accumulation and further reduces job separation over the life cycle. Finally, turning to job-to-job moves, we observe that the transition from temporary to permanent employment (TP) decreases over the worker life-cycle for highly educated workers but is steadily constant for low-educated workers. The pattern is similar to the UT transition rate. We also notice a substantial transition from permanent contract employment to temporary employment among the youths, particularly for highly educated workers. This could occur through a job-to-job move that enhances match quality.

2.3 Markov Chain Analysis

In this section, we follow a method developed in Choi et al. (2015) by proposing a way to account for the contribution of each transition to the determination of age profiles of the employment rate and the employment share of temporary contracts. 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

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

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; with N, a non-employment status. $\Gamma_{a,e}$ 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. The results are depicted 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 very well in replicating the actual profiles. Indeed, the R-squared of the regression of the dotted line against the solid line is always above 95 percent.

Results in figure 2 show a predominant proportion of temporary contracts held by young workers, regardless of their education group. This proportion gradually diminishes with worker age, albeit at a faster rate for highly educated individuals. Nonetheless, the relatively slower decline in the temporary employment share, for low-educated individuals, suggests an additional factor at play, which may manifest as idiosyncratic separation shocks in accordance with the churning viewpoint.

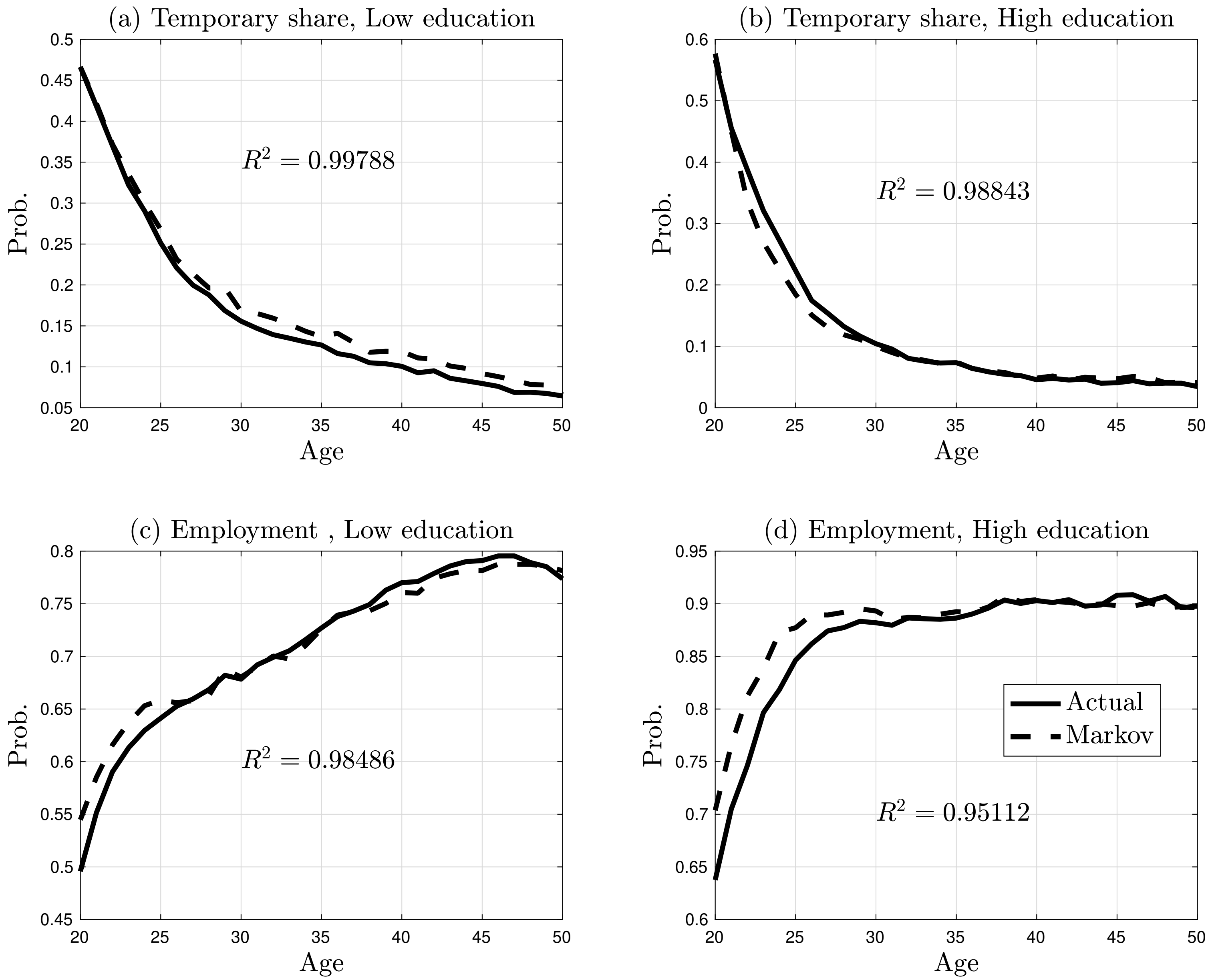
Looking at the low-education sample, the rate of employment increases throughout the lifespan until approximately mid to late 40s, at which point it begins to decline. Conversely, for individuals with higher level of education, employment increases rapidly and stabilizes at around 30 years of age. These findings suggest that there may be a differential rate of skill acquisition across education groups, as discussed in the previous sections.

2.4 Decomposition

With the constructed transition matrices, we perform a set of decomposition exercises. Two sets of labor market status are considered: 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. 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

Figure 2: Markov chain implied employment and temporary job share



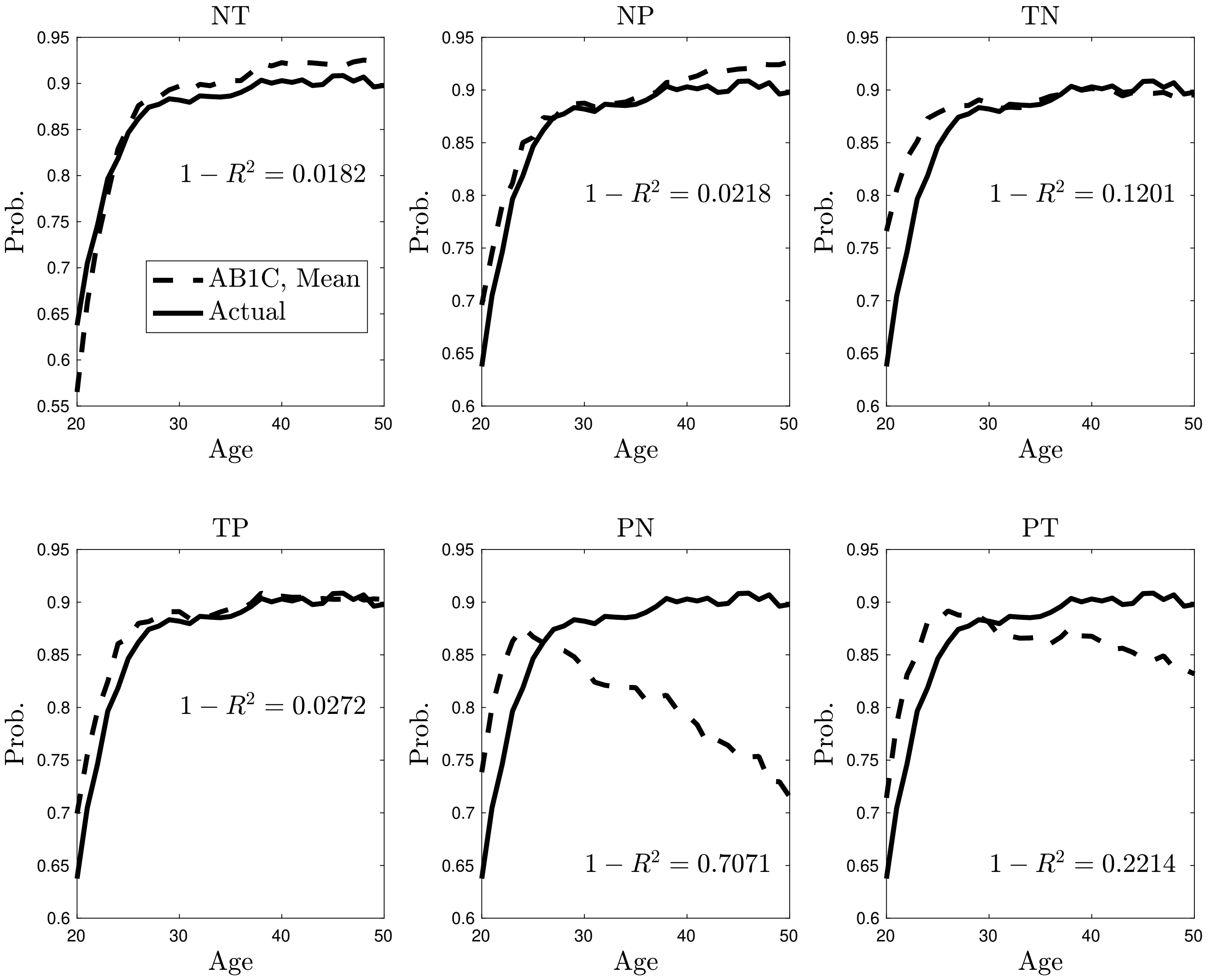
implied age profiles distributions. Figures 3 and 4 show the alternative employment profiles for both high and low-education group workers. Figures A1 and A2 in appendix A present the results for the temporary employment share. To understand the graphs, notice that the first subfigure in Figure 3, depicts 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 logic applies to the other subfigures.

