The Returns to Seniority in France
(and Why they are Lower than in the United States)

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Abstract

In this article, we estimate a joint model of participation, mobility, and wages for France. Our statistical model allows us to distinguish between unobserved person heterogeneity and state-dependence. The model is estimated using bayesian techniques using a long panel (1976-1995) for France. Our results show that returns to seniority are small, even close to zero for some education groups, in France. Because we use the exact same specification as Buchinsky, Fougère, Kramarz and Tchernis (2002), we compare their results with ours and show that returns to seniority are (much) larger in the United States than in France. This result also holds when using Altonji and Williams (1992) techniques for both countries. Most differences between the two countries relate to firm-to-firm mobility. Using a model of Burdett and Coles (2003), we explain the rationale for this. More precisely, in a low-mobility country such as France, there is little gain in compensating workers for long tenures because they will eventually stay in the firm; even when they hold firm-specific capital. But, in a high-mobility country such as the United States, high returns to seniority have a clear incentive effect.

Keywords : Participation, Wage, Job mobility, Returns to seniority, Returns to experience, Individual effects.

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1 Introduction

In the last twenty years, huge progress was made in the analysis of the wage structure. However, the understanding of wage growth - a key issue in labor economics - is not as developed. In particular, the respective roles of general experience and tenure are still debated. Indeed, experience and tenure increase simultaneously except when worker moves from firm to firm or becomes not employed. The question of worker mobility and participation should then be central in the study of wages since it potentially allows the analyst to distinguish and identify these two components of human capital accumulation. And, therefore, it should help us in assessing the respective roles of general - transferable - human capital and specific - non transferable - human capital. Of course, the question of the relative importance of job tenure and experience on wage growth has been extensively studied. For the USA, some authors have concluded that experience matters more than seniority in wage growth (Altonji and Shakotko, 1987, Altonji and Williams, 1992 and 1997). Other authors have concluded that both experience and tenure matter (Topel, 1991, Buchinsky, Fougère, Kramarz and Tchernis, 2002 BFKT, hereafter). Indeed, this question is particularly complex to analyze. And, it should not be surprising that the successive articles have uncovered various crucial difficulties and solutions that potentially affect the resulting estimates: the definition of the variables, the errors in measured seniority, the estimation methods that are used, the heterogeneity components of the model, the exogeneity assumptions that are made...

It is usually admitted that there exists an increasing relation between wage and seniority. Several economic theories can explain the relation existing between wage growth and job tenure. 1) The role of specific job tenure on the dynamics of wages has been described by human capital theory (Becker (1964), Mincer (1974)). The central point of this theory is the increase of the earnings due to the individual's investment in human capital. 2) The structure of wages can be described by job matching theory (Jovanovic, 1979, Miller 1984, Jovanovic, 1984). This theory explains both the mobility of workers from job to job and the existence of an decreasing job separation rate with job-tenure. This model relies on the main assumption that there exists a productivity of the worker-occupation pair. This productivity is, a priori, unknown. Of course, the worker's wage depends on this productivity. Indeed, the specific human capital investment will be larger when the match is less likely to terminate (see Jovanovic, 1979). Finally, a job matching model can predict an increase of the worker's wage with job seniority. 3) The dynamics of wages can be explained by deferred compensation theories that state that the form of the contract existing between the firm and employees is chosen such that the worker's choice of effort or worker's quit decision is optimal (see Salop and Salop, 1976; or Lazear 1979, 1981, 1999). In these theories, the workers starting in a firm are paid below their marginal product whereas the workers with a large tenure are paid above their marginal product. 4) More recently, equilibrium wage tenure contracts have been shown to exist within a matching model (see Burdett and Coles, 2003 or Postel-Vinay and Robin, 2002 in a slightly different context). At the equilibrium, firms post a contract that makes wage increase with tenure. Some of these models are able to characterize both workers mobility and the nature of the relation existing between wage and tenure. For instance in the Burdett and Coles model, the specificities of the wage-tenure contract heavily depend on workers' preferences as well as labor market characteristics job offers arrival rate.

Therefore, the relation between wage growth and mobility (or job tenure) may result from (optimal) choices of the firm and (or) the worker. But, it may also result from spurious duration dependence. Indeed, if there is a correlation between job seniority and a latent variable measuring worker's productivity and if, in addition, more productive workers have higher wages then there will exist a positive correlation between wage and job seniority even when conditional wages do not depend on job tenure (see, for instance Abraham and Farber, 1987, Lillard and Willis, 1978, Flinn 1986). Consequently, unobserved heterogeneity components must be taken into account as well as the endogeneity of mobility decisions. Furthermore, BFKT showed that mobility-induced costs translated into state-dependence in the mobility decision (similarly for the participation decision itself as demonstrated by Hyslop, 1999). As is well-known, all of the above points make OLS estimates of returns to seniority biased. There are multiple ways to solve this problem. One solution is the use of an instrumental variables estimator (Altonji and Shakotko, 1987). Another way to go, is to use fixed effects procedures (Abowd, Kramarz and Margolis, 1999). A final solution is to jointly model wages, mobility and participation decisions (Buchinsky, Fougère, Kramarz and Tchernis, 2002).

