Youth Labor Market Outcomes: A Model with Learning on Match Quality

A. Bucher

Discussion Paper 2011-27

Institut de Recherches Économiques et Sociales
de l'Université catholique de Louvain

IRES

UCL

Youth Labor Market Outcomes: A Model with Learning on Match Quality

Anne Bucher[1]

July 2011

Abstract

To investigate why young workers exhibit higher unemployment and separation rates, I extend the basic matching model of Pissarides by incorporating learning on match quality as Pries and Rogerson (2005). Match quality is heterogenous and is inferred from the output performance. Because matches revealed to be bad are dissolved, the separation risk decreases with job tenure. Within the framework, the specificity of youth only comes from their entry position on the labor market. Discrepancies between age-groups arise as young workers are mainly unemployed searching for their first job, or newly employed facing higher unemployment risks. The model, calibrated above French data, performs well in reproducing the intergenerational gap in worker separation and unemployment rates.

[1] A.Bucher: IRES, Université Catholique de Louvain- Place Montesquieu 3, 1348 Louvain-la-Neuve, Belgique- +32(0)10 47 4337 - e-mail: anne.bucher@uclouvain.be
This paper was previously circulated under the title "The dynamics of youth labor market integration" (TEPP working paper 2010-16). I am very grateful to Pierre Cahuc, Arnaud Cheron, Bruno Decreuse, François Langot, Etienne Lehmann and Bruno Van der Linden for their helpful comments. Further thanks are due to the 20th EALE conference's participants.
The author acknowledges financial support from the Belgian Federal Administration of Scientific Research - SPF Sciences (Grant TA/10/031A on "The consequences of an ageing workforce on the productivity of the Belgian economy" within the program "Society and Future) - resp V. Vandenberghe, and - SPF Sciences (Grant TA/00/11 on "Evaluation of the activation of job-seeking behaviour" within the program "Society and Future) - resp M. Dejemeppe.

1 Introduction

Whatever the OECD country considered, younger workers display both higher unemployment rates (figure 4, appendix A) and higher turnover (figure 5, appendix A): they experience several short-lived jobs before settling into more stable employment[2]. Although the canonical matching model has proved its strength to analyze labor market flows, it fails to account for the high levels of youth unemployment and worker separation rates. This paper asserts that introducing learning on match quality into the standard matching model helps to explain the specificity of youth labor markets observed in most OECD countries.

The matching theory points out that search frictions render time-consuming the access to employment (Mortensen (1982), Pissarides (1984, 1985)). With heterogeneities and costly acquisition of information, firms and workers have to spend time and resources to find productive matches. As many young workers start as unemployed searching their first job, the unemployment rate of a particular cohort of workers decreases from its initial level at the labor market entry to its stationary level. It results in higher youth unemployment rates. Nevertheless, for realistic values of the job finding and job destruction rates, the cohort-specific unemployment rate declines quite rapidly to its stationary level and the basic matching model is not able to reproduce the high levels of youth unemployment. The main reason is that job creations are sufficiently high to generate a fast transition into employment. Once calibrated above French data, I show that the basic model only accounts for half of the unemployment gap that is observed between young workers and workers over 25 years old. Moreover, it fails to reproduce any discrepancy in worker turnover.

To better account for the youth labor market performance, I propose a framework in which the matching process between firms and workers is costly and leads to match of different quality. Moreover, discovering the quality of a match is time-consuming so that firms and workers are not able to weed out all bad matches before engaging in production. Because matches that are inferred to be bad are terminated, new workers initially face a higher job loss risk. Introducing learning on match quality yields a model with recurring job loss in which the tenure profile of separation rates is decreasing. It is consistent with the empirical evidence from worker turnover data[3] (see figures 5 and 6). Accounting for this feature, that is not captured by the

[2]See for instance Quintini et al. (2007)

[3]The observed decrease of transition rates from employment to unemployment with job tenure is partly due

basic model, helps to reconcile the high level of youth unemployment with the evidence on job finding rates: new workers find a job quite quickly but need time to settle into stable employment. The cohort-specific unemployment rate thus declines more gradually to its stationary level.

The framework I develop borrows from Pries and Rogerson (2005) who combine the Pissarides (1985) matching model and the Jovanovic (979b) learning model. While Jovanovic (979b) assumes that match quality is gradually revealed over time by the sequence of output performances, Pries and Rogerson (2005) incorporate a stochastic learning process. There are two types of employment relationships in the economy: good and bad matches. Once engaged in production, firms and workers observe the output performance which is the sum of two unobserved components: the match quality that is constant over time, and a noisy component. This second component represents transitory factors that affect the match independently of its quality. Pries and Rogerson (2005) assume a serially uncorrelated variable with zero-mean and uniformly distributed. It implies that the bayesian revelation mechanism about match quality takes a "all or nothing" form: after each period, either uncertainty remains as before or the match quality is fully revealed. The learning probability of the match quality, thereby the separation rate, is determined by the distribution of the noisy component. In the developed framework, workers are ex-ante homogenous but face different job loss risks depending on their tenure. The specificity of young workers only comes from their entry position on the labor market: they are either unemployed or newly employed facing higher unemployment risks. The model thus contributes to explain the high levels of unemployment and separation rates observed among young workers.

To investigate the quantitative contribution of learning on match quality to youth labor market outcomes, I calibrate the model above French data. I target the job finding rate of the economy and compute the learning process to reproduce an empirically plausible profile of the worker separation rate with job tenure. I show that, under this learning process, the cohort-specific unemployment rate first increases at the labor market entry as new workers experience short-lived jobs. It starts to decrease once workers enter stable employment and converges gradually to its asymptotic level. Next, I consider the labor market outcomes of two age-groups, the 20-24 and the 25-49 years old individuals. I find that learning on match quality generates

to the use of fix-term contracts. Nevertheless, figure 6 (appendix A) suggests that in France, the tenure profile of separation rates is decreasing whatever the type of contracts. Moreover, workers of any age-group display quite similar profiles (figure 5, appendix A). Most of the decrease occurs in the first two years of the employment relationship.

84% of the differences observed between age-groups in separation rates and high level of youth unemployment. It explains 80% of the youth-adult unemployment gap simulated by the model while the remaining 20% arise from search frictions.

With regard to the theoretical literature, there are different explanations to the decreasing tenure profile of job loss risks, as learning-by-doing (Jovanovic (979a)) or learning about match quality (Jovanovic (979b)). However, from a French matched employer-employee data set, Nagypál (2007) found that learning about match quality is the main determinant of recurring job loss. Besides, Pries (2004) showed that accounting for the uncertainty about match quality that remains following match creation helps to explain the unemployment rate persistence.

A bulk of the empirical and theoretical literature examining youth labor markets emphasizes the role played by other important factors as human capital accumulation, labor market institutions or workers' search behavior. For instance, Kitao et al. (2008) proposed a model in which young workers entering the labor market pass trough a phase of job churning before being able to accumulate human capital. It results in high youth unemployment rates, that has risen more in Europe than in the United States due to increases in minimum wages. Finally, most closely related to this work is Neal (1999) who investigated the mobility patterns of young workers searching for a suitable career. Data on labor market flows suggest that young workers do not only exhibit higher but also more complex turnover[4]. Neal (1999) argued that changing first both employers and careers is and optimal job search strategy.

The next section presents the theoretical framework while the quantitative analysis is provided in Section 3.

[4] "Simple job shifts occur when workers change employers but continue doing the same type of work. Complex shifts occur when workers not only change employers but also change tasks", Neal (1999).