Results from Figures 3 and 4 indicate that employment exit probability from permanent job, PN, is the most important contributor in explaining the employment rate over the course of a lifetime for individuals with lower levels of education. However, for those with higher education, in addition to PN, job separation from temporary contract TN and job-to-job move from permanent to temporary employment, PT, also matter significantly. In particular, the PN transition emerges as the primary factor accounting for high employment rates among workers aged 30 and above, irrespective of their educational background. 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.

In summary, these findings indicate that labor market duality has different implications for age-specific employment dynamics across skill groups, as well as for the formation of youth employment.

For the dynamics of temporary employment share over the life-cycle, no specific contributor stands out when considering three states. This suggests that the distinction between unemployment and inactivity (being out of the labor force) plays a significant role in explaining the dynamics of temporary job shares across different ages. When we differentiate between unemployment and inactivity within the non-employment state, job separation from perma-

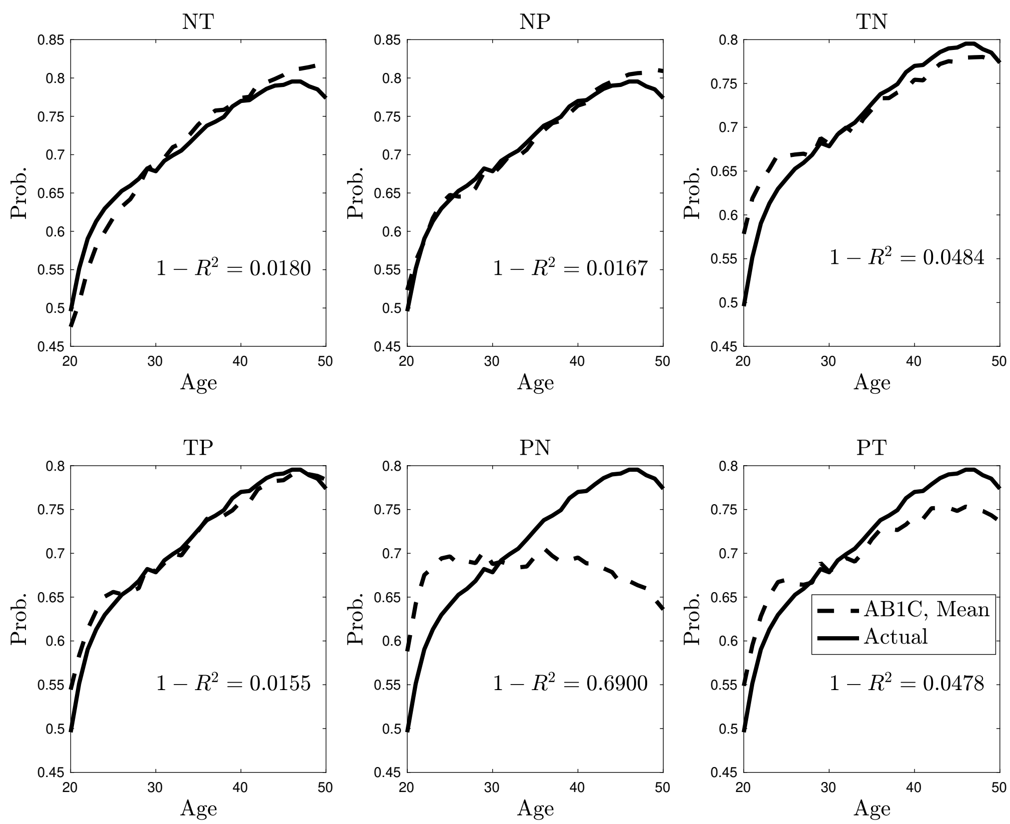
Figure 3: AB1C flow decomposition of employment by age: high-education



nent contract to unemployment (PU) emerges as the most influential factor driving these dynamics (see figures A6 and A7 in Appendix A).

Our decomposition exercise provides valuable insights for the implementation of policies aimed at influencing the overall employment rate or employment rates within specific age and skill groups. However, the nature of policy recommendations will largely depend on the theoretical model used to explain the observed transitions of workers over the life cycle in a dual labor market. In the next section, we fill this gap by proposing a model that accurately matches the observed life cycle profile of labor market transitions. 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.

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



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 $t = 0, 1, ...$ 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 ξ 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

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

where $A \in \{\underline{A}, \overline{A}\}$, $0 \leq \underline{A} \leq \overline{A}$ denotes the skill-acquisition ability of the worker. ε_t is i.i.d., normally distributed with mean zero and variance σ_ε^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

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

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 π 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:

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

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

$$\tilde{\pi}_{t_0} = \pi \tag{7}$$

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

$$y_t = \zeta x_t^\rho, \tag{8}$$

where $\zeta > 0$ and $\rho \in (0, 1)$. The output produced by a match in a generic job is equal to $\overline{y}$. We assume that $\overline{y} > 0 = \ln(x_{t_0})$ 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 δ. This probability is assumed heterogeneous across matches. Job type j and the probability δ 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 $\theta_t = v_t/(u_t + s\, n_t)$, 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 γ_j. We assume a probability $\overline{\gamma}$ of drawing a complex job, $\gamma_1 = \overline{\gamma}$.

The exogenous probability of separation is drawn from a distribution with c.d.f. $G_\delta(.|j)$, 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). Worker's 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 τ on the output of a match in a temporary job. Both F and τ represent deadweight losses that capture the effects of employment protection legislation (EPL). Alternatively, τ 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 [3]. Additionally, temporary contracts have a stochastic maximum duration. With probability ϕ, 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) He/she exits the labor market with probability ξ 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 δ;

(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;

[3] See Cahuc et al. (2016), Crechet (2022), 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) He/she exits the labor market with probability ξ, stays otherwise;

(ii) Updates skill and belief according to (4) and (6);

(iii) Receives exogenous separation shock with probability δ 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 δ' 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) He/she exits the labor market with probability ξ, and stays otherwise;

(ii) Updates skill and belief;

(iii) Receives exogenous separation shock with probability δ 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[4];

(v) Receives a potential outside offer and evaluates the current and outside surplus; continues the match or separates for a new match or unemployment.

[4]Given skill, belief and job type, we assume that P contract is always preferable to the T contract. Hence, the conversion is always profitable

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 $S_P : \Omega \times \{0,1\} \times [0,1] \to \mathbb{R}_+$ and $S_T : \Omega \times \{0,1\} \times [0,1] \to \mathbb{R}_+$ 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:

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

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

In addition, define

$$S_0(\omega, j, \delta) \equiv \max\left(S_P(\omega, j, \delta) - F, S_T(\omega, j, \delta), 0\right) \tag{10}$$

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 ω, conditional on drawing job characteristics (j, δ).

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.[5]

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 (ω, j, δ). Conditional on receiving an outside offer from a vacancy with job characteristics (j', δ'), 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[6]

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

In the case of job-to-job move, the worker surplus share in the new match is:

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

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

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

[5]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.

