Life-cycle worker flows in a dual labor market*

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Abstract

This paper considers the labor-market duality between temporary and permanent employment contracts as a source of life-cycle heterogeneity in worker flows. Using panel data from the French Continuous 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 is observed 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 and Bayesian learning about worker ability, and match-specific unemployment risk can replicate these facts. Bayesian learning is relatively more prevalent for high-education workers, whereas unemployment-risk heterogeneity is the key driver of life-cycle variation in worker flows for the low-educated. We assess the implications of the model for the effect of temporary contracts and firing costs on employment, mismatch and aggregate productivity, and the life-cycle dynamics of earnings.

JEL Codes:

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

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1 Introduction

In European countries, Employment protection legislation (EPL) reforms have been the main response to the persistently high unemployment rate in European countries over the past decades. In particular, many countries have eased restrictions on temporary jobs starting in the 1980s. Moreover, since the Great Recession, EPL reforms have been high on the policy agendas of many European governments. Many macroeconomists have argued that these reforms have failed in decreasing the unemployment rate. Moreover, it is frequently argued that the combination of high firing costs and lax restrictions on temporary jobs resulting from these reforms has resulted in dual labor market, segmented between permanent, stable jobs subject to strict firing restrictions and temporary jobs with high unemployment risk (e.g., Blanchard and Landier (2002), Cahuc and Postel-Vinay (2002), Boeri and Garibaldi (2007)). The latter view has been developed based on search models with idiosyncratic shocks and endogenous separations à la Mortensen and Pissarides (1994). This view has been challenged by authors studying the impact of temporary jobs in an environment with information frictions and Bayesian learning about workers' ability or the firm-worker match quality (see in particular, Faccini (2014) adapting Pries and Rogerson (2005)). In such an environment, temporary jobs act as a stepping stone for workers towards stable employment and decrease the unemployment rate. Hence a "churning" view interpreted as a manifestation of idiosyncratically stochastic separation shocks and a "learning" view have distinctly, if not opposed, implications for the effect of temporary jobs. Reconciling these two views might require a detour.

Furthermore, a body of work has highlighted significant differences in labor market mobility by age, experience and tenure. These have been attributed to (i) information frictions and learning; and (ii) heterogeneity in unemployment risk,and employment stability across jobs. These two mechanisms have qualitatively equivalent implications for age, experience, and tenure profiles of mobility. In particular, these imply decreasing employment to non-employment (EN), non-employment to employment (NE), and employment to employment (EE) age or experience profiles. However, these have different implications for the shape of the UPc (defined as the unemployment to permanent employment transition, conditional on a UE transition) and the temporary to permanent employment profiles (TP). Learning view would result in a decline in both profiles, whereas "churning" view implies flat UPc and TP profiles.

In this paper, we propose an empirical analysis of life-cycle mobility patterns in a dual labor market. We compute age transition-probability profiles between permanent and temporary jobs and non-employment states. Using panel data from the French Continuous 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 is observed 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 and Bayesian learning about worker ability, and match-specific unemployment risk can replicate these facts. Bayesian learning is relatively more prevalent for high-education workers, whereas unemployment-risk heterogeneity is the key driver of life-cycle variation in worker flows for the low-educated. We assess the implications of the model for the effect of temporary contracts and firing costs on employment, mismatch and aggregate productivity, and the life-cycle dynamics of earnings. In addition, we use the model to quantify the contribution of churning and learning to explaining age differences in temporary employment probability.

2 Empirical analysis

2.1 Data

We use the French continuous employment 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).[1] The EEC provides detailed socio-demographic and labor market information for individuals in a nationally representative 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

[1]See **?** and **?** for detailed discussions related to the EEC.

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 consecutive quarters. Since 2009, around 73,000 dwellings are surveyed in each quarter.

We rely on restricted-use research files, provided by the Adisp (National Archive of Data from Official Statistics) center. The restricted-use files provide household and individual identifiers allowing to track individuals over consecutive quarters.[2] The following analysis, which consists in estimating quarterly transition probabilities based on computing worker flows, relies on the longitudinal dimension of the data.

Our focuses on non-military and non-institutionalized individuals aged 20 to 50 in metropolitan (mainland) France. This age restriction allows us to abstract from the effect of schooling and retirement decisions on transition profiles, which are beyond the scope of the analysis. Since we are interested in computing quarterly worker flows, we use the sample of observation for individuals in their second interview or more, with labor market information in the previous quarter (i.e., in their previous interview). The resulting sample has 1,821,333 observations for 342,116 individuals over the 2003-2018 period.

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 labor market flows between permanent and temporary employment, and non-employment at a monthly frequency, 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 together point estimates and confidence interval for a local polynomial smoother with Epanechnikov kernel function. Notice that we do not compute instantaneous transition rates as in e.g., Shimer (2012) in our baseline analysis; we present robustness checks suggesting that our main results

[2]In contrast, the public-use files do not has household and individuals over time.

are unchanged with this correction.

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 other 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).[3] Temporary-agency contracts (*contrat d'intérim*), fixed-term contracts (*contrats à durée déterminées*), are put 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).[4]

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

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

for each month t in our sample period and each age $a=20,...,80$, 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 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 having age a at time t).