In this paper, we adopt the latter route. Therefore, we estimate jointly wage outcomes, participation and mobility decisions. The initial conditions are modelled following Heckman (1981). We include both state-dependence and (correlated) unobserved individual heterogeneity in the mobility and participation decisions. We also include correlated unobserved individual heterogeneity in the wage equation. Following BFKT, we adopt a Bayesian framework in which the model is estimated using a Gibbs Sampling technique. As our model is highly non-linear, we use data augmentation steps. This procedure allows us to obtain, at the stationarity of the algorithm, estimates of the parameters.

Our data source results from the match of the French DADS panel (giving us wages for the years 1976 to 1995) with the Echantillon Démographique Permanent (EDP, hereafter) that yields time-varying and time-invariant personal characteristics. Because we use the exact same specification as BFKT and relatively similar data sources, we are able to compare French returns to seniority with those obtained for the United States. Even though our estimates of the returns to seniority appear to be in line with those obtained by Altonji and Shakotko (1987) and Altonji and Williams (1992, 1997) for the U.S., they are in fact much smaller than those obtained by BFKT (also for the U.S.). Indeed, returns to seniority in France are virtually equal to zero. However, returns to experience are rather large and close to those estimated by BFKT.

To understand some of the reasons for these small returns in comparison to the United States, we make use of the equilibrium search model with wage-contracts proposed by Burdett and Coles (2003). We show that, for all values of the relative risk aversion coefficient, the larger the job arrival rate, the steeper the wage-tenure profiles. And, indeed, recent estimates show that the job arrival rate for the unemployed is approximately equal 1.71 per year in the US and is approximately equal to 0.56 per year in France (Jolivet, Postel-Vinay and Robin, 2004). Hence, the returns to seniority directly reflect the patterns of mobility in the two countries.

This paper is organized as follow. Section 2 presents the statistical model. Section 3 explains elements of the estimation method. Then, data sources are presented in Section 4. Section 5 shows our estimates whereas Section 6 carefully compares our results with those obtained by BFKT for the US. This Section also contains a theoretical explanation of these differences together with simulations. Finally, Section 7 concludes.

2 The Statistical Model

2.1 Specification of the General Model

We consider a joint model of wages, participation and mobility decisions. Following Heckman (1981), we introduce initial conditions because of the presence of lagged mobility and participation decisions in the main participation and mobility equations. The statistical model that we adopt here derives directly from a structural choice model of participation and mobility (see BFKT for a proof). This model induces the following equations:

Initial Conditions

$$y_{i1} = \mathbb{I}\left(X_{i1}^{Y}\delta_0^{Y} + \alpha_i^{Y,I} + v_{i1} > 0\right) \quad (1)$$

$$w_{i1} = y_{i1}\left(X_{i1}^{W}\delta^{W} + \theta_i^{W,I} + \epsilon_{i1}\right) \quad (2)$$

$$m_{i1} = y_{i1}\mathbb{I}\left(X_{i1}^{M}\delta_0^{M} + \alpha_i^{M,I} + u_{i1} > 0\right) \quad (3)$$

Main Equations

$$\begin{aligned}
(4) \qquad \forall t>1, \quad y_{it} &= \mathbb{I}\left(\underbrace{\gamma^M m_{it-1} + \gamma^Y y_{it-1} + X_{it}^Y \delta^Y + \theta_i^{Y,I} + v_{it}}_{y_{it}^*} > 0\right) \\
(5) \qquad \forall t>1, \quad w_{it} &= y_{it}\left(X_{it}^W \delta^W + \theta_i^{W,I} + \epsilon_{it}\right) \\
(6) \qquad \forall t>1, \quad m_{it} &= y_{it}.\mathbb{I}\left(\underbrace{\gamma m_{it-1} + X_{it}^M \delta^M + \theta_i^{M,I} + u_{it}}_{m_{it}^*} > 0\right)
\end{aligned}$$

y_{it} and m_{it} denote, respectively, participation and mobility, as previously defined. y_{it} is an indicator function, equal to 1 if the individual i is employed at date t. m_{it} is an indicator function that takes the following values:

	$y_{it+1}=1$	$y_{it+1}=0$
$y_{it}=1$	$m_{it}=1$ if $J(i,t+1)\neq J(i,t)$ $m_{it}=0$ if $J(i,t+1)=J(i,t)$	m_{it} censored
$y_{it}=0$	$m_{it}=0$ p.s.	$m_{it}=0$ p.s.

Table 1: Mobility

where $J(i,t)$ denotes the firm at which individual i is employed at date t.

The variable w_{it} denotes the logarithm of the annualized total labor costs. The variables X are the observable time-varying as well as the time-invariant characteristics for individuals at the different dates.

θ^I denote the random effects specific to the individuals. u, v and ϵ are the error terms. There are J firms and N individuals in the panel of length T. Notice that our panel is unbalanced. All stochastic assumptions are described now.