[6]See appendix A for sequences that give the result

for all ω, j, δ; the expected surplus of the firm conditional on an outside offer is

$$\Delta_{J,P}(\omega, j, \delta, \nu) =$$

$$\sum \gamma_j \int \max\Big\{ \min\big(S_P(\omega, j, \delta) - S_0(\omega, j', \delta'), (1-\nu)S_P(\omega, j', \delta')\big), 0\Big\} dG_\delta(\delta'|j') \tag{14}$$

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 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:

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

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

$$p' = \frac{pf\big(\ln x' - \alpha \ln x - \overline{A}\big)}{pf\big(\ln x' - \alpha \ln x - \overline{A}\big) + (1-p)f\big(\ln x' - \alpha \ln x - \underline{A}\big)} \tag{16}$$

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

$$h(x'|x, p) =$$

$$\frac{1}{x'\sigma\sqrt{2\pi}} \Bigg\{ p \exp\left[-\frac{1}{2}\frac{(\ln x' - \alpha \ln x - \overline{A})^2}{\sigma^2}\right] + (1-p)\exp\left[-\frac{1}{2}\frac{(\ln x' - \alpha \ln x - \underline{A})^2}{\sigma^2}\right] \Bigg\}, \tag{17}$$

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

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 δ. 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

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

such that (16) to (17) are satisfied. With probability ϕ, 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

$$\begin{aligned} S_P(\omega, 0, \delta) &= S_P(0, \delta) \\ &= \overline{y} - b - (1-\beta)F + \beta(1-\delta)\max\big(S_P(0,\delta), 0\big), \end{aligned} \tag{19}$$

for all $\delta \in [0, 1]$. In a temporary job, we have

$$\begin{aligned} S_T(\omega, 0, \delta) &= S_T(0, \delta) \\ &= \overline{y} - b + \beta(1-\delta)\Big[(1-\phi)\max\big(S_T(0,\delta), S_P(0,\delta) - F, 0\big) \\ &\qquad + \phi \max\big(S_P(0,\delta) - F, 0\big)\Big] \end{aligned} \tag{20}$$

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

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

for all $\delta \in (0,1)$, independently of the worker's state ω. 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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

for all ω,j,δ, and ν. Worker collects a fraction ν 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 ν 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

$$\frac{c}{\beta\, q(\theta)} = \sum_a \Bigg\{ \underbrace{\frac{u(a)}{u+s\,n} E\Big[\max(S_0(\omega,j,\delta,\nu=0),0)\Big]}_{\text{Vacancy meets unemployed}} + \underbrace{s\frac{n(a)}{u+s\,n} E\Big[\mathcal{I}_{(S_0(\omega,j',\delta',\nu')>S_0(\omega,j,\delta,\nu))}(1-\nu')\max(S_0(\omega,j',\delta',\nu'),0)\Big]}_{\text{Vacancy meets employed}} \Bigg\} \tag{28}$$

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.

Definition. *The stationary market equilibrium is a list of functions* $\{S_0, S_T, S_P, \nu, w\}$*, labor market stocks* $\{u(a), n(a)\}$ *for all age* a*, and labor market tightness* θ *such that: (i)* S_T, S_P *and* S_0 *satisfy respectively 18, 15, 10;* ν *satisfies 11 and 12;* w *solves 23 and 25 given the labor market tightness* θ*; (ii) the labor market tightness* θ *solves 28 given* S_0, S_T, S_P, ν*, the labor market stocks and the cross-sectional distribution of workers' skill, beliefs and job characteristics; (iii) the labor market stocks and distributions of workers' skill, beliefs and job characteristics are constant over time.*

4 Calibration

This section describes the calibration strategy. We perform two calibrations: one for each education group. The calibration is at the quarterly frequency. Hence, one period in the model represents a quarter in a worker's life. 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 Assigned parameters

The assigned parameters are reported in table 1. 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 χ 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 χ and the normalization of labor tightness value $\theta = 1$. On average, when a worker is not employed, his log-skill x depreciates and drifts down toward a low level of ability A_0, which we normalize to 0, in line with Kehoe et al. (2019). In addition, we normalize to one, $\zeta = 1$, the scale parameter for the complex job production function.

Among institutional parameters, only the tax τ on the output of a match in a temporary job and the probability to convert a temporary contract to a permanent one, ϕ, are preset. We set $\tau = 0$, and let y in the benchmark model be interpreted as after-tax output. We calibrate the parameter for the duration restriction ϕ 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 α. We set α to 0.9486 to match an average annual skill persistence value of 0.9 following the literature on skill or human capital accumulation. The value of the output for a generic job is chosen in such a way that the corresponding non-work income or utility is 70 percent of the output. We assume that initial belief about ability is uniform across ability level. Hence, we set the probability of having high ability belief initially to $p_0 = 0.5$.

4.2 Internally calibrated parameters

The following remaining parameters are separately calibrated to match salient features of workers' life cycle in high- and low-education groups using a simulation-based method. Those are the matching efficiency χ, the non-work income b, the firing cost F, the employed worker search intensity on the job s, the proportion of complex job $\bar{\gamma}$, the high and low level of

Table 1: Benchmark values of preset parameters

Parameter	Description	Value
β	Discount rate	0.9902
ξ	Exogenous dying probability	0.0066
$\overline{y}$	Output for generic job	1.4286
τ	Tax on temporary contract	0
η	Elasticity of matching function	0.5
ζ	Scale for complex job production function	1
ϕ	Expected max duration of TC	0.1175
α	AR1 skill dynamics persistence, employment	0.9487
p_0	Proportion having high ability beliefs A_h	0.5
A_0	Ability in skill process from unemployment	0

potential ability (A_h, A_l), the variance of disturbance embed in skill learning σ_ε, the shape parameters for job separation distribution with respect to job type, and the elasticity ρ of output with respect to skill x in the complex job. We assume the job separation δ is drawn from a beta distribution with shapes (λ_1, λ_2)

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. Additional details, including a discussion of how the parameters are informed by these moments, are provided in the appendix.

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 education group and panel (b) reports results for the high-education group.

We observe that the model fits the data very well, capturing the decline in the unemployment rate and a share of temporary contract jobs as workers age. This is a result of the combination of the behavior of transition rates over the life-cycle. Figure 6 plots the transition rates for the low-education group. As we can see, the model matches very well the transition profiles. It generates the flat profile observed in the data for UP, UT, and TP transition rates throughout the life cycle. In addition, the model delivers 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 could be due to an absence of participation margin in the model. In the data, transitions from employment to inactivity are relatively high for the oldest workers (e.g., Choi et al. (2015)), a pattern that could be reproduced in the presence of a distinction between unemployment and non-participation. Nonetheless, we are confident about our model's ability to explain employment dynamics over the life cycle, since it remarkably replicates the profile of PU transition. Indeed, PU emerges as the most important factor explaining the employment dynamics for low-education individuals over the life cycle according to our decomposition exercise in the previous section.

Figure 7 plots the transition rates for high education group. The model fairly fits the data counterpart and captures the declining shape of the transition rates. The transition UP, PU, PT, and TU are well matched but the model has difficulties with fitting the level of UT and TP in data. Overall, the model is capable of generating the salient features of transition profiles observed in the data. Again, a very interesting feature is that the model remarkably fits the age profile of PU and PT transition rates for high-education individuals. These transitions are the most important contributors in explaining total employment rate dynamics over the life cycle for high-education groups (see decomposition exercise).
In the next, we explore the role of learning versus idiosyncratic unemployment risk in fitting the observed transition rates.

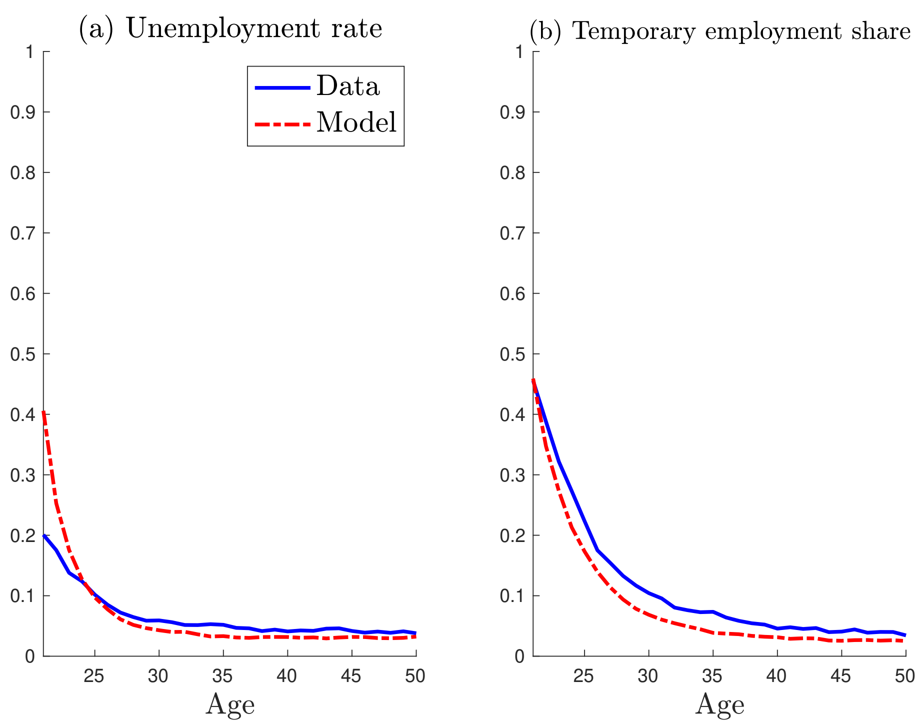
Table 2: Benchmark values of estimated parameters

Parameter	Description	Value	
		Low-educ.	High-educ.
b	Non work utility	0.9629	0.9517
F	Firing cost	1.9727	1.8942
ϕ_0	Output for generic job	0.4998	0.4974
χ	Matching efficiency	0.3216	0.3450
s	Employed search intensity	0.5	0.5
ρ	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
σ_ε	Standard deviation for skill disturbance	0.0181	0.1852
A_l	Low level of ability belief	0.0076	0.0011
A_h	High level of ability belief	0.0387	0.0251

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

(a) **Low education**

(b) **High education**



Notes: The solid blue lines denote the data and the dashed red lines denote the model.