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

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

for given j,k, where the weight of observation 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

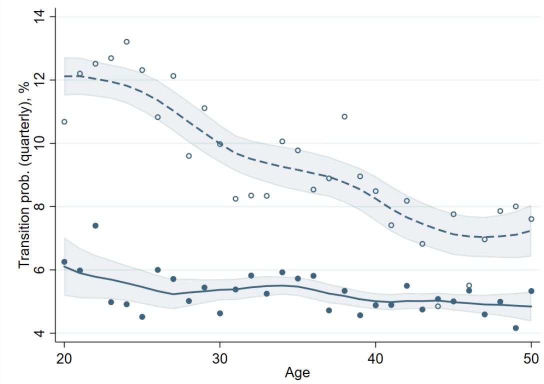
[3]In the robustness analysis, we propose an alternative classification where the apprentices are counted in T instead of P.

[4]Finally, for those individuals counted as intern or in subsidized contract (*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.

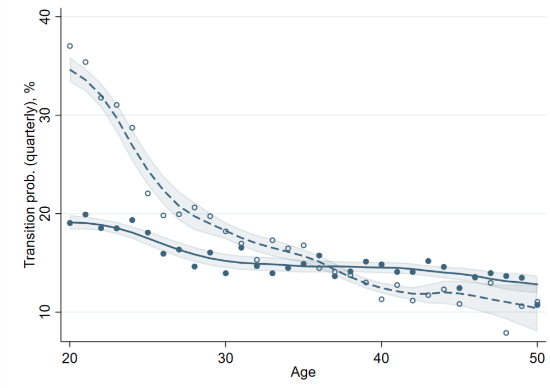
the age-specific quarterly transition probabilities. Finally, we compute smoothed age profiles and 95% confidence intervals using local polynomials with a Epanechnikov kernel function. Our results for transitions between unemployment and permanent and temporary employment are reported in figure 1. We depict the life-cycle transition profiles by education groups. We consider the primary and secondary-education individuals (referring to the low-education group) from one side and the tertiary-education individuals (referring to the high-education group) from the other. In the appendix, we show transitions in and out of participation.

Empirical findings. Broadly speaking, transition probabilities display substantial variations over the working life of individuals and a sharp difference across education groups. First, job finding rates, as measured by UP and UT transitions rates, exhibit a decreasing profile for high-education workers but a flat profile for low-education individuals. Unsurprisingly, high-education unemployed workers are more likely to be employed with a permanent contract than their peers of low education. This pattern holds for jobs in temporary contracts before age 38 and reverses afterward. A possible explanation is that at these ages, a higher proportion of high-educated job seekers are finding a temporary job for which low educated have a higher comparative advantage. This is consistent with the learning view of temporary contracts acting as a screening device about worker ability for a permanent position. Intuitively, this learning process takes more time for high-education workers. Second, separation rates, as measured by TU and PU, decline for both education groups. However, TU decreases much more sharply for the high-education groups. The job separation rate from temporary employment becomes steady, starting at around 28 for high education, whereas, for those with low education, it is about 35. This suggests a different skill accumulation across worker education groups. Finally, turning to the job-to-job move, we observe that the transition from temporary to permanent employment (TP) falls over the worker life-cycle for the high-education group and is steadily constant for the low-education group. The pattern is typically similar to the UT transition rate. We also notice a substantial transition from permanent contract employment to temporary one among the youths, especially for high education workers. This could happen through a job-to-job move that enhances match quality.

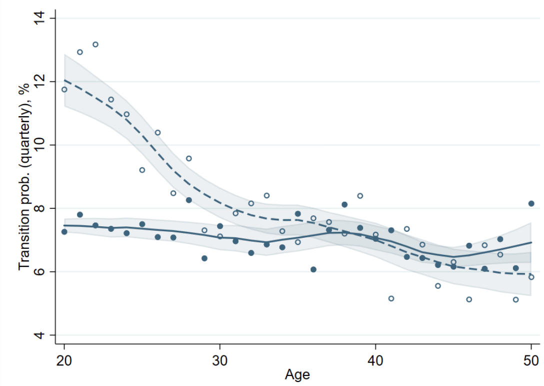
Figure 1: Age profiles of quarterly transition probabilities, by education group



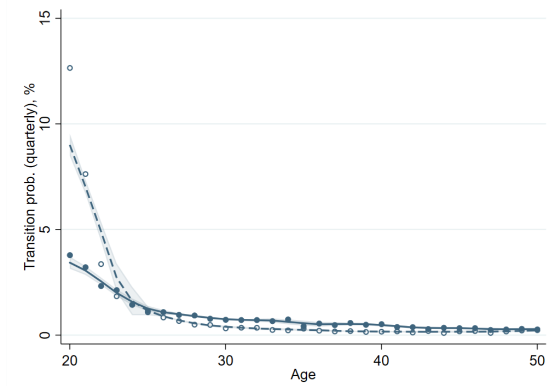
(a) UP



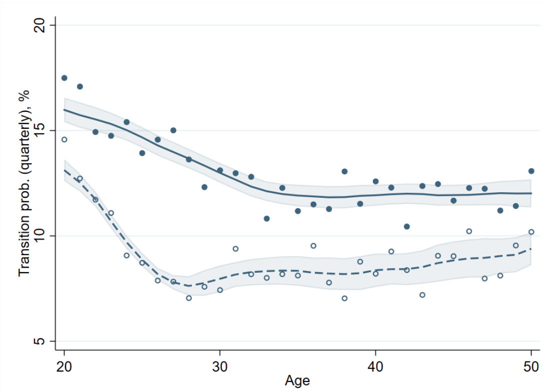
(b) UT



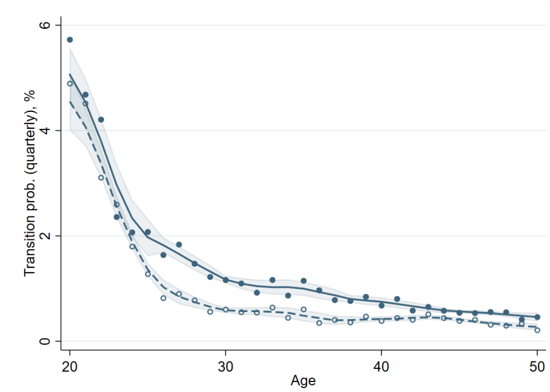
(c) TP



(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.