2 The Model

The model builds on the standard matching framework[5], in which searching for a job or a worker are costly and time-consuming activities, but differs from it with respect to job destruction. Following Pries and Rogerson (2005), I incorporate learning on match quality to yield a model with recurring job loss.

2.1 The environment

Time is discrete. All agents are forward-looking, risk-neutral and have a common discount factor β. The analysis is conducted in steady state.

The labor market is populated by a unit mass of homogenous workers who are either employed or unemployed. I assume that in each period, a fraction δ of workers called young enters the labor force. Labor force inflows represent new entrants coming from education. To account for school-to-work transitions, I assume that not all entries flow into unemployment: a fraction ζ of new workers starts directly as employed in their first job. All workers may leave the labor market at rate δ so that the labor force is constant. Workers face an endogenous measure of identical firms. Each firm has one job that can be either vacant or filled.

The process that brings firms and workers together is captured by the matching function $m(u, v)$, where u and v are respectively the unemployment rate and the vacancy rate of the economy. Let $\theta \equiv \frac{v}{u}$ denote the labor market tightness. The probability of an unemployed finding a job is $p(\theta) \equiv \frac{m(u,v)}{u} = m(1, \theta)$. The probability of a firm finding a worker is $q(\theta) \equiv \frac{m(u,v)}{v} = m(1/\theta, 1)$. As workers exit the labor force with rate δ, the number of matches formed in each period equals $(1-\delta)m(u, v)$. Then, $(1-\delta)p(\theta)$ and $(1-\delta)q(\theta)$ are respectively the probability of a worker entering employment and the probability of a firm filling a vacancy. The matching function is strictly increasing with respect to each of its arguments and exhibits constant returns to scale[6]. In consequence, for $0 < \theta < \infty$, $q'(\theta) < 0$ and $p'(\theta) > 0$. The limits of the probabilities are : $\lim_{\theta\to\infty} p(\theta) = 1$; $\lim_{\theta\to\infty} q(\theta) = 0$ and $\lim_{\theta\to 0} p(\theta) = 0$; $\lim_{\theta\to 0} q(\theta) = 1$. Congestion externalities arise in the labor market because of search frictions. Unemployed work-

[5]See Pissarides (2000) for the derivation of the model with exogenous or endogenous job destruction.

[6]See Blanchard and Diamond (1991) and Petrongolo and Pissarides (2001). The latter summarizes the wealth of support for a Cobb-Douglas matching function with constant returns to scale.

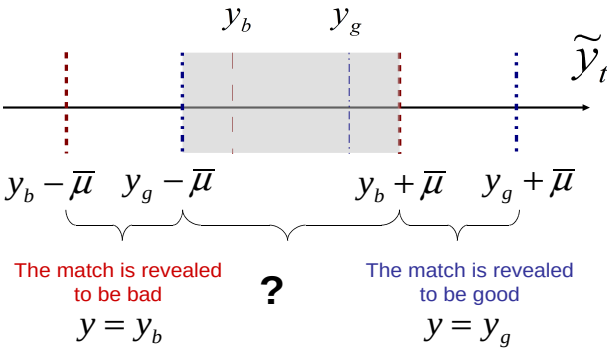
ers find a job more easily when there are less job seekers relative to the vacancies.

A unit of production is a matched worker-firm pair. At the end of period t, firms and workers observe the output flow $\tilde{y}_t = y + \mu_t$, which is the sum of two unobserved components: y is the match quality and μ_t is a noisy component. Although workers are ex-ante identical, there are two types of matches in the economy. Good matches produce y_g and bad matches produce $y_b < y_g$. The match quality is persistent: a good match remains good as long as it remains intact, and a bad match is not productive enough to be formed. If all uncertainty was resolved during the job search process, only good matches would be formed. Instead, I introduce information imperfections that prevent firms and workers from observing the match quality before engaging in production. In consequence, some bad matches are formed and dissolved once their quality is revealed. Job creation decisions depend on on the proportion of good matches in the economy, ψ, which is common knowledge. ψ represents the probability of forming a good match[7]. Once formed the match, the firm and the worker attempt to infer its true quality from the observed output flow. The observation of y is contaminated by transitory factors, μ_t, that affect the match independently of its quality. The learning process is thus time-consuming. While Jovanovic (1979b) assumes that match quality is gradually revealed, Pries and Rogerson (2005) incorporate stochastic accumulation of information: μ is a mean zero *iid* random variable, uniformly distributed on $[-\bar{\mu}, \bar{\mu}]$. The observed output flow of a i-type match $\tilde{y}_{i,t}$ is thus drawn from a uniform distribution over $[y_i - \bar{\mu}; y_i + \bar{\mu}]$ for $i = \{b, g\}$. It implies that the learning process takes a "all-or-nothing" form, (see figure 1):

- If $\tilde{y}_t > y_b + \bar{\mu}$, the match is revealed to be good, while if $\tilde{y}_t < y_g - \bar{\mu}$ the match is revealed to be bad.
- If $\tilde{y}_t \in [y_g - \bar{\mu}, y_b + \bar{\mu}]$, firms and workers cannot determine whether the observation reflects more the fundamental quality of the match rather than a temporary spell of bad or good fortune. They attempt to infer the information next period according to the new realization of $\tilde{y}$.

[7]Here I differ from Pries and Rogerson (2005) who assume that the value of ψ is drawn from a general distribution at the time of meeting. Firms and workers evaluate the potential of their match before engaging in production. Not all matches turn out to be potentially good enough to be formed. This assumption is required to analyze how labor market institutions or policies affect hiring practices by inducing firms to be more or less selective. As I do not investigate hiring practices, I assume homogeneity in potential match quality.

Figure 1: The learning process



Under this learning process, the probability to infer match quality each period equals:

$$
\begin{aligned}
&p(\tilde{y}_t > y_b + \bar{\mu}) + p(\tilde{y}_t < y_g - \bar{\mu}) \\
=&1 - p(\mu_t \leq y_b - y + \bar{\mu}) + p(\mu_t < y_g - y - \bar{\mu})
\end{aligned}
$$

Let α denote this probability. Given the uniform distribution of μ_t, one can show that:

$$\alpha = \frac{y_g - y_b}{2\bar{\mu}}$$

The probability to infer good and bad match quality is respectively $\alpha\psi$ and $\alpha(1-\psi)$. If the observation is such that bad quality is revealed, the firm and the worker agree to separate and search for a new match. I consider only equilibria in which matches revealed to be bad are dissolved[8]. Besides, all jobs are assumed to be hit by an idiosyncratic shock that renders them unproductive with probability s. In this economy, worker turnover results from the reallocation process between firms and workers searching for a good match rather than from the output's fluctuations (as in Mortensen and Pissarides (1994)). All new matches are formed while the quality is unknown and are thus subject to high separation rates. Once the quality of the match is revealed, surviving matches become more stable and face a lower dissolution rate. This generates empirically plausible profiles of worker separation rates by job tenure (see figure 2, section 2).

The timing of events is the following: job search occurring in t entails production in $t+1$. At the end of the period, firms and workers observe the output flow $\tilde{y}_{t+1}$ and either reveal the

[8]The calibration of y_g is such that bad matches are not productive enough to be formed or retained (see section 2).

true match quality or not. Some matches turn out to be dissolved; whatever the cause of the separation, firms and workers are allowed to search for a new suitable match next period[9].