2.2 Stochastic Assumptions

The next equations present our stochastic assumptions for the individual effects:

$$\theta^I = \left(\alpha^{Y,I}, \alpha^{M,I}, \theta^{Y,I}, \theta^{W,I}, \theta^{M,I}\right) \quad \text{of dimension} \quad [5N,1]$$

Moreover, let us assume that[1]

$$\theta_i^I | \Sigma_i^I \sim \mathcal{N}(0, \Sigma_i^I) \tag{7}$$

where the variance-covariance matrix in this prior distribution has the following form:

$$\Sigma_i^I = D_i \Delta_\rho D_i \qquad \text{with} \tag{8}$$

$$\Delta_\rho = CC' \qquad \text{where} \tag{9}$$

$$C = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ \cos_1 & \sin_1 & 0 & 0 & 0 \\ \cos_2 & \sin_2 \cos_3 & \sin_2 \sin_3 & 0 & 0 \\ \cos_4 & \sin_4 \cos_5 & \sin_4 \sin_5 \cos_6 & \sin_4 \sin_5 \sin_6 & 0 \\ \cos_7 & \sin_7 \cos_8 & \sin_7 \sin_8 \cos_9 & \sin_7 \sin_8 \sin_9 \cos_{10} & \sin_7 \sin_8 \sin_9 \sin_{10} \end{pmatrix} \tag{10}$$

and

$$D_i = \begin{pmatrix} \sigma_{i1}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{i2}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{i3}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{i4}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{i5}^2 \end{pmatrix} \qquad \text{with} \tag{11}$$

$$\sigma_{ij}^2 = \exp(\overline{x_i^F}' \gamma_j) \quad i = 1...N \quad j = 1...5 \tag{12}$$

Therefore, individuals are independent, but their different individual effects are correlated. We use in (9) a Cholesky decomposition for the correlation matrix, the matrix C can be expressed using a trigonometric form as shown above. For the diagonal variance matrix, we use a factor decomposition: x_i^F denotes the factors specific to individual i.

Finally, we assume that the idiosyncratic error terms follow:

[1]The subscript $\cos_i$ is used to avoid $\cos(\eta_i)$ with $\eta_i \in [0, \pi]$

$$
\begin{pmatrix} v_{it} \\ \epsilon_{it} \\ u_{it} \end{pmatrix} \sim_{iid} \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{yw}\sigma & \rho_{ym} \\ \rho_{yw}\sigma & \sigma^2 & \rho_{wm}\sigma \\ \rho_{ym} & \sigma\rho_{wm} & 1 \end{pmatrix} \right) \tag{13}
$$

Crucially here, because experience and seniority are direct - but complex - outcomes of the various participation and mobility decisions, these two variables are a complicated function of both individual and idiosyncratic error terms. Therefore, the person effect and the idiosyncratic error term in the wage equation are both correlated with the experience and seniority variables through the correlation of individual effects and idiosyncratic error terms across our system of equations. Hence, our system allows for correlated random effects.

3 Estimation

As in BFKT, we adopt a Bayesian setting. Our model estimates are given by the mean of the posterior distribution of the various parameters. At each step of an iterated procedure, we need to draw from the posterior distribution of these parameters. As the posterior distribution of the model is not tractable, we use the Gibbs Sampling algorithm to draw from this law at each step.

3.1 Principles of the Gibbs Sampler

Given a parameter set and data, the Gibbs sampler relies on the recursive and repeated computations of the conditional distribution of each parameter, conditional on all others and conditional on the data. We thus need to specify a prior density for each parameter. Let us just recall that the conditional distribution satisfies:

$$
l(p|\mathcal{P}_{(p)}, data) \propto l(data|\mathcal{P})\pi(p)
$$

where p is a given parameter, $\mathcal{P}_{(p)}$ denotes all other parameters, and $\pi(p)$ is the prior density of p.

In addition to increased separability, the Gibbs Sampler allows an easy treatment of latent variables through the so-called data augmentation procedure. Therefore, completion of the censored observations becomes possible. In particular, in our model, we do not observe latent variables m^*_{it}, y^*_{it}. Censored or unobserved data are simply “augmented ”.

Finally, the Gibbs Sampler procedure does not involve optimization algorithms. Simulation of conditional densities is the only computation required. Notice however that when the densities have no conjugate (i.e.

when the prior and the posterior do not belong to the same family), we use the standard Hastings-Metropolis algorithm.

3.2 Application to our Problem

In order to use Bayes' rule, we have to write the full conditional likelihood that is the density of all variables (observed and augmented variables, here y, w, m, m^*, y^*) given all parameters (parameters of interest and augmented parameters, denoted $\mathcal{P}$ later on). We thus have to properly define the parameter set and to properly "augment "our data.