3 Model

3.1 Environment

We present a model with heterogeneous workers and jobs. This model features uncertainty and Bayesian learning about worker ability and match-specific unemployment risk. We show below that a model with these main ingredients is qualitatively consistent with salient empirical facts regarding our analysis of transition probabilities by age in section 2.

Time is discrete, goes forever, 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 (or production units) 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 $x \in \mathbb{R}_+$. A newborn worker has skill $x = 1$ when employed. A worker employed at time t accumulate skills following the process

$$\ln x_{t+1} = A + \alpha \ln x_t + \varepsilon_{t+1} \tag{3}$$

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 where $\alpha \in (0, 1)$. We assume that the process for skill dynamics differs between employment and unemployment: an unemployed worker faces the following skills process

$$\ln x_{t+1} = A_0 + \alpha \ln x_t + \varepsilon_{t+1}, \tag{4}$$

We assume $A_0 \leq 0$: on average, skill depreciates when the worker is unemployed.

We assume that the skill-acquisition probability A is drawn at the worker's birth. A fraction π are born with skill $A = \overline{A}$, the remaining fraction has $A = \underline{A}$. The ability A for a given worker is ***not*** observed by any agents in the economy, nor the realization of the disturbance term in (3). However, the skill level x_t is observable and can be relied upon as a signal informative for 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 (3).

As such, the agents use the realized skill levels implied by (3) and (4) 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 $t+1$ posterior beliefs are updated based on the realized (log) skill level following

$$\tilde{\pi}_{t+1} = \frac{\tilde{\pi}_t \exp\Big\{ -\frac{1}{2}\frac{(\ln x_{t+1} - \alpha \ln x_t - \overline{A})^2}{\sigma^2}\Big\}}{\tilde{\pi}_t \exp\Big\{ -\frac{1}{2}\frac{(\ln x_{t+1} - \alpha \ln x_t - \overline{A})^2}{\sigma^2}\Big\} + (1-\tilde{\pi}_t)\exp\Big\{ -\frac{1}{2}\frac{(\ln x_{t+1} - \alpha \ln x_t - \underline{A})^2}{\sigma^2}\Big\}} \tag{5}$$

when the worker is employed, which follows from the normality assumption of the log-skill process.

Moreover, the initial beliefs for a worker born at time t_0 are described by distribution parameters equal to their population counterparts:

$$\tilde{\pi}_{t_0} = \pi_{t_0} \tag{6}$$

for all $t_0 \geq 0$.

Jobs. Given their skills, workers sort into jobs that are characterized by the type of skill they employ and are further differentiated by the intensity they make use of 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

$$y_t = \zeta x_t^{\rho}, \tag{7}$$

where $\zeta > 0$ and $\rho \in (0, 1)$ are parameters. 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. Hence, with probability δ, the match becomes permanently unproductive. 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 agents in the labor market.

A remark should be raised here. We assume unidimensional skills for workers. However, this goes against a growing strand of the literature studying the implications of multidimensional skills for the sorting and earnings dynamics of individuals in the labor market (Lise and Postel-Vinay (2020); Guvenen et al. (2020); Lindenlaub (2017)). We see this simplification as not critical for key results presented in this paper [how/why?: we can show in an appendix that the key outcomes of interest of the learning model hold when we assume multidimensional skills] and is somehow beyond the scope of our study. The main mechanism we rely on to explain the observed empirical sorting pattern is the simultaneous presence of information frictions about ability and some heterogeneity in job stability. Given that we already consider a state space that is already large, we reserve the multidimensional-skill case for future work.

Search and matching. The labor market features search frictions, and search is random. Workers are either unemployed or employed, and firms (production units) have jobs that are either vacant or occupied. An unemployed worker receives period utility $b > 0$, and the per-period cost of 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 stochastic. The value of m represents the number of contacts between workers and firms per period given the mass of vacancies and job seekers (i.e., the mass of worker-firm pairs entering into contact in the labor market). The contact rate of an unemployed worker is $p(\theta) = \chi\theta^{1-\eta}$, 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, so $\gamma_1 = \overline{\gamma}$.

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.

As in Postel-Vinay and Robin (2002), we assume full bargaining power to the firm combined with sequential auctions and Bertrand competition. 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) (among others): the worker's surplus share is endogenous, and the result of competition between firms; the wage received by the worker and which is the outcome of this competition is the wage implementing this share of the surplus (more details below).

This specification presents the advantage of allowing us to introduce on-the-job search at a modest computational cost. This element enables the model to feature a job ladder with heterogeneous risk of unemployment. This element and Bayesian learning about ability are the keys to explaining the stylized facts we highlight regarding transition rates. This specification allows us to do so at a modest computational cost while having a rich state space in our model. Essentially, 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 on-the-job search outcomes.[5] This simplifies the computation of surplus functions dramatically, even in the presence of a rich state space (see Lise and Postel-Vinay (2020)).