2.2 The Equilibrium

Let Π^v, Π_n and Π_g be the values to a firm of respectively, an unfilled employment position, a match of unknown quality and a match that has been revealed to be good. Π^v satisfies:

$$\Pi^v = -c + \beta\Big\{(1-\delta)q(\theta)\Pi_n + [1-(1-\delta)q(\theta)]\Pi^v\Big\} \tag{1}$$

Posting a vacancy implies a per period fixed cost c. With probability $(1-\delta)q(\theta)$, the firm meets a worker who remains on the labor market and the position is filled. In equilibrium, all profit opportunities are exploited so that the rent from vacant jobs is drove to zero ($\Pi^v = 0$). In steady state, the values of a match, Π_n and Π_g, satisfy:

$$\Pi_n = \psi y_g + (1-\psi)y_b - w_n + \beta(1-\delta)(1-s)\Big\{\alpha\psi\Pi_g + (1-\alpha)\Pi_n\Big\} \tag{2}$$

$$\Pi_g = y_g - w_g + \beta(1-\delta)(1-s)\Pi_g \tag{3}$$

These values equal current period profits, that is the expected output minus the wage (w_j for $j = \{n, g\}$), plus the job continuation value. The expected output flow of matches with unknown quality is a weighted average of good and bad qualities as $E(\tilde{y}_t) = E(y) + E(\mu_t) = \psi y_g + (1-\psi)y_b$. The expected output of matches known to be good equals y_g. With the exogenous probability $\delta + (1-\delta)s$, the job becomes vacant following either the worker's exit from the labor market or a shock. Symmetrically, the worker remains on the labor market and the match remains productive with probability $(1-\delta)(1-s)$. If the quality is unknown (consider the value Π_n), the firm and the worker decide whether or not to separate according to the output performance. With probability $\alpha\psi$, the observed output flow is sufficiently high to infer good quality and the firm continues with the value Π_g. With probability $\alpha(1-\psi)$, the observed output flow is sufficiently low to infer bad quality. Matches revealed to be bad are terminated so that the firm starts searching for a new match. With probability $(1-\alpha)$ the match quality remains unknown. The firm and the worker then continue producing independently of the past realizations of $\tilde{y}$[10].

[9] Contrary to Pries and Rogerson (2005), I do not assume that a job ceases to exist when hit by a shock. This assumption is required by the authors to distinguish worker turnover from job turnover.

[10] The quality remains unknown if the observed output flow is between $y_g - \bar{\mu}$ and $y_b + \bar{\mu}$. According to the calibration of $\bar{\mu}$, some realizations of the output flow could be lower than or equal to bad quality: $y_g - \bar{\mu} \leq \tilde{y} \leq y_b$

Let V^u, V_n and V_g be the values to a worker of respectively unemployment, being in a match of unknown quality and being in a match that is known to be good. We have:

$$V^u = z + \beta(1-\delta)\Big\{p(\theta)V_n + [1-p(\theta)]V^u\Big\} \tag{4}$$

$$V_n = w_n + \beta(1-\delta)\big[s + (1-s)\alpha(1-\psi)\big]V^u + \beta(1-\delta)(1-s)\Big\{\alpha\psi V_g + (1-\alpha)V_n\Big\} \tag{5}$$

$$V_g = w_g + \beta(1-\delta)sV^u + \beta(1-\delta)(1-s)V_g \tag{6}$$

Job seekers enjoy some real return z that integrates home production. With probability δ, the worker exits the labor market and gets zero. Workers employed in a match of unknown quality flow into unemployment with probability $(1-\delta)[s + (1-s)\alpha(1-\psi)]$, which is higher than the transition probability from good matches to unemployment, $(1-\delta)s$. In the developed framework, access to stable employment is time-consuming due to learning on match quality.

The expected joint surplus of a match equals $S_j = V_j - V^u + \Pi_j$ for $j = \{n, g\}$. Substituting the value functions into this expression gives:

$$S_n = \psi y_g + (1-\psi)y_b + \beta(1-\delta)(1-s)\big[\alpha\psi S_g + (1-\alpha)S_n\big] - [1-\beta(1-\delta)]V^u \tag{7}$$

$$S_g = y_g + \beta(1-\delta)(1-s)S_g - [1-\beta(1-\delta)]V^u \tag{8}$$

A match that is known to be good yields a higher surplus than a match with unknown quality ($S_g > S_n$). At the time of meeting, the firm and the worker bargain over wages to share S_n. The initial negotiation is thus based on the expected output flow $\psi y_g + (1-\psi)y_b$. Once the match is revealed to be good, the wage is renegotiated according to the true quality y_g. As is standard, I use the Nash bargaining solution in which the worker's threat point is the value of being unemployed and the employer's threat point is the value of a vacancy. Let γ denote the worker's bargaining power. The sharing rule is given by:

$$\Pi_j = (1-\gamma)S_j \tag{9}$$

(see figure 1). However, separation would not be optimal if this is due to a temporary spell of bad fortune rather than to bad quality. The expected gains in the future would recover the present loss. As μ has mean zero and is independently distributed, the firm and the worker continue producing as long as the bad quality has not been revealed.

The free entry condition and the sharing rule imply:

$$\frac{c}{(1-\delta)q(\theta)} = \beta(1-\gamma)S_n \tag{10}$$

The labor market tightness is such that the expected cost of hiring a worker equals the expected share of surplus that the firm gets from a new match.

From equations (4) and (10), one can show that:

$$[1-\beta(1-\delta)]V^u = z + \beta(1-\delta)p(\theta)\gamma S_n = z + \frac{\gamma}{1-\gamma}c\theta \tag{11}$$

Substituting this expression into (7) and (8) yields:

$$S_n = \psi y_g + (1-\psi)y_b + \beta(1-\delta)(1-s)\big[\alpha\psi S_g + (1-\alpha)S_n\big] - z - \frac{\gamma}{1-\gamma}c\theta \tag{12}$$

$$S_g = y_g + \beta(1-\delta)(1-s)S_g - z - \frac{\gamma}{1-\gamma}c\theta \tag{13}$$

The expected joint surplus of a match is linear and decreasing in θ. Equation (10) thus has a unique solution for θ as the right hand side is increasing in θ while the left hand side is decreasing in θ. Because of congestion externalities, an improve in the labor market tightness reduces the probability to a firm of filling a vacancy and increases the probability to a worker of finding a job. The cost of hiring a worker thus raises and the match surplus is reduced as the workers' outside option increases.

Using the bargaining rule, one can recover the wage functions:

$$w_n = \gamma\big\{\psi y_g + (1-\psi)y_b + c\theta\big\} + (1-\gamma)z \tag{14}$$

$$w_g = \gamma\{y_g + c\theta\} + (1-\gamma)z \tag{15}$$

For $\psi < 1$, we have $w_n < w_g$. As long as the match quality remains unknown, workers initially face both a higher unemployment risk and a lower wage.

At the steady state, the mass of unemployed workers (denoted u) and of workers employed in unknown matches (denoted e_n) are determined by the flow equilibrium conditions:

$$\begin{aligned}&\underbrace{\delta(1-\zeta)}_{Entry\ as\ unemployed} + \underbrace{(1-\delta)\Big\{s(1-u)+(1-s)\alpha(1-\psi)e_n\Big\}}_{Separations:\ shocks\ and\ revelation\ of\ bad\ quality}\\ &= \underbrace{\delta u}_{Exit\ from\ the\ labor\ force} + \underbrace{(1-\delta)p(\theta)u}_{Match\ formation}\end{aligned} \tag{16}$$

$$\begin{aligned}&\underbrace{\delta\zeta}_{Entry\ as\ employed} + \underbrace{(1-\delta)p(\theta)u}_{Match\ formation}\\ &= \underbrace{\delta e_n}_{Exit\ from\ the\ labor\ force} + \underbrace{(1-\delta)se_n}_{Shocks} + \underbrace{(1-\delta)(1-s)\alpha e_n}_{Revelation\ of\ match\ quality}\end{aligned} \tag{17}$$

The mass of workers employed in matches known to be good equals $1-u-e_n \equiv e_g$.