The parameter set is the following:

$$\left(\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \Sigma^I\right) \tag{14}$$

and $\mathcal{P}$ denotes:

$$\mathcal{P} = \left(\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \Sigma^I; \theta^I\right) \tag{15}$$

When completing the data, special care is needed for mobility, a censored variable. Four cases must be distinguished depending of the values of (y_{it-1}, y_{it}). Completion is different conditional on these values. For a given individual i and conditional on both parameters and random effects, we define X_t the completed endogenous variable as:

$$\begin{aligned}
X_t &= y_t y_{t-1} X_t^{11} + y_{t-1}(1-y_t) X_t^{10} + y_t(1-y_{t-1}) X_t^{01} + (1-y_t)(1-y_{t-1}) X_t^{00} \\
X_t^{11} &= \left(y_t^*, y_t, w_t, m_{t-1}^*, m_{t-1}\right) \\
X_t^{10} &= \left(y_t^*, y_t, m_{t-1}^*\right) \\
X_t^{01} &= (y_t^*, y_t, w_t) \\
X_t^{00} &= (y_t^*, y_t) \\
X_1 &= y_1 X_1^1 + (1-y_1) X_1^0 \\
X_1^1 &= (y_1^*, y_1, w_1) \\
X_1^0 &= (y_1^*, y_1)
\end{aligned}$$

Notice also that we do not need to complete the mobility equation at date T[2]. For a given individual i, her

[2]Even though our notations do not make this explicit, all our computations allow for an individual-specific entry and exit date in the

contribution to the completed full conditional likelihood is:

$$
\begin{aligned}
&L(\underline{X}_T^i|\mathcal{P}) = \left(\prod_{t=2}^{T} l(X_{it}|\mathcal{P},\mathcal{F}_{i,t-1})\right) l(X_{i1})\\
&\underline{X}_T^i = (X_{i1},...,X_{iT})\\
&\mathcal{F}_{i,t-1} = \left(\underline{X}_{it-1}\right)
\end{aligned}
$$

with:

$$
\begin{aligned}
l(X_{it}|\mathcal{P},\mathcal{F}_{i,t-1}) \quad = \quad & (l(X_{it}^{11}|\mathcal{P},\mathcal{F}_{i,t-1}))^{y_{it-1}y_{it}}(l(X_{it}^{10}|\mathcal{P},\mathcal{F}_{i,t-1}))^{y_{it-1}(1-y_{it})}\\
& (l(X_{it}^{01}|\mathcal{P},\mathcal{F}_{i,t-1}))^{(1-y_{it-1})y_{it}}(l(X_{it}|\mathcal{P},\mathcal{F}_{i,t-1}))^{(1-y_{it-1})(1-y_{it})}
\end{aligned}
$$

Thus, the full conditional likelihood writes as:

$$
\begin{aligned}
&L(\underline{X}_T|\mathcal{P}) = \left(\frac{1}{V^w}\right)^{\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}}{2}} \left(\frac{1}{V^m}\right)^{\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1} y_{it}}{2}}\\
&\prod_{i=1}^{N}(\mathbb{I}_{y_{i1}^*>0})^{y_{i1}}(\mathbb{I}_{y_{i1}^*\leq 0})^{1-y_{i1}} \exp\left(-\frac{1}{2}(y_{i1}^*-m_{y_{i1}^*})^2\right)\exp\left(-\frac{y_{i1}}{2V^w}(w_{i1}-M_{i1}^w)^2\right)\\
&\prod_{t=2}^{T}(\mathbb{I}_{y_{it}^*\leq 0})^{1-y_{it}}(\mathbb{I}_{y_{it}^*>0})^{y_{it}} \exp\left(-\frac{1}{2}(y_{it}^*-m_{y_{it}^*})^2\right)\\
&\exp\left(-\frac{y_{it}}{2V^w}(w_{it}^*-M_{it}^w)^2\right)\left((\mathbb{I}_{m_{it-1}^*\leq 0})^{1-m_{it-1}}(\mathbb{I}_{m_{it-1}^*>0})^{m_{it-1}}\right)^{y_{it-1}y_{it}}\exp\left(-\frac{y_{it-1}}{2V^m}(m_{it-1}^*-M_{it-1}^m)^2\right)
\end{aligned}
$$

with:

- $V^w = \sigma^2(1-\rho_{yw}^2)$
- $V^m = \dfrac{1-\rho_{yw}^2-\rho_{ym}^2-\rho_{wm}^2+2\rho_{yw}\rho_{ym}\rho_{wm}}{1-\rho_{yw}^2}$
- $M_{it}^m = m_{m_{it}^*} + \underbrace{\dfrac{\rho_{y,m}-\rho_{w,m}\rho_{y,w}}{1-\rho_{y,w}^2}}_{a}(y_{it}^*-m_{y_{it}^*}) + \underbrace{\dfrac{\rho_{w,m}-\rho_{y,m}\rho_{y,w}}{\sigma(1-\rho_{y,w}^2)}}_{b}(w_{it}-m_{w_{it}})$
- $M_{it}^w = m_{w_{it}} + \sigma\rho_{y,w}(y_{it}^*-m_{y_{it}^*})$

and the residual correlations are parameterized by:

panel.

$$(16)\qquad \theta = \begin{pmatrix} \theta_{yw} \\ \theta_{ym} \\ \theta_{wm} \end{pmatrix}$$

$$(17)\qquad \begin{pmatrix} \rho_{yw} \\ \rho_{ym} \\ \rho_{wm} \end{pmatrix} = \begin{pmatrix} \cos(\theta_{yw}) \\ \cos(\theta_{ym}) \\ \cos(\theta_{yw})\cos(\theta_{ym}) - \sin(\theta_{yw})\sin(\theta_{ym})\cos(\theta_{wm}) \end{pmatrix}$$