Institutions: permanent and temporary employment contracts. There are permanent and temporary contracts (PC and TC). Denote by n_P the mass of workers in a permanent contract and by n_T the mass in a temporary contract. A permanent contract has firing costs of F, and a temporary contract has no firing costs. Temporary contracts are regulated. Restrictions on these contracts are captured by a tax τ on the output of a match in

[5] [Explain a little bit more]

a temporary job. F and τ are deadweight losses that capture EPL regulations. Alternatively, τ can be interpreted as a reduce-form approach for capturing contractual frictions inherent to temporary jobs allowing to rationalize the coexistence of permanent and temporary jobs as seen in the data—an aspect that we see as being beyond the scope of this paper.[6] Moreover, temporary contracts have stochastic maximum duration: with probability ϕ, the contract ends and must be converted into a permanent contract to continue the match. Existing legislation only allows the conversion of a temporary contract to a permanent one.

Timing. Unemployed worker:

(i) Dies (exits the labor market) with probability ξ, stays in the labor market with the complement probability;

(ii) If stays in the labor market, observe new skills x_t implied by process (4).

(iii) Search and receives an offer with probability $p(\theta)$; receives no offer with the complement probability;

(iv) If receives an offer, draws a job type $j = 0, 1$ and an exogenous separation probability δ;

(v) Based on skills, beliefs, the job type, and the probability of separation, the agents evaluate the surplus in a PC and a TC and decide whether they form a match or not and the type of contract, if applicable;

(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) Dies/survives;

(ii) Updates skills and beliefs according to (3) and (5);

(iii) Exogenous separation with probability δ;

[6] See Cahuc et al. (2016) [...] for papers studying the coexistence of permanent and temporary contracts.

(iv) Receives an outside offer with probability $sp(\theta)$, and draw, if applicable, 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 profitable to the worker and if the associated surplus is positive, and chooses the best contract type; otherwise, stays in the current match.

(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 skills and beliefs from stage (ii) is positive; otherwise, the worker returns to unemployment.

Temporary worker:

(i) Dies/survives;

(ii) Updates skills and beliefs;

(iii) Exogenous separation with probability δ;

(iv) With probability $1 - \phi$, the agents are free to choose between a TC and PC and choose the contract type yielding the more surplus; with the complement probability, the agents are required to convert the TC into a PC;

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

3.2 Value functions

We now consider a steady-state recursive equilibrium of the labor market and drop time subscript. We consider free entry of vacancies so that the expected discounted profit of a vacancy is zero. For extra clarity, let the dying probability $\xi = 0$ for the ease of the model's presentation (alternatively, let the dying probability lie in the relevant discount factors). We denote by a and a' the current and next-period value of a given variable a.

Let $\omega = (p, x) \in \Omega \equiv [0, 1] \times \mathbb{R}_+$ be a vector describing the worker's state: the beliefs 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. These functions depend on the worker's state ω, on the risk of unemployment, $\delta \in [0, 1]$ and on the job type (generic or complex), indexed by $j \in \{0, 1\}$. Let $U : \Omega \to \mathbb{R}_+$ be the worker's lifetime discounted utility value of unemployment.

As is well known [ref], firing costs enter in the firm's outside option of an ongoing match (i.e., in periods after the match's initial date) but not at the hiring stage (i.e., at the initial date of the potential match). As such, this introduces a distinction between an ongoing and a hiring stage in a permanent contract; we shall use S_P to denote the surplus in the continuation stage, implying that the surplus at hiring is $S_P - F$. Following the same argument, in the stage where the agents consider converting the TC into a PC (we shall call this stage the *conversion* stage), the surplus function is $S_P - F$.

Full bargaining power to the firm and the assumption that non-work income b is independent of skills imply that the worker's lifetime discounted utility value of unemployment is simply

$$U(p) = \frac{b}{1 - \beta}, \tag{8}$$

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

In addition, define

$$S_0(\omega, j, \delta) \equiv \max\big(S_P(\omega, j, \delta) - F, S_T(\omega, j, \delta), 0\big) \tag{9}$$

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 a worker with skill state p, conditional on drawing job characteristics (j, δ). This reflects that both permanent and temporary jobs are available at the hiring stage.

Wage renegotiation takes place as in Postel-Vinay and Robin (2002) and Lise and Postel-Vinay (2020) (among others), adapted to a case with 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. 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.[7] [This is equivalent to assuming that workers can threaten to sue firms in court after a separation due to the on-the-job search to force them to increase the wage up to the level such that the profits are equal to firing costs].

Denotes by $\sigma \in [0,1]$ the surplus share of a worker in a given match [update notation]. Due to the firm's full bargaining power, workers hired from unemployment have $\sigma = 0$. In subsequent periods, workers use outside offers to trigger competition between employers and improve their surplus, implying that $\sigma \geq 0$ in general. Conditional on receiving an outside offer from a vacancy with job characteristics (j', δ'), the worker in a permanent contract with state (j, δ) moves to the new job if $S_0(\omega, j', \delta') > S_P(\omega, j, \delta)$ and stays with the same employer otherwise (assuming $S_P(\omega, j, \delta) \geq 0$). Conditional on staying, the worker receives an updated surplus share given by

$$\sigma' = \mathcal{I}\big(\sigma S_P(\omega, j, \delta) > S_0(\omega, j', \delta')\big)\sigma + \mathcal{I}\big(\sigma S_P(\omega, j, \delta) > S_0(\omega, j', \delta')\big)\frac{S_0(\omega, j', \delta')}{S_P(\omega, j, \delta)}; \tag{10}$$

and the worker who leaves receives a surplus share in the new match

$$\sigma' = \frac{S_P(\omega, j, \delta)}{S_0(\omega, j', \delta')}. \tag{11}$$

As a result, the workers expected surplus conditional on receiving an offer (with probability $sp(\theta)$) is, given the current surplus share σ

$$\Delta_{W,P}(\omega, j, \delta; \sigma) = \sum \omega_j \int \min\Big\{ \max\big(\sigma S_P(\omega, j, \delta), S_0(\omega, j', \delta'), 0\big), \max(S_P(\omega, j, \delta), 0)\Big\} dG_\delta(\delta'|j'), \tag{12}$$