Definition 1. *A steady-state equilibrium is a list θ, u and e_n that satisfies:*

1. *The following equation, that is derived from equations (10), (12) and (13):*

$$\frac{c}{(1-\delta)q(\theta)} = \frac{\beta(1-\gamma)}{\big[1-\beta(1-\delta)(1-s)(1-\alpha)\big]}\Bigg\{\psi y_g + (1-\psi)y_b - z - \frac{\gamma}{1-\gamma}c\theta + \frac{\beta(1-\delta)(1-s)\alpha\psi\big(y_g - z - \frac{\gamma}{1-\gamma}c\theta\big)}{\big[1-\beta(1-\delta)(1-s)\big]}\Bigg\} \tag{18}$$

2. *The flow equations (14) and (15).*

<u>*Existence and uniqueness:*</u> *From equation (10), there exists a unique equilibrium if*

$$\lim_{\theta\to 0}\Bigg\{\frac{c}{(1-\delta)q(\theta)} - \beta(1-\gamma)S_n(\theta)\Bigg\} < 0$$

which is satisfied under the following condition:

$$c < \frac{\beta(1-\delta)(1-\gamma)}{\left[1-\beta(1-\delta)(1-s)(1-\alpha)\right]}\left\{\psi y_g + (1-\psi)y_b - z + \frac{\beta(1-\delta)(1-s)\alpha\psi}{\left[1-\beta(1-\delta)(1-s)\right]}(y_g - z)\right\}$$

If the cost of a vacancy is low enough (lower than the expected discounted future output net of home production), there exists a labor market equilibrium in which firms post vacancies while the fundamental quality of a match is inferred only by engaging in production.

2.3 The dynamics of cohort-specific unemployment

This paper asserts that learning on match quality helps to explain the high level of youth unemployment in a matching framework. To understand this point, I propose to analyze the unemployment dynamics with or without learning on match quality for a particular cohort of workers. At each period, a new cohort of size δ enters the labor market while a fraction δ of each cohort exits the labor market. Cohorts are indexed by the age A of their members. Let u_A and e_A denote the mass of respectively, unemployed and employed workers from the cohort of age A. Normalizing the cohort-specific labor force to unity yields $u_A + e_A = 1$. The initial condition prevailing at the labor market entry implies $u_0 = (1-\zeta)$, with ζ the fraction of new workers beginning as employed in their first job. As a starting point, consider that unemployed workers find a job with probability p. The model with learning on match quality differs from the standard matching model with respect to job destruction.

The standard matching model emphasizes the accumulation of information that occurs during the search process. Access to employment is time-consuming ($p < 1$) but uncertainty about match quality is resolved at the time of meeting so that matches of poor quality are not formed. All workers face a constant separation probability s. The dynamics of the cohort-specific unemployment rate is the following:

$$u_{A+1} = (1-\delta)(1-p)u_A + (1-\delta)s(1-u_A) \tag{19}$$

For $\zeta = 0$, all young workers start as unemployed and the cohort-specific unemployment rate unambiguously decreases towards its stationary level[11]. Consequently, young workers, defined as new entrants on the labor market, display higher unemployment rates. Nevertheless, a fast

[11] The stationary level of the cohort-specific unemployment rate is reached at age $\bar{A}$ for which $u_{\bar{A}+1} = u_{\bar{A}}$. In

transition into employment (high level of p) accelerates the pace at which the cohort-specific unemployment rate declines to its stationary level, thus reducing the unemployment gap between young and older workers. For values of p and s characterizing the French economy, the standard matching model is not able to reproduce the high level of youth unemployment (see the quantitative analysis, section 2.2).

The model developed in this paper considers that uncertainty about match quality remains following match formation. Workers are now either unemployed, employed in a match with unknown quality or employed in a match that has been revealed to be good ($e_A = e_{n,A} + e_{g,A}$). The initial conditions prevailing at the labor market entry imply $u_0 = (1-\zeta)$ and $e_{n,0} = \zeta$. The unemployment rate of a particular cohort reaches its stationary level according to the following dynamics:

$$u_{A+1} = (1-\delta)(1-p)u_A + (1-\delta)s(1-u_A) + (1-\delta)(1-s)\alpha(1-\psi)e_{n,A} \tag{20}$$

$$with \;\; e_{n,A+1} = (1-\delta)pu_A + (1-\delta)(1-s)(1-\alpha)e_{n,A} \tag{21}$$

The addition of a third state in which workers are employed in unknown matches makes the cohort-specific unemployment rate converges more slowly to its stationary level[12]. New entrants experience short-lived jobs and multiple spells of unemployment before settling into a good match. Consequently, the youth-adult unemployment gap increases with respect to the standard matching model. The youth labor market outcomes generated by the framework depend on the transition rates between the different states of the labor market, as the school-to-work transition, the job finding rate and the learning process. For instance, the higher school-to-work transitions, the lower the youth unemployment rate. This is consistent with OECD data: It is well known that education systems by apprenticeship results in smoother school-to-work transitions, as observed in Germany and Denmark (contrary to France or Belgium).

the basic matching model, it equals:

$$u_{\bar{A}} = \frac{(1-\delta)s}{\big[(1-\delta)(1-p-s)\big]}$$

[12]In the model with learning on match quality, the stationary level of the unemployment rate of a particular cohort equals:

$$u_{\bar{A}} = \frac{\big[1-(1-\delta)(1-s)(1-\alpha)\big](1-\delta)s}{\big[1-(1-\delta)(1-s)(1-\alpha)\big]\big[(1-\delta)(1-p-s)\big] - (1-\delta)^2(1-s)\alpha(1-\psi)p}$$

3 Youth labor market outcomes

To investigate the youth labor market outcomes generated by the framework, I introduce two stochastic age-groups. New workers enter the labor force as young and face a probability λ of remaining young next period. Conversely, $(1-\lambda)$ is the probability of entering the adult age-group. Recall that all workers exit the labor force with probability δ[13]. Within the framework, the specificity of youth only comes from their entry position on the labor market. Discrepancies between age-groups arise with search frictions and learning on match quality. Basically, as young workers need time to find both a job and a good stable match, they exhibit higher separation and unemployment rates. In order to take into account typical age-specific unemployment rates, I consider a youth population composed by 20-24 years old individuals starting working, and adult workers who are between 25 and 49 years old[14]. I derive some employment statistics from the French Labor Force Survey of 2002. The model is computed by requiring that the equilibrium matches salient features of the worker turnover data for the whole population (20-49 years old individuals). I then quantitatively analyze the role played by learning on match quality on the youth labor market outcomes. The labor market flows by age-group are detailed in Appendix B.

3.1 Calibration

The month is taken as unit of time. The probability λ is fixed to 0.98 so that the average duration of youth is 5 years[15]. The proportion of 20-24 years old individuals among the considered labor force was observed to be 16.23% in France in 2002. In the developed framework, it is given by $l^y = \frac{\delta}{1-\lambda(1-\delta)}$ (Appendix B). The value of δ is fixed to 0.32% in order to reproduce[16] $l^y = 0.1623$. The fraction of new workers entering as employed, ζ, is set according to the monthly transition rate from school to employment.

The value of home production is normalized to 1. In order to rule out equilibria in which matches revealed to be bad are preserved, I set[17] $y_b = z$.

[13] Assuming that only adult workers can exit the labor force as they retire would introduce age-specificity. Chéron A. et al. (2008) pointed out that the distance to retirement implies age-differentiated labor market flows. This paper does not consider the age-related horizon effect.