4.4 Model Mechanisms

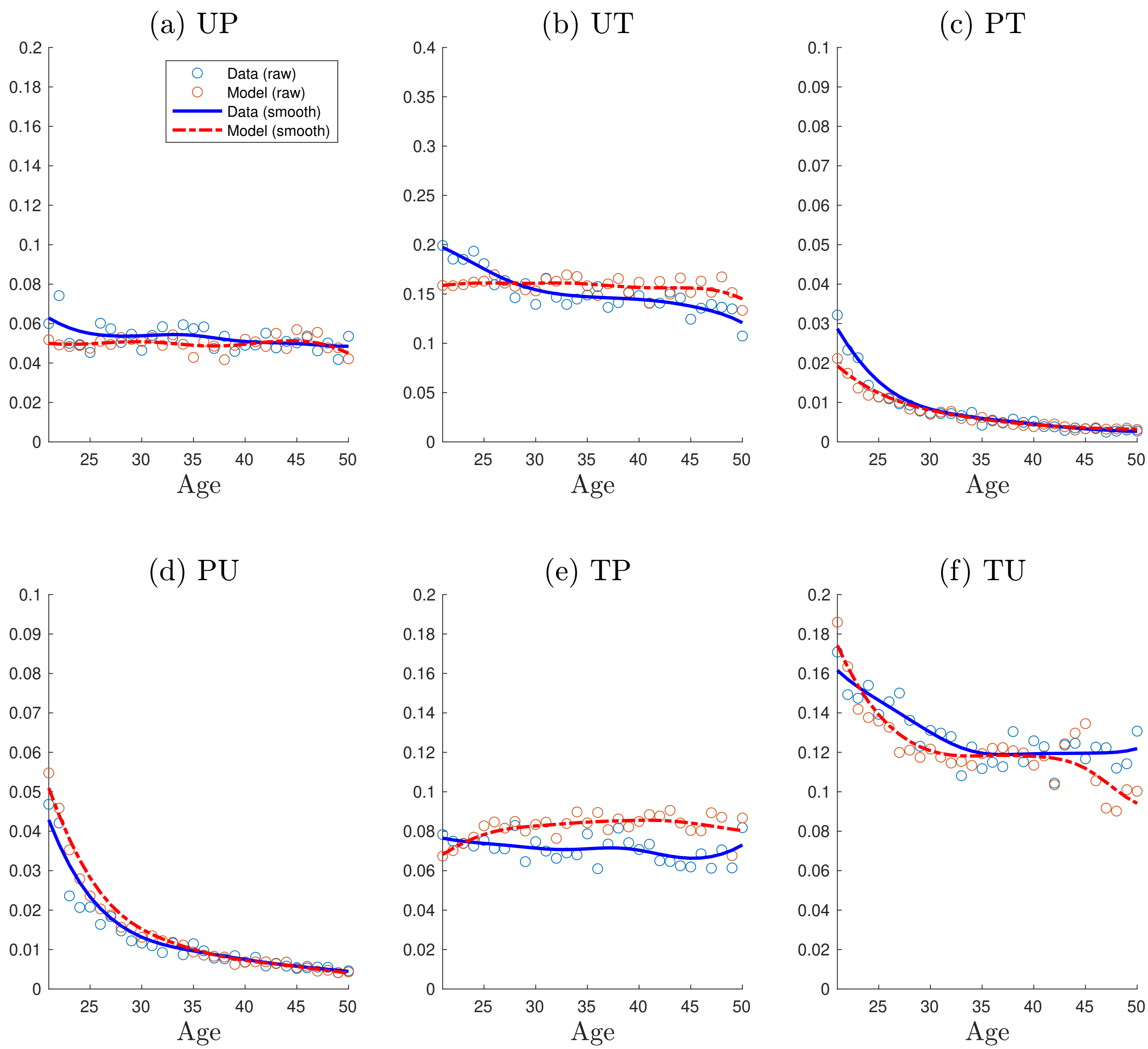
How does the model achieve desirable life-cycle properties for the worker flows across skill groups? It is instructive to zoom into the three channels captured by the model: skill accumulation, learning about worker ability, and idiosyncratic unemployment risk.

We argue that the model generates a declining profile for employment exit transitions (PU, TU) and job-to-job transition (PT), regardless of the education group, due to skill accumulation. As workers age, they accumulate skills on the job, possibly through learning by doing, and become less likely to separate from their current employment. This is intuitive in a finite-lived model, as older workers are less inclined to engage in on-the-job search, while younger workers are more likely to search and improve their match quality. Conversely, the relatively flat life-cycle profile of job-finding rates (UP, UT) for the low-skill group primarily results from idiosyncratic unemployment risk. In contrast, the declining profile observed among high-skill workers is driven by learning about worker ability. Hence, Bayesian learning plays a more significant role for high-education workers, whereas heterogeneity in unemployment risk is the primary factor contributing to the life-cycle variation in worker flows for the low-educated group.

To test our theory, 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 δ. More precisely, to eliminate the learning in the model, we significantly reduce the standard deviation of the disturbance σ_ε, ($\sigma_\varepsilon \longrightarrow 0$). This reduction effectively diminishes the noise in the worker's ability signal, which reflects the firm's choice of recruitment and screening practices. With lower noise, the ability of the worker is revealed upon contact, eliminating the need for a screening process and, consequently, the learning mechanism. To eliminate the idiosyncratic unemployment risk, we substantially increase the second shape parameter of the beta distribution for job separation draws, ensuring that $\delta = 0$ becomes nearly zero with high probability. 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 recalibrate the model to match the labor market tightness $\theta = 1$, consistent with the benchmark case. The results of these counterfactual scenarios are presented in Figure 8.