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

$$\Delta_{J,P}(\omega, j, \delta; \sigma) = \sum \omega_j \int \max\Big\{ \min\big(S_P(\omega, y, \delta) - S_0(\omega, y', \delta'), (1-\sigma) S_P(\omega, y', \delta'), 0\Big\} dG_\delta(\delta'|j'). \tag{13}$$

[7] 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.

Observe that $\Delta_W(\omega, j, \delta; \sigma) + \Delta_J(\omega, j, \delta; \sigma) = \max(S_P(\omega, j, \delta), 0)$ for all $\sigma \in [0, 1]$: in net terms, on-the-job search do not generate gains since, in the case of a job change, 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 (with free entry of vacancies, see above) can be expressed as

$$S_P(\omega, j, \delta) = f(x, y) - b + (1 - \beta) F + \beta(1 - \delta) \int \max\left\{S_P(\omega', j, \delta), 0\right\} dH_x(x'|\omega), \tag{14}$$

such that the next-period worker's state vector

$$\omega' = (\omega', x'), \tag{15}$$

has beliefs ω' updated following

$$p' = f(x's, x, p) = \frac{p \exp\left\{-\frac{1}{2}\frac{(\ln x' - \alpha \ln x - \overline{A})^2}{\sigma^2}\right\}}{p \exp\left\{-\frac{1}{2}\frac{(\ln x' - \alpha \ln x - \overline{A})^2}{\sigma^2}\right\} + (1 - p) \exp\left\{-\frac{1}{2}\frac{(\ln x' - \alpha \ln x - \underline{A})^2}{\sigma^2}\right\}} \tag{16}$$

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

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

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

Hence, the surplus function (14) 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).

Finally, the max operator reflects that continuation occurs if the realized surplus is positive (separation occurs otherwise). Importantly, the 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, these gains and losses offset each other: with exogenous bargaining power to the worker equal to zero, on-the-job search outcomes only change the distribution of the surplus over time, leaving the total surplus unchanged [since there is no net gains or losses to a job-to-job move: in such the case, the surplus is valued in equal terms as in the case where the worker stays in the same match but extract the entire surplus].

Along the same line of argument, the total worker-firm match surplus in a temporary job is

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

such that (16) to (17) are satisfied. The temporary job surplus has a current value independent of firing costs since these costs only apply to permanent jobs. 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 or to convert the contract (or they may separate), as reflected in the maximands for the next-period expectations. Notice that the option to continue into a permanent job is evaluated using the surplus function $S_P - F$, as per the distinction between the ongoing and conversion stage for a PC discussed above.

Finally, notice that the assumptions of zero bargaining power to the worker and that the unemployment income is independent of skills imply that the surplus in a generic job is independent of skills. As such, the surplus of a generic ($j = 0$) permanent job satisfies

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

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

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

Notice that since the surplus is time and skill invariant in steady-state and since we have $\overline{y} \geq b$, we have that the equilibrium surplus in a permanent job can be written as

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

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 surplus higher than in a PC (otherwise, the TC would not have been formed in the first place). Hence, the surplus in a TC solves

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

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

3.3 Wages

To derive the equilibrium wage functions, it is useful to denote by $W_{P,i}(\omega, y, \delta; \sigma)$ the value function of a worker in a permanent contract receiving surplus share $\sigma \in [0,1]$, 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

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

Further, using (12), the worker's surplus can be written as

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

for all $i, \omega, y, \delta, \sigma$, where $w_{P,i}(\omega, y, \delta; \sigma)$ denotes the wage. From the perspective of the worker, the surplus gains in the eventuality of a contact with an outside firm, $\Delta_, W, P$, (with probability $sp(\theta)$) shows 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

$$
\begin{aligned}
&W_T(\omega, j, \delta; \sigma) - U = w_{P,i}(\omega, y, \delta; \sigma) - b + \beta(1-\delta) \\
&\times \int \Big\{ (1-\phi)\Big[(1 - sp(\theta))\sigma \max(S_T(\omega', y, \delta; \sigma), S_P(\omega', y, \delta; \sigma) - F, 0) + sp(\theta)\Delta_T(\omega', y, \delta; \sigma)\Big] \\
&\qquad + \phi\Big[(1 - sp(\theta))\sigma \max(S_P(\omega', y, \delta; \sigma) - F, 0) + sp(\theta)\Delta_{P,0}(\omega', y, \delta; \sigma)\Big]\Big\} dH_x(x'|\omega),
\end{aligned}
\tag{25}
$$

where

$$
\begin{aligned}
&\Delta_{W,T}(\omega, j, \delta; \sigma) = \\
&\int\int \min\Big\{\max\big(\sigma S_T(\omega, j, \delta), S_0(\omega, y', \delta'), 0\big), \max(S_T(\omega, j, \delta), S_P(\omega, j, \delta) - F, 0)\Big\} \\
&\qquad\qquad\qquad\qquad \times dG_\delta(\delta'|y')dG_y(y') \\
&\Delta_{W,P,0}(\omega, j, \delta; \sigma) = \\
&\int\int \min\Big\{\max\big(\sigma(S_P(\omega, j, \delta) - F), S_0(\omega, y', \delta'), 0\big), \max(S_P(\omega, j, \delta) - F, 0)\Big\} \\
&\qquad\qquad\qquad\qquad \times dG_\delta(\delta'|y')dG_y(y')
\end{aligned}
\tag{26}
$$