[14] Chéron A. et al. (2008) pointed out that the labor market outcomes of older workers strongly depend on the distance to retirement. As I assumed that all workers exit the labor force at the same rate, workers over 50 years old are excluded from the analysis.

[15] The probability λ could be computed to analyze the discrepancies between [20-29] and [30-49] years old individuals. The corresponding results are provided as a robustness test in Appendix C.2.

[16] As the labor force is constant, δ is both the labor market entry and exit rate. Its value could be calibrated either according to the proportion of new entrants among the labor force or according to the proportion of workers exiting the labor force. It gave similar results, provided in Appendix C.1.

[17] $y_b = z$ is a sufficient condition to ensure that $\Pi_b < \Pi^v$ since one would obtain $\Pi_b = (1-\gamma)(y_b - z) - \gamma c\theta +$

In the developed framework, recurring job loss arises as learning on match quality generates higher unemployment risks at the beginning of the employment relationship. The values of s, α and ψ are thus computed by requiring that the equilibrium matches salient features of the tenure profile of the worker separation rate (it refers to the transition rate from employment to employment). French data reveals that most of the decrease in the overall separation rate occurs in the first two years of employment[18] (see figures 5 and 6, Appendix A). In the developed framework the worker separation rate at higher tenure tends to s. Its value is thus fixed to the average monthly worker separation rate from jobs with tenure higher than 2 years. I choose a value of ψ that reproduces a targeted overall separation rate of 0.94% (annual rate of 11.9%). The probability of match quality revelation, α, is computed to match the average worker separation rate at 1 month. It is defined theoretically as $(1-\delta)\big[s+(1-s)\alpha(1-\psi)\big]$. The targeting of these three moments allows the model to reproduce quite well the tenure profile of worker separation rates (see figure 2). The calibrated value of α turns out to be 0.1282 which implies an average learning process of 7.8 months. It is close to the findings of Pries (2004): he estimated a value of 0.13 for the United States.

The targeted hiring rate is 9.82%. The value of c is computed to ensure that the desired tightness is an equilibrium value. Finally, the value of good quality y_g remains to be calibrated. It turns out that this value has no effect on the findings as I do not investigate the impact of public policies. I arbitrarily set $y^g = 1.25$ so that, given the probability α, the lowest value of the observed output flow is positive[19]($y^b - \bar{\mu} > 0$, see figure 1). The calibration is summarized in Table 1 and a sensitivity analysis is provided Appendix C.

$\beta(1-\delta)(1-s)\Pi_b$ from equations similar to (3) and (15).

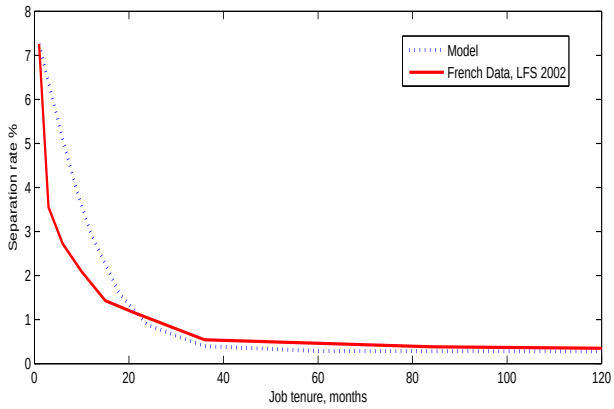
[18]The observed decrease in the overall separation rate can be partly due to the use of fixed-term contracts and to separations that occur during trial periods of regular contracts. In France, the maximum duration of trial periods is fixed to 4 months for low-skilled workers and to 8 months for high-skilled workers. Temporary jobs and trial periods can be used as a screening device to sort bad matches. See for instance Nagypal E. (2002) and Faccini R. (2008).

[19]The definition of the learning probability α implies $y^g = y^b + 2\bar{\mu}\alpha$. In order to ensure that the lowest observed output flow has positive value ($\bar{\mu} < y^b$), the calibrated value of good quality has to verify $y^g < (1+2\alpha)y^b$.

Table 1: Calibration

Parameters		Values	Targets
Discount factor	β	0.9966	Annual interest rate, $r = 4\%$
Elasticity of the matching function w.r.t u	φ	0.5	Petrongolo B. and Pissarides C. (2001)
Efficiency parameter of the matching function	A	0.27	To reproduce $q(\theta) = 0.73$, Den Hann W.J. et al. (2000)
Worker's bargaining power	γ	0.5	Hosios A. (1990)
Labor force's entry rate	δ	0.0032	To reproduce l^y =16.23%, French LFS 2002
Fraction of new workers beginning as employed	ζ	0.71	French LFS 2002
Probability for a worker to remain young	λ	0.9833	The youth population is composed by 20-24 years old individuals: $\frac{1}{1-\lambda} = 60$ months
Unemployment income	z	1	Normalization
Bad match quality	y_b	z	Equilibrium in which bad matches are dissolved
Good match quality	y_g	1.25	To verify $y^b - \bar{\mu} > 0$
Cost of a vacancy	c	1.23	French LFS, monthly hiring rate = 9.82%
Separation rate of good matches	s	0.0028	French LFS, monthly worker separation rate from jobs with tenure > 2 years = 0.28%
Probability that the match quality is revealed	α	0.1282	French LFS, monthly worker separation rate at 1 month = 7.26%
Probability that the match is good	ψ	0.45	French LFS, monthly worker separation rate = 0.94%

Figure 2: Separation rates by job tenure - French data LFS 2002 and simulations



3.2 Quantitative analysis

The first column of Table 2 summarizes the main labor market statistics observed in France in 2002. The youth unemployment rate is 2.5 times higher than the rate for workers over 25 years old. A young unemployed worker in one month has a probability of being employed in the next month that is 1.43 times higher than for adult workers. However, he has an average risk of being separated from his job (taking all types of contracts together) that is 3.77 times higher.

I first propose to analyze the discrepancies generated by the standard matching model. Search frictions are the only source of imperfections: uncertainty about match quality is resolved during the search process so that matches of poor quality are not formed. I set $\psi = 1$. Given the previous value of y^g, the cost of a vacancy, c, and the destruction rate, s, are computed to reproduce the hiring and separation rates of the French economy (respectively 9.82% and 0.94%). The simulation results, provided in the last column of Table 2, suggest that the basic matching model generates only half of the unemployment gap observed in France between young and adult workers. Given the values of the job finding and job destruction rates, the unemployment rate of a particular cohort of workers declines quite rapidly from its initial level at the labor market entry toward its stationary level (see figure 3). The stationary level is reached about 6 years after the labor market entry.

In the developed framework, learning on match quality slows down the pace at which the unemployment rate of a particular cohort of workers decreases to its stationary level. According to figure 3, the cohort-specific unemployment rate first increases due to recurring job loss: new

workers try out jobs and quit matches that are revealed to be bad. From the eighth month on the labor market, the unemployment rate starts to decline toward its stationary level as the cohort of workers finally enter stable employment. While both models are computed to yield identical unemployment rates for the whole population (approximatively 9.3%), in the model with learning on match quality, the cohort-specific unemployment rate declines more gradually to its stationary level, which is lower than in the basic model. Therefore, the intergenerational unemployment gap is higher. Conditional on job tenure, workers of any-age group will have the same trajectory of employment. However, young workers enter the labor force as unemployed or employed in a match with unknown quality, thus facing higher unemployment risks. Simulation results of the model with learning on match quality are reported in the second column of Table 2. The model performs well in reproducing discrepancies between age-groups in unemployment and separation rates[20]. Learning on match quality generates almost 84% of the discrepancies in separation flows observed between young and adult workers. As the model does not account for the discrepancies in the job finding rate, the unemployment gap between youth and adults turns out to be 1.12 times higher than the observed one.