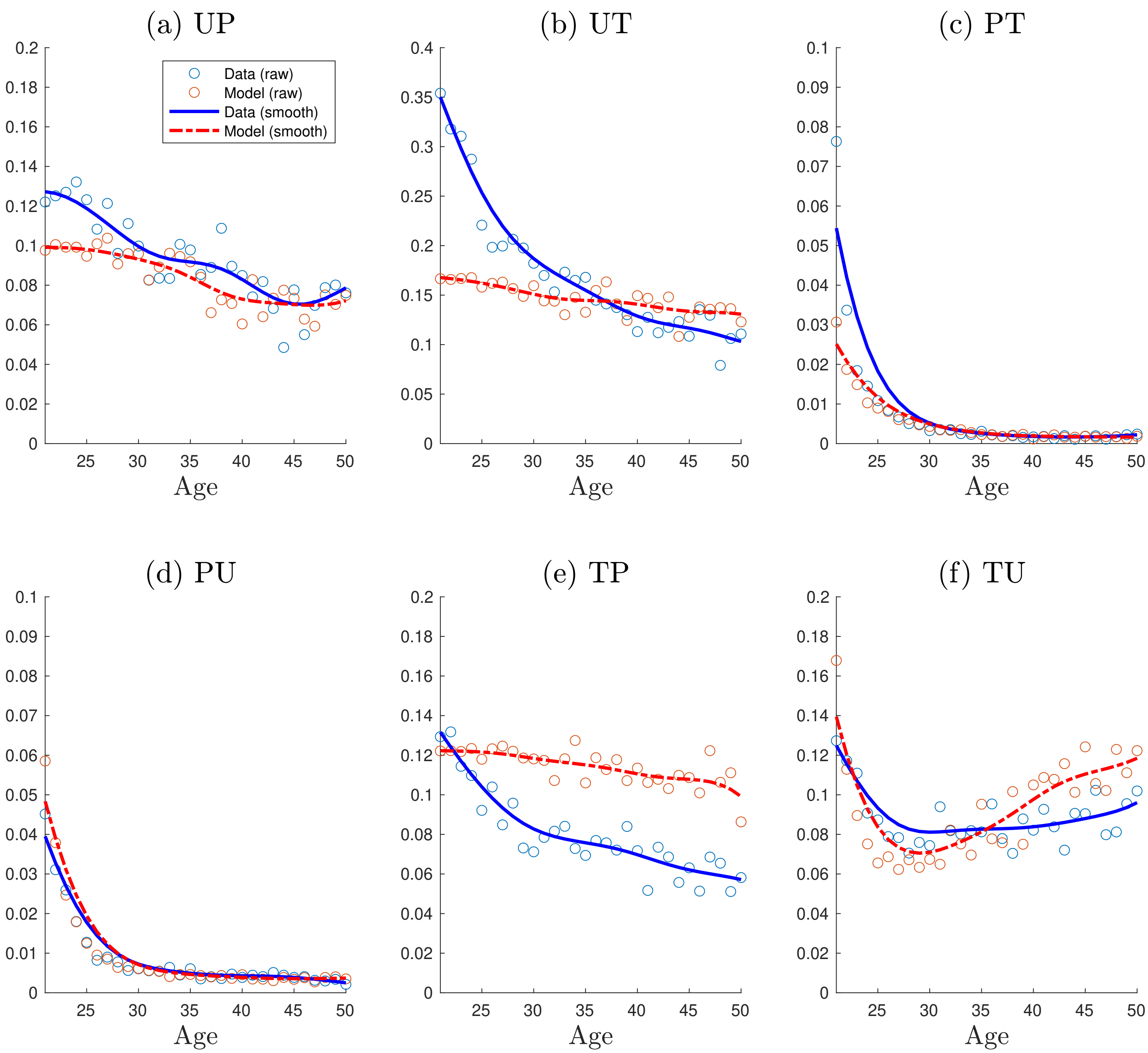
Panel (a) of Figure 8 depicts a scatter plot comparing the UP transition between the benchmark model and the model with only the learning mechanism, for high-education individuals. The same logic applies to the other subfigures. As we can see, the learning model yields higher R−squared compared to the 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 high 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: Low-educated individuals possess a comparative advantage in generic jobs, where their observable skills are sufficient for employment. On the other hand, high-educated individuals have a 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 unfolds over the life cycle. As a result, the fraction of high-education workers who face a higher probability of immediate ability revelation increases with age. For these older workers, the probability of finding a job is lower since they may be perceived as having lower abilities based on their observed characteristics when they are unemployed, searching for a job.

Figure 6: Target transition profiles - low education



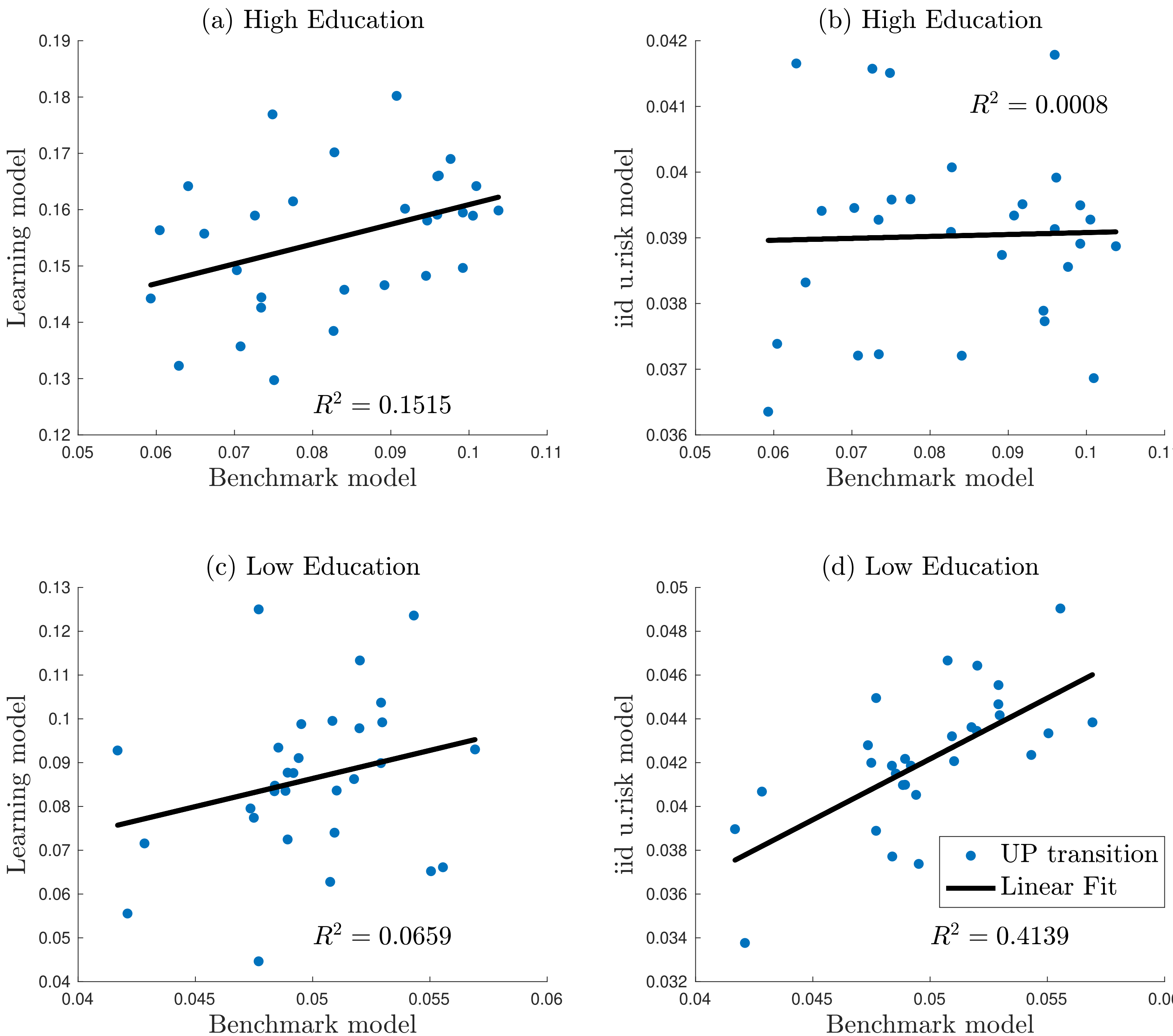
Notes: The plots show quarterly transition probabilities. The solid blue lines denote the data and the dashed red lines denote the model.

Figure 7: Target transition profiles - high education



Notes: The plots show quarterly transition probabilities. The solid blue lines denote the data and the dashed red lines denote the model.

Figure 8: Role of learning versus idiosyncratic unemployment risk



5 Conclusion

This paper examines life-cycle patterns of worker flows in a dual labor market characterized by the presence of permanent contracts subject to high firing costs and temporary contracts. A decomposition analysis relying on estimates of worker flows based on French Labor survey data shows that this duality between temporary and permanent employment has an important age component and different implications for age-specific employment dynamics across education groups, as well as for the formation of youth employment.

We propose a model that matches the observed life cycle profile of labor-market transitions. The model generates a declining profile for employment exit transitions (PU, TU) and job-to-job transitions (PT), regardless of the education group, due to skill accumulation. We use this model to investigate the primitive sources of these patterns. On the other hand, the relatively flat life-cycle profile of job-finding rates (UP, UT) for the low-skill group primarily results from idiosyncratic unemployment risk. In contrast, the declining profile observed among high-skill workers is driven by learning about worker ability. Hence, Bayesian learning plays a more significant role for high-education workers, whereas heterogeneity in unemployment risk is the primary factor contributing to the life-cycle variation in worker flows for the low-educated group. Furthermore, the model provides a tool for assessing the effect of temporary contracts and firing costs on employment, aggregate productivity, and the life-cycle dynamics of earnings.