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

$$
\begin{aligned}
w_{P,i}(\omega, j, \delta; \sigma) &= \sigma f(x, y) + (1-\sigma)b + \sigma(\mathcal{I}(i=1) - \beta)F \\
&\quad - sp(\theta)\int \Big(\Delta_{W,P}(\omega', y, \delta; \sigma) - \sigma \max(S_P(\omega', y, \delta; \sigma), 0)\Big) dH_x(x'|p)
\end{aligned}
\tag{27}
$$

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

$$
\begin{aligned}
&w_T(\omega, y, \delta; \sigma) = \sigma f(x, y) + (1-\sigma)b \\
&- sp(\theta)(1-\phi)\int \Big(\Delta_{W,T}(\omega', y, \delta; \sigma) - \sigma \max(S_T(\omega', y, \delta; \sigma), S_P(\omega', y, \delta; \sigma) - F, 0)\Big) dH_x(x'|\omega) \\
&- sp(\theta)\phi\int \Big(\Delta_{W,P,0}(\omega', y, \delta; \sigma) - \sigma \max(S_P(\omega', y, \delta; \sigma) - F, 0)\Big) dH_x(x'|\omega)
\end{aligned}
\tag{28}
$$

for all ω, y, δ, and σ. [In the two cases, the worker collects a fraction σ of the match output net of the expected gains from renegotiation due to on-the-job search, and a fraction $1-\sigma$ of the annuity value of unemployment; in the case of a PC taken at the continuation stage ($i = 1$), the worker also collects a fraction σ of the annuity value of firing costs, and the same fraction of the discounted firing costs].

3.4 Policy functions and labor market flows

3.5 Labor-market tightness

4 Calibration

This section describes the calibration strategy and validates the model by evaluating its ability to match untargeted features of the data. The model is parameterized separately to the high and the low-education group using the French continuous employment survey (*Enquête Emploi en Continu*, EEC) for 2003-2018. 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 (cite..). 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. In addition, we assume a uniform distribution of beliefs about ability. Hence, we set the probability of having high ability belief to $p_0 = 0.5$. We show that our main results are robust to an alternative specification for p_0.

Table 1: Benchmark values of preset parameters

Parameter	Description	Value
β	Discount rate	0.99024
ξ	Exogenous dying probability	0.00655
$\overline{y}$	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	0.94868
p_0	proportion having high ability beliefs A_h	0.5
A_0	Ability in skill process from unemployment	0

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 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.

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, unemployment, and employment share profiles, computed from 2003-2018 EEC data: the age profiles of the UP, UT, PT, PU, TP, and TU's transitions rates ; the unemployment age profile ; 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 model's endogenously estimated parameters are reported in table 2, and the model fit to the data is displayed in figures 2, 3, and 4.

Figure 2 plots the unemployment rate and the share of temporary employment in the model along with its empirical counterpart. Panel (a) presents result for low education group and panel (b) reports result 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 result is combination of the behavior of transition rates over the life-cycle. 3 plots the transition for low education group. As we can see, the model fits 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 job 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.

Figure 3 plots the transition 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. The intuition for why is a combination of uncertainty, Bayesian learning about worker ability and match-specific unemployment risk.

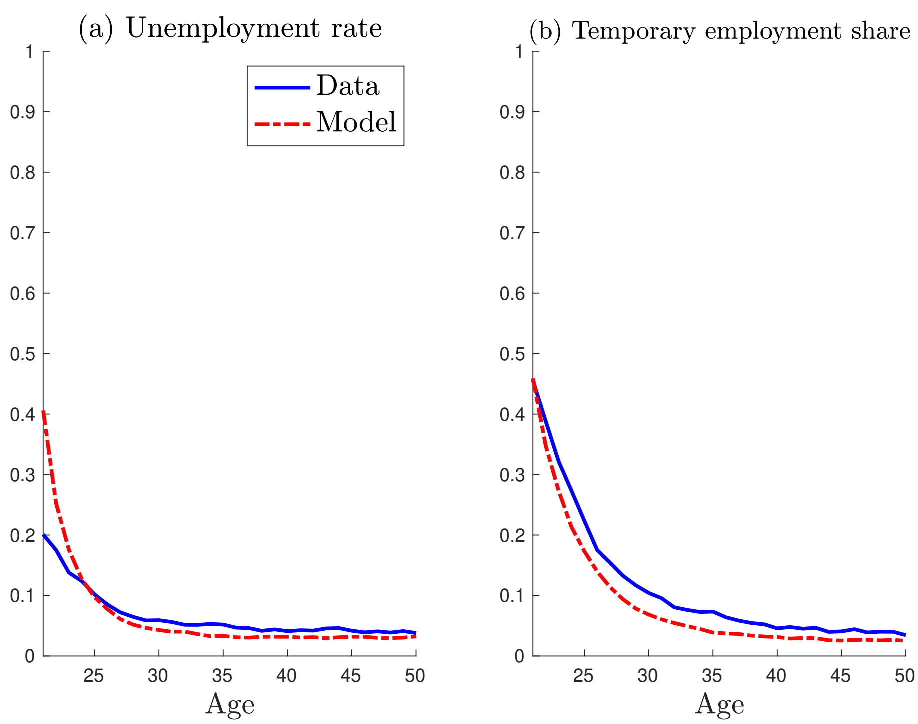
Table 2: Benchmark values of estimated parameters