Finally, we define the various prior distributions as follows:

$$\begin{aligned}
&\delta_0^Y \sim \mathcal{N}(m_{\delta_0^Y}, v_{\delta_0^Y}) \qquad \delta_0^M \sim \mathcal{N}(m_{\delta_0^M}, v_{\delta_0^M}) \\
&\delta^Y \sim \mathcal{N}(m_{\delta^Y}, v_{\delta^Y}) \qquad \gamma^Y \sim \mathcal{N}(m_{\gamma^Y}, v_{\gamma^Y}) \\
&\gamma^M \sim \mathcal{N}(m_{\gamma^M}, v_{\gamma^M}) \qquad \delta^W \sim \mathcal{N}(m_{\delta^W}, v_{\delta^W}) \\
&\delta^M \sim \mathcal{N}(m_{\delta^M}, v_{\delta^M}) \qquad \gamma \sim \mathcal{N}(m_\gamma, v_\gamma) \\
&\sigma^2 \sim \mathcal{IG}(\frac{v}{2}, \frac{d}{2}) \qquad \theta \sim_{iid} \mathcal{U}[0, \pi] \\
&\eta_j \sim_{iid} \mathcal{U}[0, \pi] \quad j = 1...10 \qquad \gamma_j \sim_{iid} \mathcal{N}(m_{\gamma_j}, v_{\gamma_j}) \quad j = 1...5
\end{aligned}$$

Based on these priors and the full conditional likelihood, all posterior densities can be evaluated (details can be found in the Appendix). The Gibbs Sampler can be used for estimation purposes using data sources that we describe in some detail now.

4 Data

The data on workers come from two data sources, the Déclarations Annuelles de Données Sociales (DADS) and the Echantillon Démographique Permanent (EDP) that are matched. Our first source, the DADS (Déclarations Annuelles de Données Sociales), is an administrative file based on mandatory reports of employees' earnings by French employers to the Fiscal administration. Hence, it matches information on workers and on their employing firm. This dataset is longitudinal and covers the period 1976-1995 for all workers employed in the private and semi-public sector and born in October of an even year. Finally, for all workers born in the first four days of October of an even year, information from the EDP (Echantillon Démographique Permanent) is also available. The EDP comprises various Censuses and demographic information. These sources are presented in more detail in the following paragraphs.

The DADS data set: Our main data source is the DADS, a large collection of matched employer-employee information collected by INSEE (Institut National de la Statistique et des Etudes Economiques) and maintained in the Division des revenus. The data are based upon mandatory employer reports of the gross earnings of each employee subject to French payroll taxes. These taxes apply to all “declared ”employees and to all self-employed persons, essentially all employed persons in the economy.

The Division des revenus prepares an extract of the DADS for scientific analysis, covering all individuals employed in French enterprises who were born in October of even-numbered years, with civil servants excluded.[3] Our extract runs from 1976 through 1995, with 1981, 1983, and 1990 excluded because the underlying administrative data were not sampled in those years. Starting in 1976, the division revenus kept information on the employing firm using the newly created SIREN number from the SIRENE system. However, before this date, there was no available identifier of the employing firm. Each observation of the initial data set corresponds to a unique individual-year-establishment combination. The observation in this initial DADS file includes an identifier that corresponds to the employee (called ID below) and an identifier that corresponds to the establishment (SIRET) and an identifier that corresponds to the parent enterprise of the establishment (SIREN). For each observation, we have information on the number of days during the calendar year the individual worked in the establishment and the full-time/part-time status of the employee. For each observation, in addition to the variables mentioned above, we have information on the individual’s sex, date and place of birth, occupation, total net nominal earnings during the year and annualized net nominal earnings during the year for the individual, as well as the location and industry of the employing establishment. The resulting data set has 13,770,082 observations.

The Echantillon Démographique Permanent: The division of Etudes Démographiques at INSEE maintains a large longitudinal data set containing information on many socio-demographic variables of all French individual. All individuals born in the first four days of the month of October of an even year are included in this sample. All questionaires for these individuals from the 1968, 1975, 1982, and 1990 Censuses are gathered into the EDP. Since the exhaustive long-forms of the various Censuses were entered under electronic form only for a fraction of the population leaving in France (1/4 or 1/5 depending on the date), the division des Etudes Démographiques had to find all the Censuses questionaires for these individuals. The INSEE regional agencies were in charge of this task. But, not all information from these forms were entered. The most important socio-demographic variables are however available.[4]

For every individual, education measured as the highest diploma and the age at the end of school are collected. Since the categories differ in the three Censuses, we first created eight education groups (identical to

[3]Individuals employed in the civil service move almost exclusively to other positions within the civil service. Thus the exclusion of civil servants should not affect our estimation of a worker’s market wage equation. see Abowd, Kramarz, and Margolis (1999).

[4]Notice that no earnings or income variables have ever been asked in the French Censuses.

those used in Abowd, Kramarz, and Margolis, 1999). The following other variables are collected: nationality (including possible naturalization to French citizenship), country of birth, year of arrival in France, marital status, number of kids, employment status (wage-earner in the private sector, civil servant, self-employed, unemployed, inactive, apprentice), spouse's employment status, information on the equipment of the house or appartment, type of city, location of the residence (region and department). At some of the Censuses, data on the parents education or social status are collected.