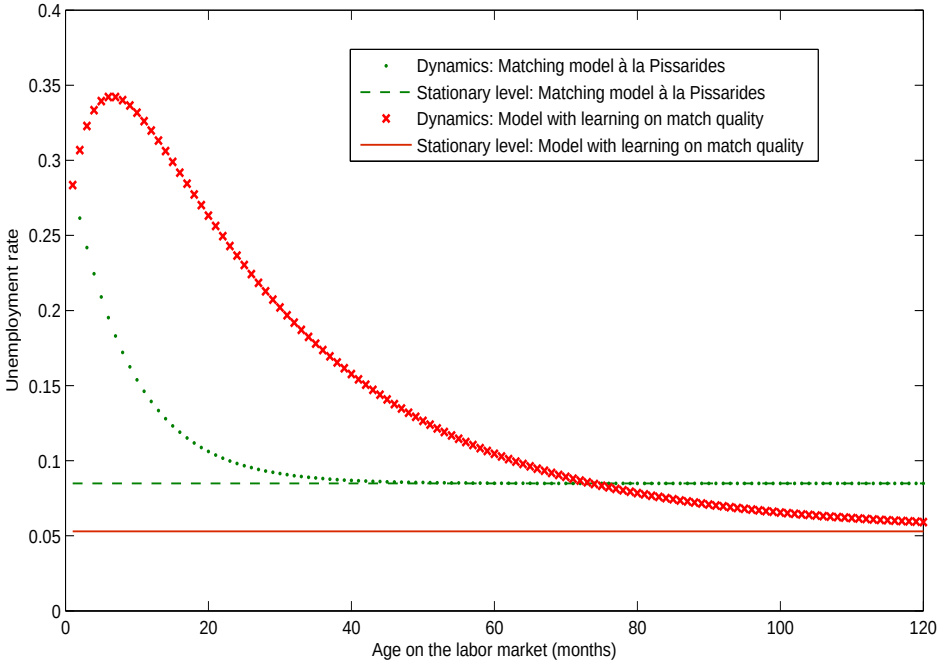
Finally, in order to investigate quantitatively the contribution of learning on match quality to the youth-adult unemployment gap generated by the framework, I proceed with the simulation for $\zeta = 1$. Young workers begin as employed but may have to experience several short-lived jobs before finding a productive match. In consequence, the discrepancies in the unemployment rate are due to the uncertainty that remains following match creation. According to the simulation results, that are provided in the third column of Table 2, learning on match quality accounts for 82% of the simulated unemployment gap: the ratio between youth and adult unemployment reaches 2.3 while the model with $\zeta < 1$ reproduces a ratio of 2.79. The quantitative analysis suggests that discrepancies in unemployment are mainly due to learning on match quality rather than to search frictions.

[20]Computing and simulating the model to match worker turnover observed in France in 1994 gave similar results. They are available upon request.

Table 2: Simulation results

	French Data 2002	Simulations of the model	Simulations with $\zeta = 1$	Simulation of an economy *à la* Pissarides C. (2000)
Unemployment rate, (%):	7.14	9.3	8.46	9.3
[20-24]	15.59	20.14	16.07	11.83
[25-49]	6.24	7.21	6.99	8.82
Youth relative to Adult	2.5	2.79	2.3	1.34
Separation rate, (%):	0.94	0.94	0.94	0.94
[20-24]	2.86	2.27	2.27	0.94
[25-49]	0.76	0.72	0.71	0.94
Youth relative to Adult	3.77	3.16	3.19	1
Hiring rate, (%):	9.82	9.82	9.82	9.82
[20-24]	12.89	9.82	9.82	9.82
[25-49]	9.00	9.82	9.82	9.82
Youth relative to Adult	1.43	1	1	1

Figure 3: The dynamics of cohort-specific unemployment



4 Conclusion

Although the canonical matching model has proved its strength to explain important features of labor markets, it fails to account for the specificity of youth labor markets observed in OECD countries. By introducing learning on match quality in the standard matching model, the paper provides a more complete understanding of youth labor market outcomes. As access to both employment and stable employment is time-consuming, it seems natural that young workers face difficulties when entering the labor market market. The quantitative analysis suggests that learning on match quality generates huge discrepancies in separation and unemployment rates between age-groups, in spite of any age-specificities. From this perspective, improving the reallocation process between firms and workers searching for a good match should facilitate the labor market integration of young workers. Pries and Rogerson (2005) suggested that the labor market institutions as dismissal costs, minimum wages and unemployment benefits, prevent the screening process of match quality. There is also much to learn about the role played by educational systems. Higher education levels can reduce mismatch while education by apprenticeship can be used to improve the learning process on match quality.

References

Blanchard O. and Diamond P.A. (1991). The aggregate matching function. *NBER Working Papers W3175*, 159–201.

Bucher A. (2010). The dynamics of youth labor market integration. *TEPP working paper* (16).

Chéron A., Hairault J-O., and Langot F. (2008). Life-cycle equilibrium unemployment. *IZA Discussion Papers 3396*.

Den Hann W.J., Ramey G., and Watson J. (2000). Job destruction and propagation of shocks. *American Economic Review 90*(3), 482–498.

Faccini R. (2008). Reassessing labor market reforms: Temporary contracts as a screening device. *EUI Working Papers 27*.

Hosios A. (1990). On the efficiency of matching and related models of search and unemployment. *Review of Economic Studies 57*, 279–298.

Jovanovic B. (1979a). Firm-specific capital and turnover. *Journal of Political Economy 87*, 1246–60.

Jovanovic B. (1979b). Job matching and the theory of turnover. *Journal of Political Economy 87*, 972–90.

Kitao S., Ljungqvist L., and Sargent T. (2008). A life cycle model of trans-atlantic employment experiences. *Working Paper*.

Mortensen D. (1982). The matching process as a noncooperative bargaining game. *in The Economics of Information and Uncertainty, J. McCall*, 233–254.

Mortensen D. and Pissarides C. (1994). Job creation and job destruction in the theory of unemployment. *Review of Economic Studies 61*(3), 397–415.

Nagypal E. (2002). The cost of employment protection in the presence of match-specific learning. *mimeo*.

Nagypal E. (2007). Learning by doing vs. learning about match quality: Can we tell them apart? *Review of Economic Studies 74*, 537–566.

Neal D. (1999). The complexity of job mobility among young men. *Journal of Labor Economics 17*(2), 237–261.

Petrongolo B. and Pissarides C. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature 39*, 390–431.

Pissarides C. (1984). Search intensity, job advertising, and efficiency. *Journal of Labor Economics 2*(1), 128–143.

Pissarides C. (1985). Short-run equilibrium dynamics of unemployment vacancies, and real wages. *American Economic Review 75*(4), 676–690.

Pissarides C. (2000). Equilibrium unemployment theory. *Cambridge: MIT Press*.

Pries M. (2004). Persistence of employment fluctuations: A model of recurring job loss. *Review of Economic Studies 71*(1), 193–215.

Pries M. and Rogerson R. (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy 113*(4), 811–839.

Quintini G., Martin J.P., and Martin S. (2007). The changing nature of the school-to-work transition process in oecd countries. *IZA Discussion Papers 2582*.