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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 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:

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

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:

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

where ν 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 ν', the updated surplus share. Thus, we have:

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

that is:

$$\nu' = \min\big\{\frac{S}{\tilde{S}}, \max\big(\frac{S_0}{\tilde{S}}, \nu\frac{S}{\tilde{S}}\big)\big\} \tag{32}$$

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

$$\nu' = \min\big\{1, \max\big(\frac{S_0}{S}, \nu\big)\big\} \tag{33}$$

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

$$\nu' = \min\big\{\frac{S}{S_0}, \max\big(1, \nu\frac{S}{S_0}\big)\big\} \tag{34}$$

which imply that:

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

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

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,

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

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

$$\Gamma_{a,e} = \begin{pmatrix} II_{a,e} & IU_{a,e} & IT_{a,e} & IP_{a,e} \\ UI_{a,e} & UU_{a,e} & IT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & TT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & IT_{a,e} & PP_{a,e} \end{pmatrix} \tag{38}$$

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

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

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 Tables and Figures

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

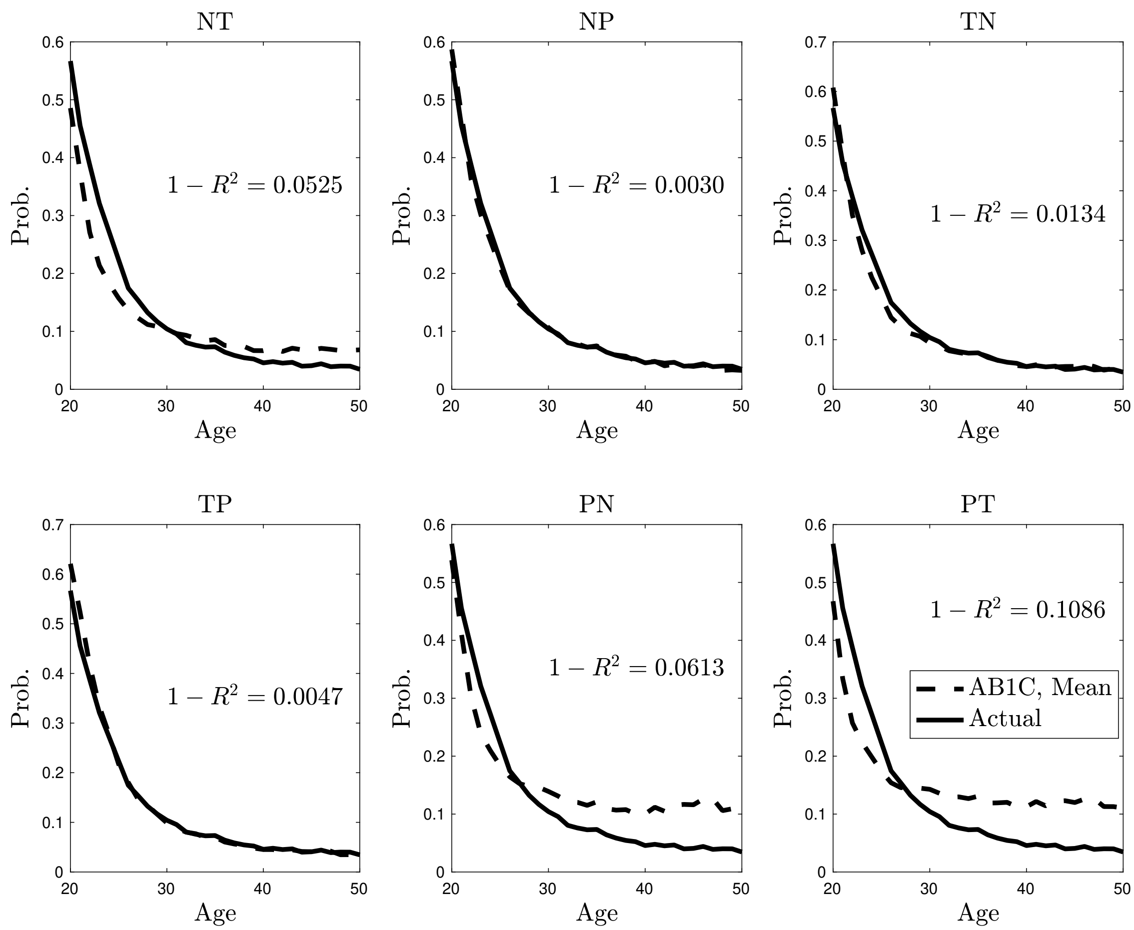


Figure A2: AB1C Decomposition of the importance of Flows: temporary employment share, Low education (3 states)

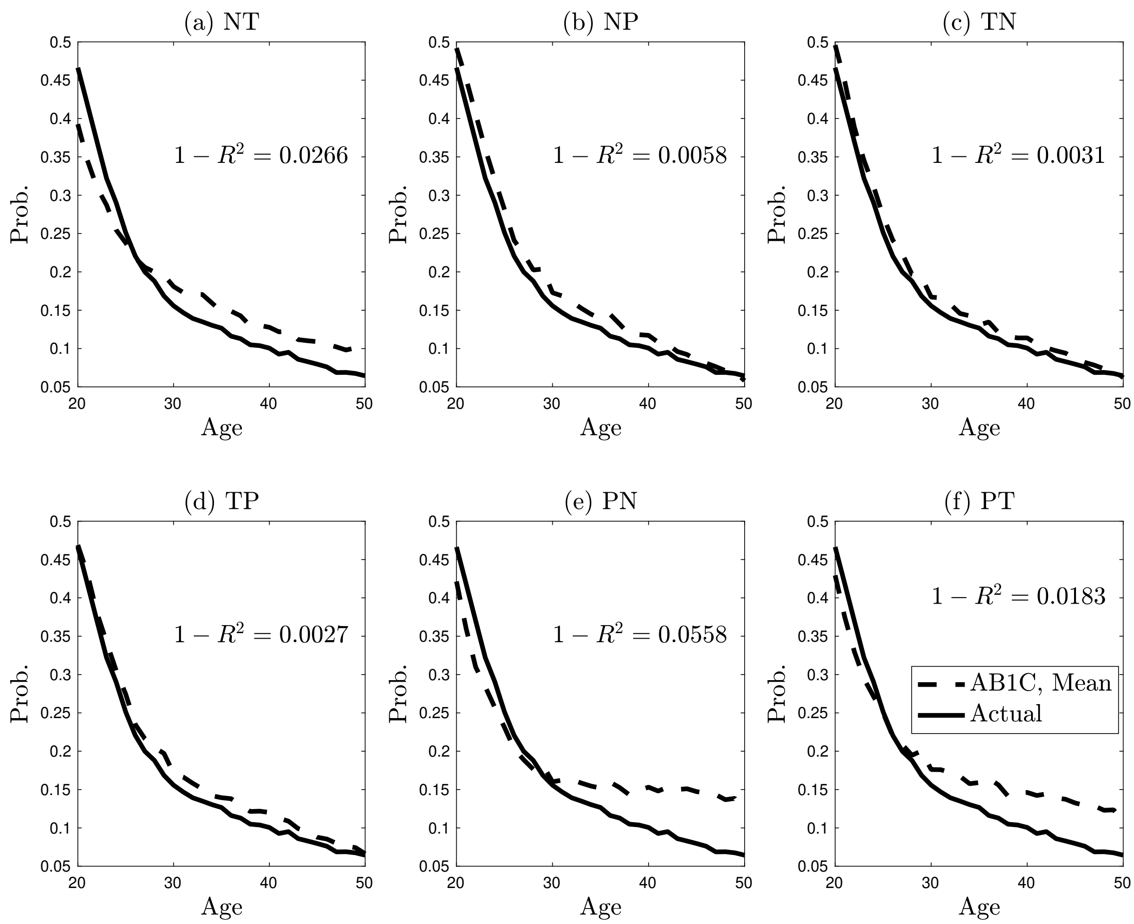


Figure A3: Markov chain simulated employment and temporary job share (4 states)