In addition to the Census information, all French town-halls in charge of Civil Status registers and ceremonies transmit information to INSEE for the same individuals. Indeed, any birth, death, wedding, and divorce involving an individual of the EDP is recorded. For each of the above events, additional information on the date as well as the occupation of the persons concerned by the events are collected.

Finally, both Censuses and Civil Status information contain the person identifier (ID) of the individual.

Creation of the Matched Data File: Based on the person identifier, identical in the two datasets (EDP and DADS), it is possible to create a file containing approximately one tenth of the original 1/25th of the population born in october of an even year, i.e. those born in the first four days of the month. Notice that we do not have wages of the civil-servants (even though Census information allows us to know if someone has been or has become one), or the income of self-employed individuals. Then, this individual-level information contains the employing firm identifier, the so-called SIREN number, that allows us to follow workers from firm to firm and compute the seniority variable. This final data set has approximately 1.5 million observations.

5 Results

5.1 Specification and Identification

First, we describe the variables included in each equation. The wage equation is standard for most of its components and includes, in particular, a quadratic function of experience and seniority. It also includes the following individual characteristics: the sex, the marital status and if unmarried an indicator for living in couple, an indicator for living in the Ile de France region, the département (roughly a U.S. county) unemployment rate, an indicator for French nationality for the person as well as for his (her) parents, and cohort effects. We also include information on the job: an indicator function for part-time work, and 14 indicators for the industry of the employing firm. We also include year indicators. Finally, and following the specification adopted in BFKT, we include a function, denoted J_{it}^{W}, that captures the sum of all wage changes that resulted from the moves until date t. This term allows for a discontinuous jump in one's wage when he/she changes jobs. The jumps are allowed to differ depending on the level of seniority and total labor market experience at the point in time when the individual changes jobs. Specifically,

(18)
$$J_{it}^{W}=(\phi_0^s+\phi_0^e e_{i0})\,d_{i1}+\sum_{l=1}^{M_{it}}\left[\sum_{j=1}^{4}\left(\phi_{j0}+\phi_j^s s_{t_l-1}+\phi_j^e e_{t_l-1}\right)d_{jit_l}\right].$$

Suppressing the i subscript, the variable d_{1t_l} equals 1 if the lth job lasted less than a year, and equals 0 otherwise. Similarly, $d_{2t_l}=1$ if the lth job lasted between 1 and 5 years, and equals 0 otherwise, $d_{3t_l}=1$ if the lth job lasted between 5 and 10 years, and equals 0 otherwise, $d_{4t_l}=1$ if the lth job lasted more than 10 years and equals 0 otherwise. The quantity M_{it} denotes the number of job changes by the ith individual, up to time t (not including the individual's first sample year). If an individual changed jobs in his/her first sample then $d_{i1}=1$, and $d_{i1}=0$ otherwise. The quantities e_t and s_t denote the experience and seniority in year t, respectively.[5]

Turning now to the mobility equation, most variables included in the wage equation are also present in the mobility equation at the exclusion of the J_{it}^W function. However, an indicator for the lagged mobility decision and indicators for having children between 0 and 3, and for having children between 3 and 6 are now included in this equation but are not present in the wage equation.

The participation equation is very similar to the mobility equation. For obvious reasons though, seniority that was present in the latter equation is now excluded. And for the same reason, other variables specific to a job - the part-time status and the employing industry - are excluded from the participation equation. Now, the lagged participation decision (or employment status) is included in the participation equation whereas this variable is meaningless in the mobility equation since mobility implies participating in both the previous and the contemporaneous years, as discussed in the Statistical Model Section.

Finally, the initial mobility and participation equations are simplified versions of these equations.

As is directly seen from the above equations, we have used multiple exclusion restrictions. For instance, and for obvious reasons, the industry affiliation is included in both wage and mobility equations but not in the participation equation. Conversely, the children variables are not present in the wage equation but are included in the two other equations (this exclusion was decided after due testing). Furthermore, the J_{it}^W function is included in the wage equation but not in the participation and mobility equations. Unfortunately, there appears to be no good exclusion that would guarantee convincing identification of the initial conditions equations,

[5]This specification for the term J_{it}^W produces thirteen different regressors in the wage equation. These regressors are: a dummy for job change in year 1, experience in year 0, the numbers of switches of jobs that lasted less than one year, between 2 and 5 years, between 6 and 10 years, or more than 10 years, seniority at last job change that lasted between 2 and 5 years, between 6 and 10 years, or more than 10 years, and experience at last job change that lasted less than one year, between 2 and 5 years, between 6 and 10 years, or more than 10 years.

except functional form (the normality assumptions).

5.2 Results for Certificat d'Etudes Primaires Holders (High-School Dropouts)

In France, apart from those quitting the education system without any diploma (with the possible confusion of missing response to the education question in the various Censuses), the Certificat d'Etudes Primaires (CEP hereafter) holders are those leaving the system with the lowest possible level of education. They are essentially comparable to High-School dropouts in the United States. Table 1 presents estimation results for the wage equation for each education group. Table 2 presents estimation results for the participation equation, once again for each education group. Table 3 presents estimation results for the inter-firm mobility equations for the four education groups. Table 4 presents estimation results for the initial conditions equations, and Table 5 gives our estimates of the variance-covariance matrices for the individual effects (across the five equations) and for the idiosyncratic effects (across the three main equations).