A Stylized facts

Figure 4: Unemployment rates by age-group - OECD 2005

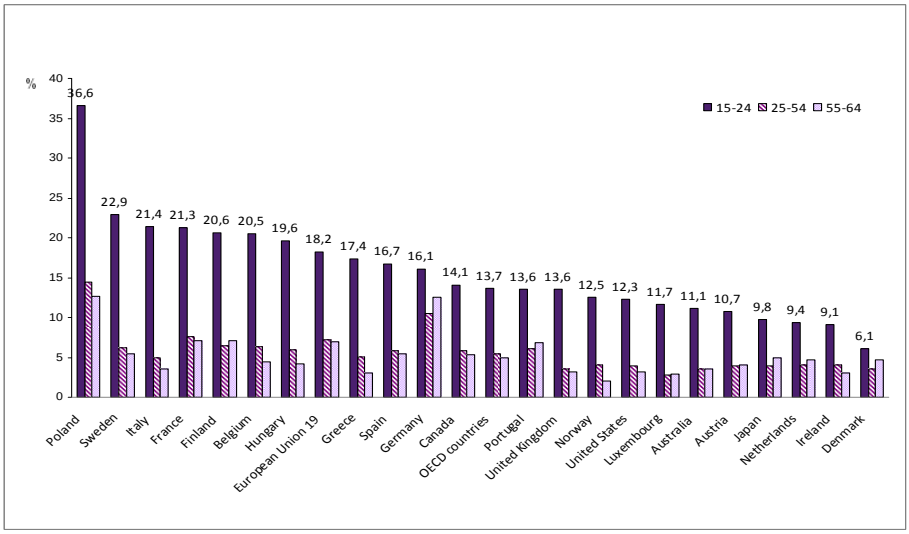
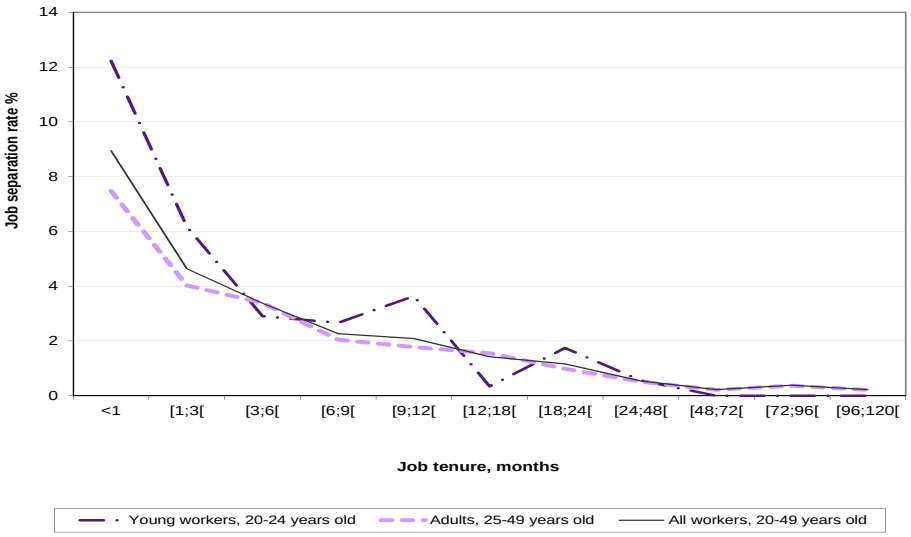
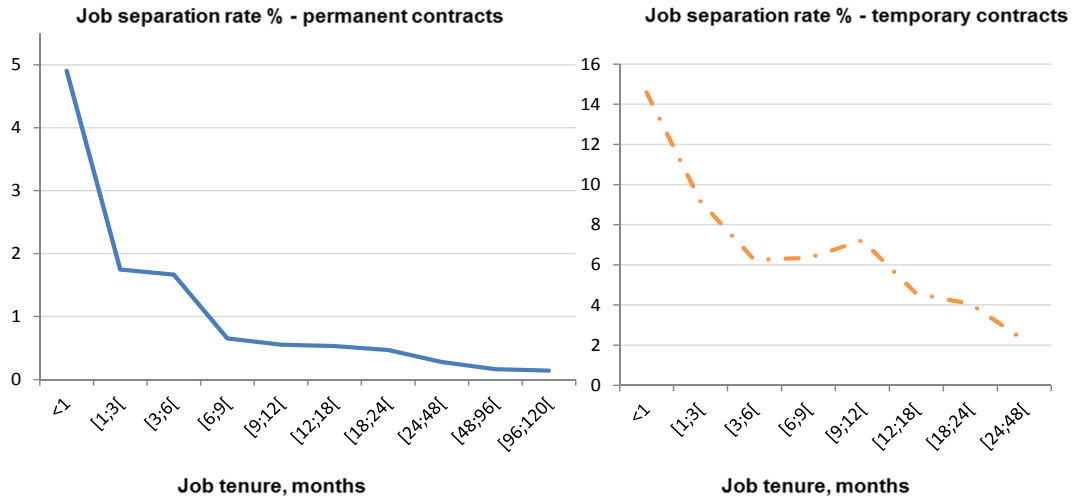


Figure 5: Separation rates by job tenure and age-group - France 2002



Source: Author's calculations from the French LFS 2002. The population is composed by men aged between 20 and 49 years old.

Figure 6: Separation rates by job tenure and type of contracts - France 2002



Source: Author's calculations from the French LFS 2002. The population is composed by men aged between 20 and 49 years old.

B Labor market flows by age-groups

The proportions of young and adult workers in the economy are denoted by respectively l^y and l^a. The evolution of these two populations satisfies:

$$l^y_{t+1} = \delta + \lambda(1-\delta)l^y_t$$
$$l^a_{t+1} = (1-\lambda)l^y_t + (1-\delta)l^a_t$$

The mass of young workers at period $t+1$ is composed by new entrants and by workers who remain young and who do not exit the labor force at period t. The mass of adult workers at period $t+1$ is composed by ageing young workers and by adult workers who remain on the labor market.

At steady state, the proportion of young workers is given by:

$$l^y = \frac{\delta}{1-\lambda(1-\delta)} \tag{22}$$

The equilibrium flow equations satisfy:

- Unemployment:

$$\delta(1-\zeta) + (1-\delta)\lambda\Big\{s(e^y_n + e^y_g) + (1-s)\alpha(1-\psi)e^y_n\Big\}$$
$$= \delta u^y + (1-\delta)(1-\lambda)u^y + (1-\delta)p(\theta)\lambda u^y$$

$$(1-\delta)\Big\{s\big[(1-\lambda)(e^y_n + e^y_g) + e^a_n + e^a_g\big] + (1-s)\alpha(1-\psi)\big[(1-\lambda)e^y_n + e^a_n\big]\Big\}$$
$$+ (1-\delta)(1-\lambda)[1-p(\theta)]u^y = \delta u^a + (1-\delta)p(\theta)u^a$$

- Matches of unknown quality:

$$\delta\zeta + (1-\delta)p(\theta)\lambda u^y = \delta e^y no + (1-\delta)(1-\lambda)e_n^y + (1-\delta)[s + (1-s)\alpha]\lambda e_n^y$$

$$(1-\delta)p(\theta)[(1-\lambda)u^y + u^a] + (1-\delta)(1-s)(1-\alpha)(1-\lambda)e_n^y$$
$$= \delta e_n^a + (1-\delta)[s + (1-s)\alpha]e_n^a$$

- Matches revealed to be good:

$$(1-\delta)(1-s)\alpha\psi\lambda e_n^y = \delta e_g^y + (1-\delta)(1-\lambda)e_g^y + (1-\delta)s\lambda e_g^y$$

$$(1-\delta)(1-s)\alpha\psi\big\{(1-\lambda)e_n^y + e_n^a\big\} + (1-\delta)(1-s)(1-\lambda)e_g^y$$
$$= \delta e_g^a + (1-\delta)se_g^a$$

C Sensitivity analysis

C.1 The labor market entry and exit process

The value of δ was previously fixed to reproduce the share of young workers among the labor force. However, in the developed framework, I considered a constant labor force so that δ is both the labor market entry and exit rate. I now propose to compute the model by fixing δ either to the proportion of new entrants among the labor force (0.21%, French LFS 2002) or to the proportion of workers exiting the labor market (0.11%, French LFS 2002). Results are provided in Table 3: According to both simulations, signal extraction problems generate respectively 86% and 88% of the intergenerational discrepancies in separation rates.