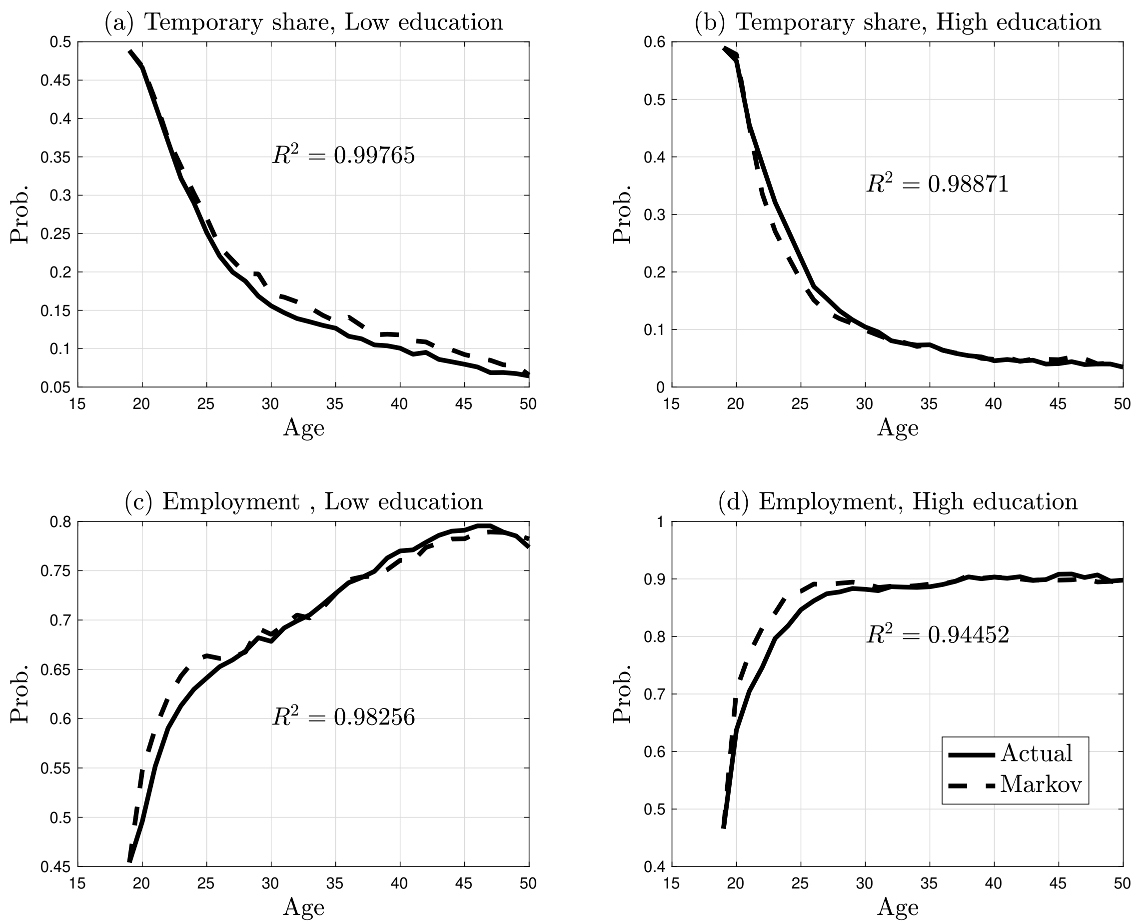
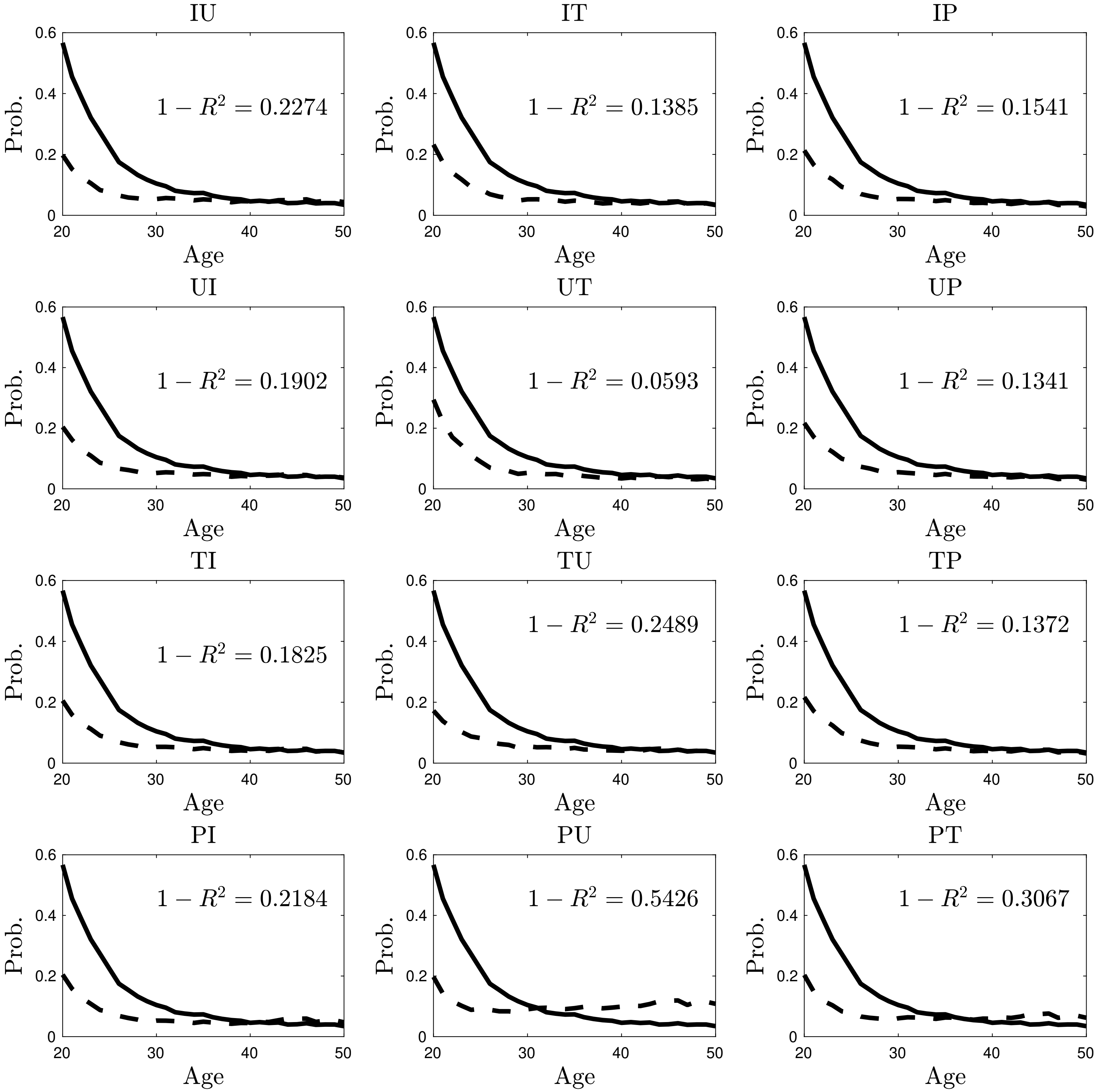
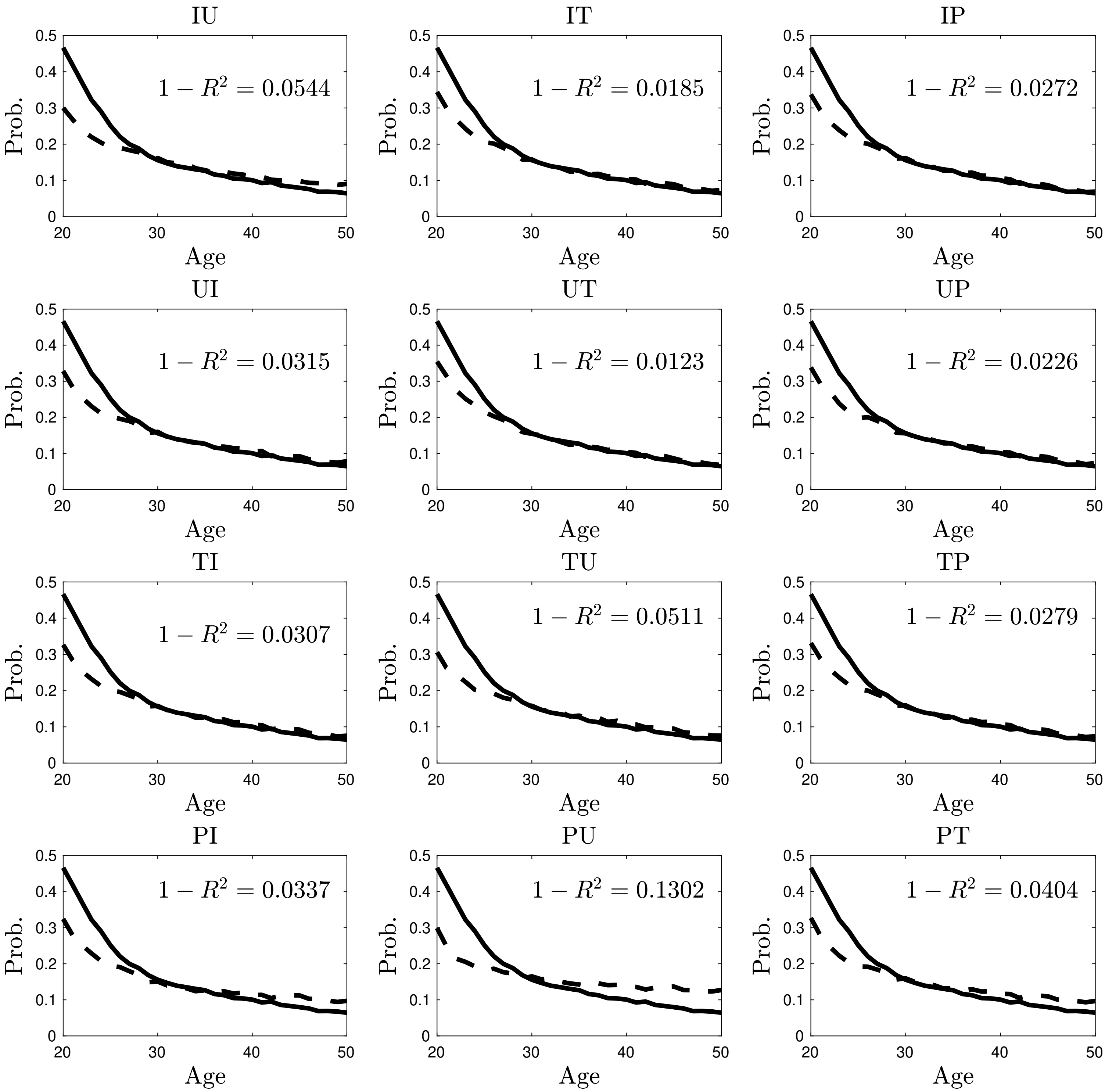