Parameter	Description	Value	
		Low-educ. group	High-educ. group
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 2: Target unemployment and temporary employment share profiles - Model vs. Data

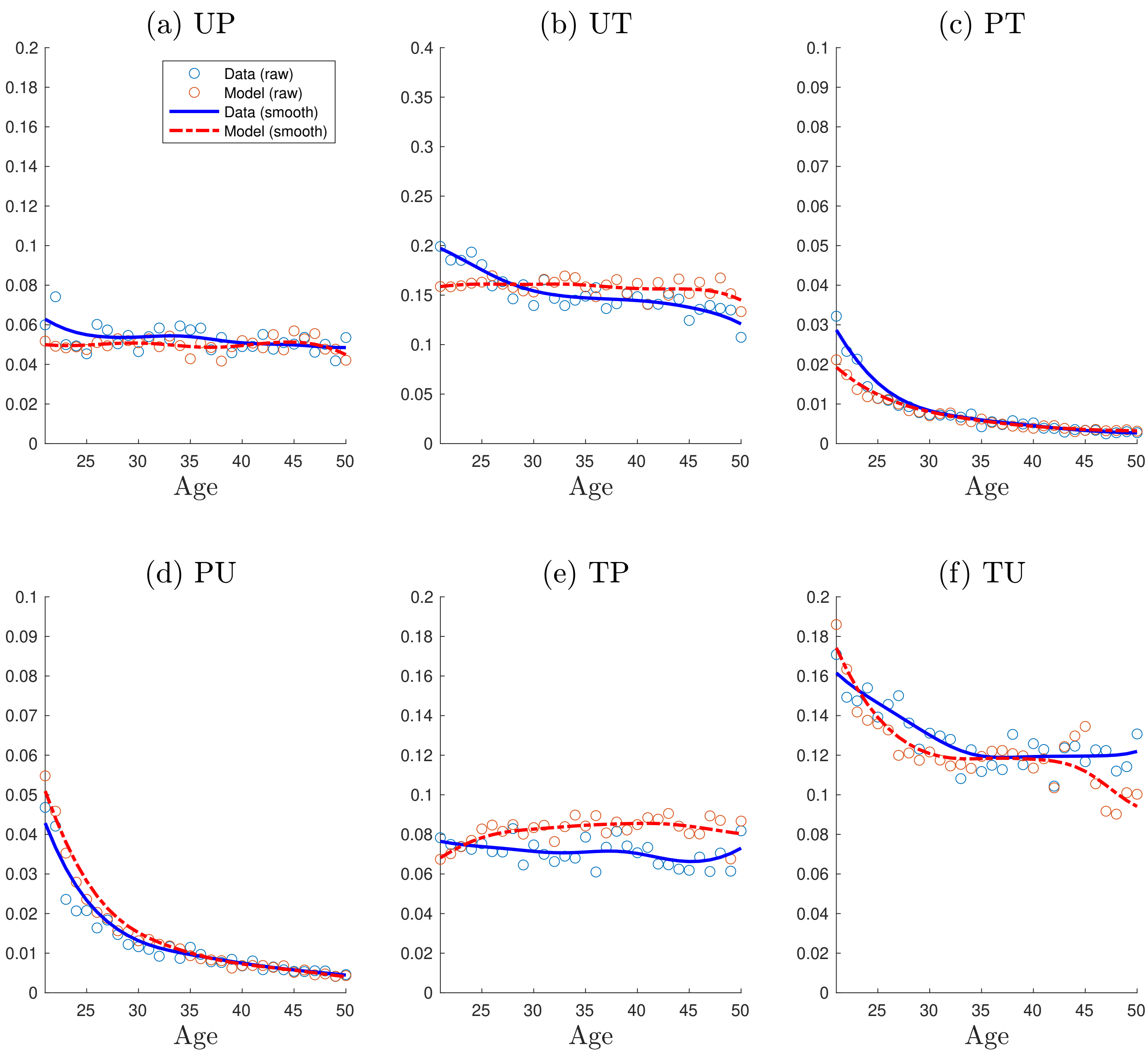
(a) **Low education**

(b) **High education**



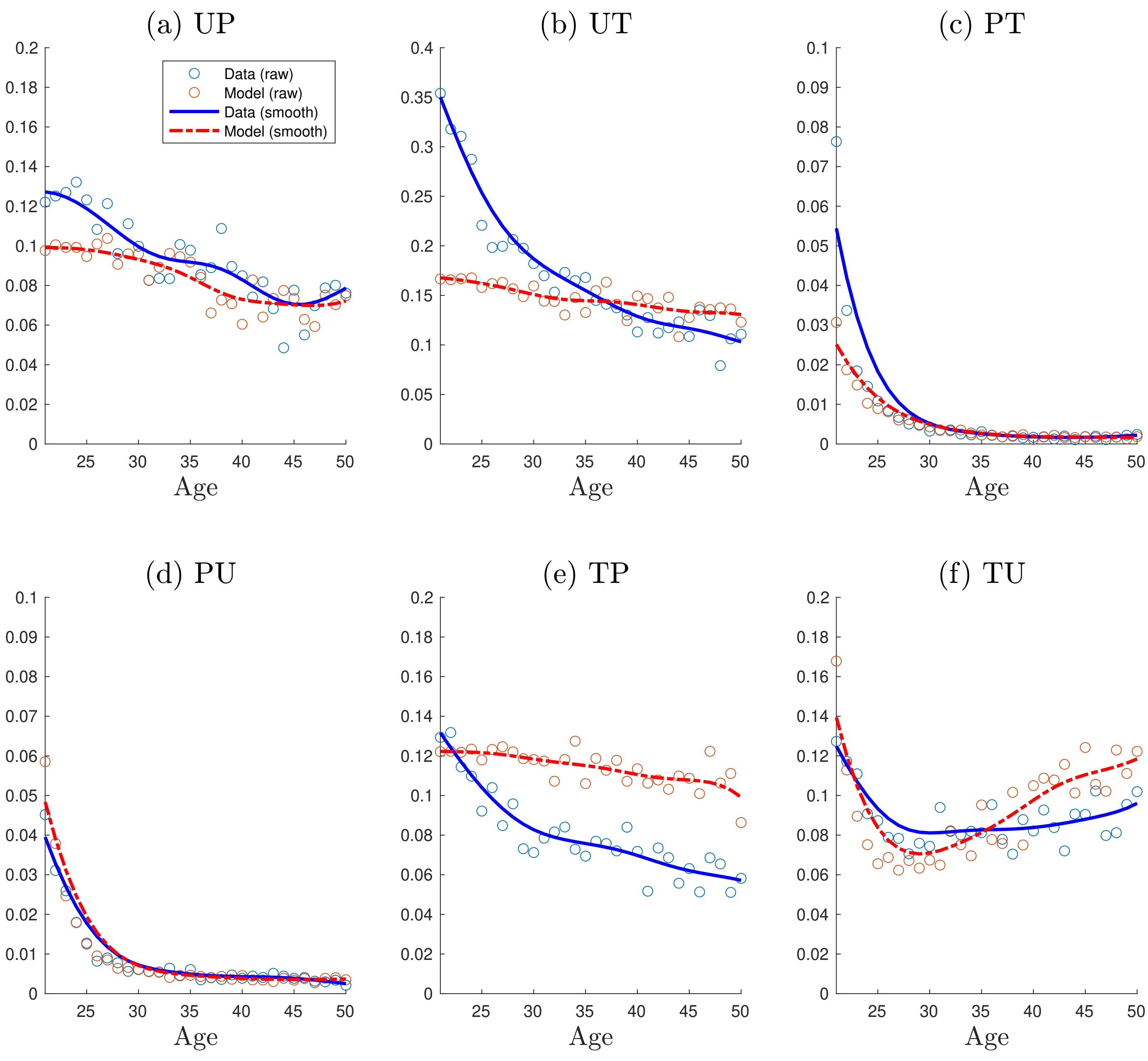
Notes: The solid blue lines denote the data and the dashed red lines denote the model.

Figure 3: 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 4: 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.

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A Markov chain analysis.

See Choi et al. (2015) and Lalé and Tarasonis (2018). We follows the method proposed by Choi et al. (2015), adapted to a labor-market with permanent and temporary jobs. We are interested in computing the contribution of the age variation of each transition probability between states I, U, T, P in the age variation of the unemployment rate and the employment share of temporary jobs [note: we consider four states here but we could stop aroung 40-45 or so since we are interested in understanding youth labor-market outcomes]. We adapt the method of Choi et al. (2015). Let

$$S_{a,e} = \begin{pmatrix} I_{a,e} \\ U_{a,e} \\ T_{a,e} \\ P_{a,e} \end{pmatrix} \tag{29}$$

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

$$\Gamma_{a,e} = \begin{pmatrix} II_{a,e} & IU_{a,e} & IT_{a,e} & IP_{a,e} \\ UI_{a,e} & UU_{a,e} & IT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & TT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & IT_{a,e} & PP_{a,e} \end{pmatrix} \tag{30}$$

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

$$S_{a,e} = \left(\prod_{a'=1}^{a-1} (\Gamma_{a',e})^4 \right) S_{a_0(e),e}, \tag{31}$$