Wage Equation: Since estimating returns to seniority is one of the main motivations for adopting the joint system estimation strategy, we first see that the returns are small, 0.3% per year (in the first years). Returns to experience are ten times larger than returns to tenure. Results of Table 1 show that the timing of the mobilities in a career barely matters. More precisely, for the CEP category, each switch of job adds approximately 65% to the wage. However, one must add to the constant a component proportional to seniority and experience at exit of the last job. But virtually none of these coefficients are significantly different from zero. Early moves in the career are not good and moves after long stays in a job are marginally detrimental.

In this first table, two more facts are worthy of notice. First, and confirming results by Abowd, Kramarz, Lengermann, and Roux (2004), interindustry wage differences are relatively compressed (when compared with groups with a higher level of education), a consequence of minimum wages for a category that includes many workers at the bottom of the wage distribution. Second, when correcting for mobility and participation, low-education foreigners are better paid than nationals.

Participation and Mobility Equations: Tables 2 and 3 present our estimates of the participation and mobility equations respectively, for CEP workers. Table 4 presents our estimates for the initial conditions, for the same CEP workers. Most results are unsurprising. For instance, having low-age children lowers participation but has no effect on mobility. More interesting are the coefficients on the lagged mobility and lagged participation. In contrast with most previous estimates, we are able to apportion state-dependence and heterogeneity. Unsurprisingly, past participation and past mobility favors participation. More surprisingly though past mobility is associated with more mobility today. Therefore, workers are mobile both because some of them may be high-mobility workers. But, lagged dependence is obviously a reflection of French labor market institutions where workers often go from short-term contracts to short-term contracts, irrespective of their "tastes". Unfortunately, our data sources do not tell us the nature of the contract. Furthermore, this last result stands in sharp contrast with those obtained by BFKT who estimate a negative sign, more in line with the free choice view of mobility. Furthermore, seniority affects positively mobility, in contrast to what is found in BFKT for this group.

Stochastic Components: Table 5 presents estimates of variance-covariance components of the individual effects for our five equations in the first panel and of the residuals of the three main equations in the second panel. The results clearly show that those who participate are also relatively high-wage workers (both in terms of individual effects and in terms of error term).

5.3 Results for CAP-BEP holders (Vocational Technical School, basic)

One element that distinguishes continental education systems, the French as well as the German, is the existence of well-developed apprenticeship training. Indeed, this feature is well-known for Germany but it is also quite important in France. Students who obtain the CAP (Certificat d'Aptitude Professionnelle) or the BEP (Brevet d'Enseignement Professionnel) have spent part of their education in firms and the rest within schools where they were taught both general and vocational subjects. It has no real equivalent in the US system.

Wage Equation: Returns to tenure, presented in Table 1, for workers with a vocational technical education are negative, almost significantly so. We believe that negative returns are not only possible but confirmed by many features of the French labor market, as well as other empirical evidence that we discuss now. Most important to understand this feature is the J^W function. Results are indeed very similar to those obtained for high-school dropouts. In particular, job changes always entail a large wage gain, roughly equal to 65%, unrelated to the seniority at the moment of the change. However, and in contrast with dropouts, a move very early in the career has a small negative effect (-0.5%) and more significant, a move late in a career within a firm. Indeed, moves after more than 10 years of seniority generate a wage loss of more than -2% per year of seniority which is not compensated by the 1.3% increase per year of experience.

Participation and Mobility Equations: The estimated coefficients for the participation equation are very similar to those obtained for the previous group. More interestingly, and related to the wage equation, we find no evidence of lagged dependence in mobility. However, mobility is only mildly related to seniority (more seniority inducing less mobility). Hence, workers appear to move at virtually all tenures, because they lose nothing – on the contrary – by doing so, with one exception though for very long tenures. Notice also that having young children affects strongly both participation and initial participation equation, in contrast to college-educated groups.

Stochastic Components: For this group, most components are not significantly different from zero. Only participation and wage person effects are positively correlated. In contrast, the same correlation is negative, significantly so but mildly, for the idiosyncratic error terms.

5.4 Results for Baccalauréat Holders (High-School Graduates)

High-school graduation in France means that students have succeeded in a national exam, called the Baccalauréat. It is a passport to higher education, even though not all holders of the Baccalauréat go to a University. And, furthermore, since many students who attend university never obtain a degree the group here potentially includes workers who never completed any degree in the higher education system.

Wage Equation: Indeed, results for this group, presented again in Table 1, are very similar to those given for the CEP holders. Returns to experience are large but returns to seniority are essentially zero. However, the estimates for the J^W function are very striking. First, there is a clear decrease in returns to mobility when comparing short job spells and long job spells. In particular, mobility after ten years in a job brings approximately a 35% bonus when mobility after up to 5 years in a job appears to add 100%. In addition, the component proportional to seniority is very negative for the long job spells, destroying 3.5% per year. Hence, a mobility after ten years in a job generates an average loss of at least 35% of the wage in comparison with mobilities at shorter tenures. Notice though that the component proportional to experience is increasing with experience and partly compensate for these relative losses.