Figure A4: AB1C Decomposition of the importance of Flows: temporary employment share, High education (4 states)



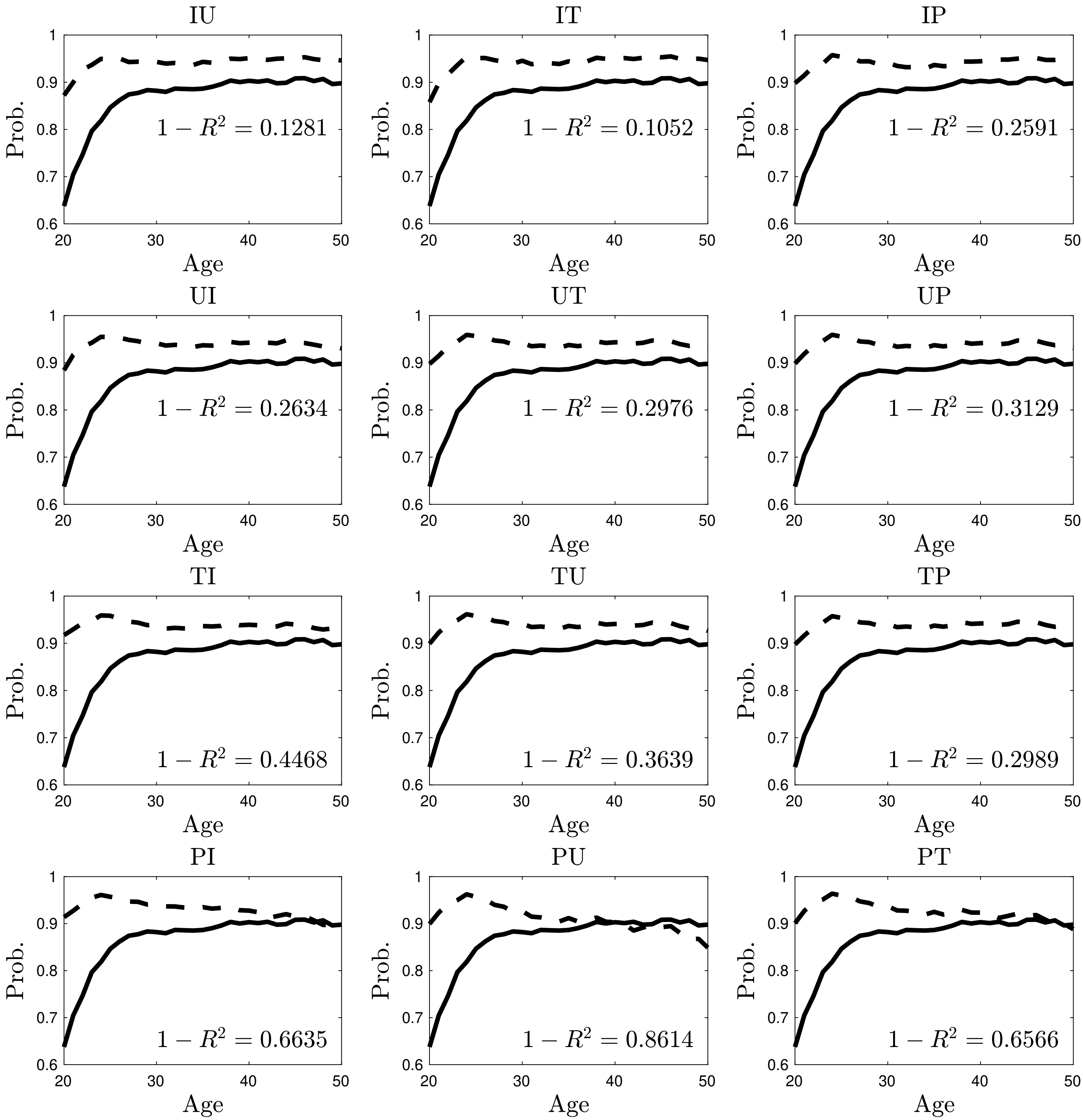
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

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



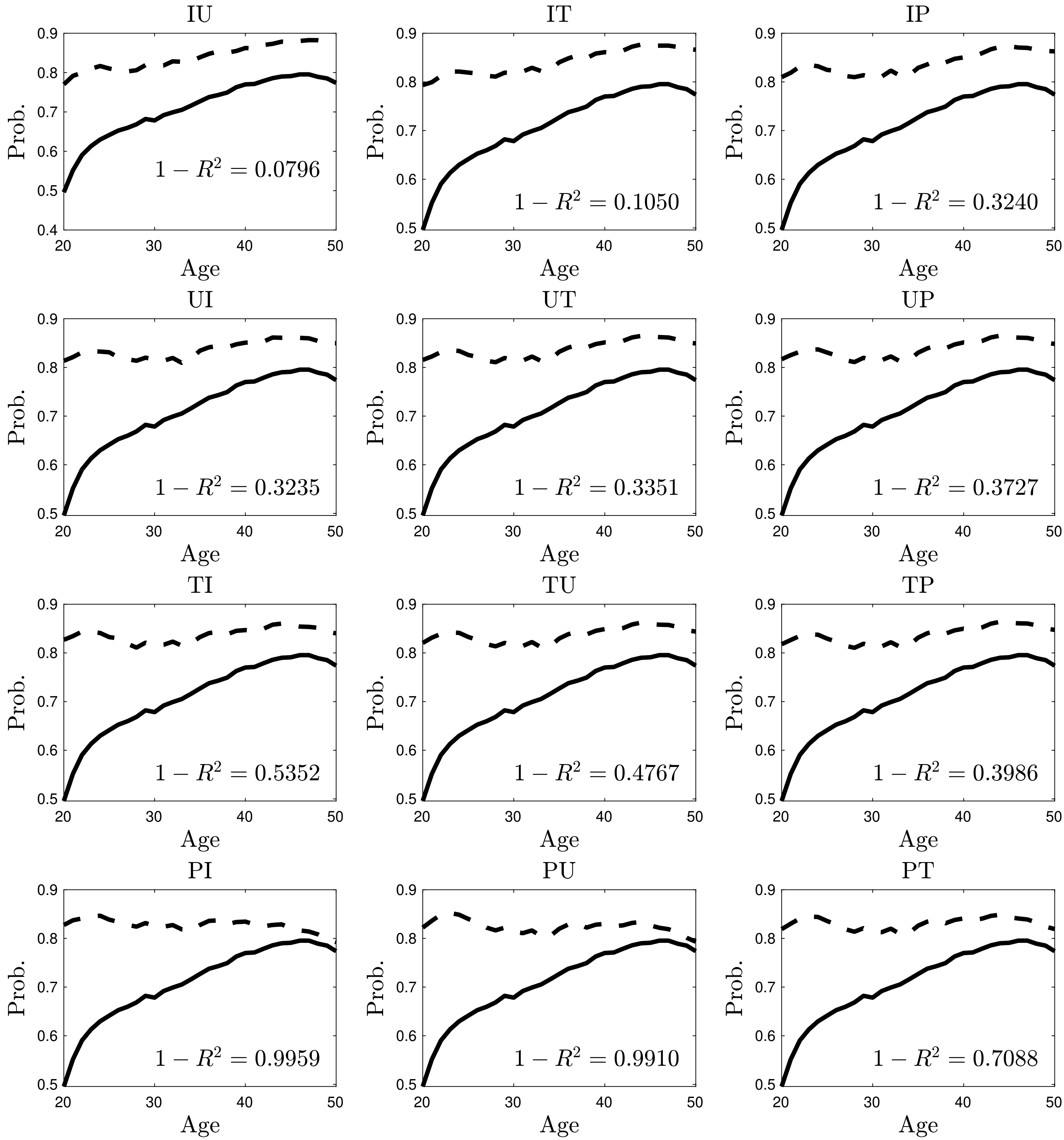
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

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 counterpart