where $a_0(e)$ represents the initial age in our sample for the different education groups $(a(1) = 19, a(2) = 22, a(3) = 25)$. Notice that the age-specific transition matrix is taken at the power 4, since our transition probabilities are quarterly. Using (31), we can compute the life cycle path of U_a, T_a, and P_a that is implied by the estimated transition probability matrix, for a given initial state vector, $S_{a(0),e}$. Two approaches are possible: take the observed initial vector (Choi et al., 2015) or compute the initial state that minimize a distance measure between the implied and the actual age-profile distributions (Lalé and Tarasonis, 2018). Approach 2 can be used if approach 1 does not offer a good fit. Hence, we must first check the fit of the implied age-profile with the observed initial state vector.

The decomposition proceeds as follows: (i) pick a transition rate for which the contribution is to be assessed; (ii) fix the value of this transition rate to its average sample value; (iii) construct a counterfactual transition matrix with this alternative transition probability, by adjusting the element on the associated diagonal to keep the transition matrix well-defined; (iv) compute the counterfactual implied age profiles distributions.

Question: how much of the youth unemployment rate is explained by transitions in and out of temporary jobs? Assess the contribution of the age-specific shape of the UT, IT, TP, TU, and TI. Hypotheses: the high TU rate of low-skill youths explains a substantial part of the high unemployment rate/temporary job rate for this group. This contrasts with the case of the high skill group, for which the TP shape has a negative contribution to the U rate. This is suggestive evidence coming from an accounting exercise that the temporary jobs have very different implications for the age-specific unemployment dynamics across skill groups, and for the formation of youth unemployment. A model is required to identify plausible causal mechanisms.