Table 3: Sensitivity tests on δ

		Calibration	
		$\delta = 0.21\%$	$\delta = 0.11\%$
Learning probability		0.1173	0.1076
Match quality signal		0.4	0.348
	French Data 2002	Simulation results	
Unemployment rate, (%):	7.14	9.10	8.92
[20-24]	15.59	21.35	22.85
[25-49]	6.24	7.55	8.01
Youth relative to Adult	2.5	2.83	2.85
Separation rate, (%):	0.94	0.94	0.94
[20-24]	2.86	2.50	2.78
[25-49]	0.76	0.77	0.84
Youth relative to Adult	3.77	3.24	3.32
Hiring rate, (%):	9.82	9.82	9.82
[20-24]	12.89	9.82	9.82
[25-49]	9.00	9.82	9.82
Youth relative to Adult	1.43	1	1

C.2 Stochastic age-groups

One can question the age-groups' choice. To test the robustness of the model, simulations are done considering the following age-groups: [20-29] and [30-49] years old individuals.

The probability λ is now fixed to so that the average duration of youth is 10 years. The value of δ is set to 0.37% in order to match a proportion of 20-29 years old individuals among the labor force of 30.84% (French LFS 2002). The remaining parameters are computed as previously. The revelation probability of match quality turns out to be $\alpha = 0.1329$ (average learning process of 7.5 months) and the proportion of good matches ψ equals 47%. Results are quite similar to the previous ones (Table 4). The model is now able to match 78.3% of the differences in unemployment risks between young and adult workers, and 84.7% of the unemployment gap between young and adults comes from the time-consuming learning process. As the age-group of young workers is larger, the observed discrepancies in unemployment and separation rates get reduced.

Table 4: Simulation results

	French Data 2002	Simulations	Simulations with $\zeta = 1$
Unemployment rate, (%):	7.14	9.39	8.43
[20-29]	11.71	15.57	12.85
[30-49]	5.65	6.63	6.47
Youth relative to Adult	2.07	2.35	1.99
Separation rate, (%):	0.94	0.94	0.94
[20-29]	1.97	1.63	1.63
[30-49]	0.63	0.66	0.65
Youth relative to Adult	3.14	2.46	2.49

C.3 The learning process

According to the benchmark calibration, the probability α equals 0.1282 implying an average learning process of 7.8 months. I provide the simulation results corresponding to the values $\alpha = 0.143$ and $\alpha = 0.1176$, implying respectively an average learning process of 7 and 8.5 months. Table 5 shows that these learning processes generate respectively 86.3% and 82% of the intergenerational discrepancies in separation rates.

Table 5: Simulation results

	French Data 2002	Simulations $\alpha = 0.1282$ (7.8 months)	Simulations $\alpha = 0.1429$ (7 months)	Simulations $\alpha = 0.176$ (8.5 months)
Unemployment rate, (%):	7.14	9.3	9.32	9.26
[20-24]	15.59	20.14	20.42	19.88
[25-49]	6.24	7.21	7.16	7.21
Youth relative to Adult	2.5	2.79	2.85	2.76
Separation rate, (%):	0.94	0.94	0.945	0.93
[20-24]	2.86	2.27	2.33	2.22
[25-49]	0.76	0.72	0.71	0.72
Youth relative to Adult	3.77	3.16	3.25	3.09
Hiring rate, (%):	9.82	9.82	9.82	9.82
[20-24]	12.89	9.82	9.82	9.82
[25-49]	9.00	9.82	9.82	9.82
Youth relative to Adult	1.43	1	1	1

Finally, I propose to simulate the model for a range of likely α-values. According to Pries (2004), the learning process on match quality takes in average 7.7 months in the United States. There are no evidence suggesting that information imperfections are either stronger or weaker in United States than in Europe. In France, the average trial period of regular contracts is 6 months. Therefore I consider an average learning process taking from 6 to 12 months. Figure 7 represents discrepancies in unemployment and separation rates generated by the framework[21] while figure 8 represents the shape of the separation probability with job tenure[22]. Simulation results suggest that the lower the learning probability (the slower the learning process), the lower

[21] Intergenerational discrepancies are measured by the ratio between the youth and adult unemployment/separation rates.

[22] The value of α that yields to empirically plausible tenure profiles of job separation rates is the one used in the benchmark calibration.

the discrepancies between young and workers over 25 years old. This is due to the decrease in job separations since less matches are revealed to be bad. For likely values of probability α, the model generates between 73.8% and 89.6% of the discrepancies observed in unemployment risks: whatever the time spend to learn about match quality, signal extraction problems seem to be a major factor of intergenerational discrepancies in labor market outcomes.

Figure 7: Discrepancies in unemployment and separation rates - French data LFS 2002 and Simulation results according to the learning process

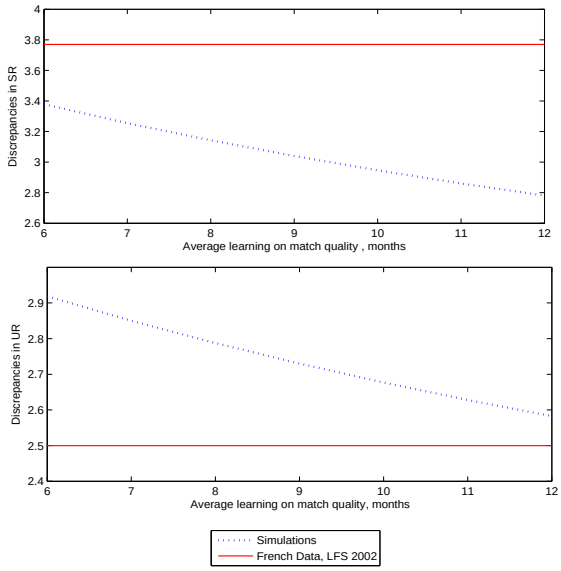
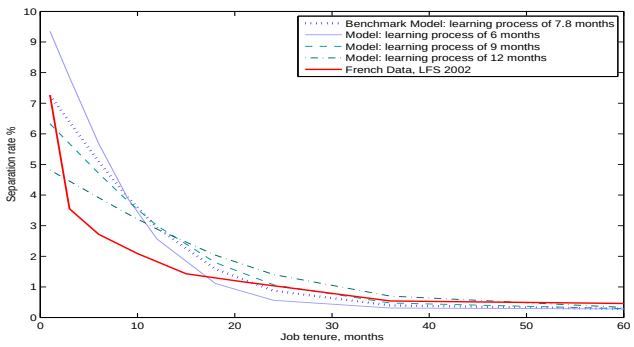


Figure 8: Separation rates by job tenure - French data LFS 2002 and Simulation results according to the learning process



Institut de Recherches Économiques et Sociales
Université catholique de Louvain

Place Montesquieu, 3
1348 Louvain-la-Neuve, Belgique

ISSN 1379-244X D/2011/3082/027