Participation and Mobility Equations: Most results are very consistent with those obtained previously for the CEP holders (all in Tables 2 and 3) . Interestingly though, the positive lagged dependence of mobility disappears and even becomes marginally negative, a result that is consistent with results for the US. In contrast to results obtained for CEP holders, the seniority coefficient in the mobility equation is not significantly different from zero. Hence, the Baccalauréat group is quite special in that display no clear pattern of mobility within a job, a potential reflection that careers where affected by involuntary job losses, at long tenures.

Stochastic Components: For workers in this category, central are the positive correlations between the participation and the wage equations that come both from individual effects and from idiosyncratic terms. But high-wage individuals are low-mobility workers. In addition, the participation and mobility idiosyncratic error terms are highly positively correlated, another proof that non-participation (non-employment) and mobility are negatively associated.

5.5 Results for University and Grandes Ecoles Graduates

Another element that distinguishes the French education system from other continental education systems as well as from the American system is the existence of a very selective set of so-called Grandes Ecoles that work in parallel with Universities. The former system delivers masters degrees mostly in engineering and in business. It is very selective, in contrast to the rest of higher education.

Wage Equation: Interestingly, results for the group of graduates stand in sharp contrast with those obtained for the other education groups (see Table 1). Not because returns to experience differ but mostly because returns to seniority are now sizeable, approximately 1% per additional year. [6] Furthermore, the estimated J^W function is also specific to that group. More precisely, wage gains not only come from the number of job changes but also from the timing of these changes. Optimally, job changes after at most 5 years in that job are those most profitable since they add 4.5% per year of seniority to the starting point of the new job. Hence, say after 5 years in a job, a graduate worker loses from the lost seniority (5%) but gains from the move (approximately 80%) and from the moment of the move (23%) and may lose something if the move was made too early in the career. Notice that any move made later in the career, i.e. after 5 years of experience entails no loss nor gain due to experience.

Other interesting facts must be noted for this group of graduates. First, working part-time entails much bigger losses than for other groups. Furthermore, sizeable inter-industry wage differences can be found. As mentioned above, such results are perfectly in line with those estimated by Abowd, Kramarz, Lengermann, and Roux (2004) in their comparison of France and the United States. Wage differences mostly come from the upper part of the wage distribution. Finally, for all other education groups, foreigners were better compensated than nationals. Here, this is the contrary. Getting a higher education may be a solution to employment problems for those born abroad (Maghreb, Portugal,...). But, even though we can not use the word discrimination, pay is lower potentially reflecting a limited access to the Grandes Ecoles, the most selective and high-paying education within this graduate group.

Participation and Mobility Equations: Mobility for this group displays no lagged dependence. Furthermore, workers' mobility is virtually not related to seniority. And there is no relation between mobility and experience; evidence that engineers and professionals careers entail job changes at all ages. In the participation equation, the relatively large coefficient on the lagged participation indicator is a reflection of the labor market orientation of those endowed with a higher graduate education. Furthermore, and in contrast to all other groups, participation choices are not affected by having young children. Indeed, this very educated group obviously

[6](Results for the group of University Technical University undergraduates are very similar to those presented in this subsection. Hence we do not report them.

selected their education because they wanted to work (remember that participation is, in fact, employment).

Stochastic Components: As found before, high-participation individuals are also high-wage individuals, but this much less so than for other groups, another reflection that the choice of a high-level education signals a high willingness to work and, indeed, to find a job. And, individuals faced with a positive idiosyncratic wage shock are also faced with a positive mobility shock.

6 A Comparison with the United States

6.1 Facts

In this subsection, we compare our results with those obtained by BFKT for the United States using exactly the same model specification with two initial equations for mobility and participation, with three equations for wage, mobility and participation, the last two including lagged dependence. In addition, the same stochastic assumptions were made, that is the error terms were the sum of an individual effect (one for each of the five equations, all potentially correlated) and an idiosyncratic term for the three main equations (all potentially correlated). The model was estimated for three education groups: high-school dropouts, high-school graduates, and college graduates. The PSID was used for estimation. Some variables included in BFKT were not available in the panel that we use, in particular race. We present a comparison of the estimates for a subset of the parameters that we believe are the most telling and important. Estimates for the College Educated group are presented in Table 6 whereas estimates for High-School Dropouts are presented in Table 7.

The first difference to be noted is essentially in the estimated returns to seniority. They are large in the United States and small in France. We discuss this fact in the next subsection extensively. Related to this, we see that returns to experience are slightly larger in France than in the United States for the two groups. But the total of returns to experience and returns to seniority is much larger in the U.S.. Indeed, when considering how wages behave after job mobility, we have to compare the estimated J^W functions. Here again, some differences stand out. First, the part proportional to the number job to job switches appear to be better compensated in France than in the U.S.; in particular, those movements out of jobs that lasted at most 5 years. Whereas in the United States, movements out of jobs that lasted more than 10 years are much better compensated than other movements. Notice the similarities across countries in the part of the J^W function proportional to seniority for the college educated: movements exactly after 5 years in a job appear to be most profitable. However, for the high-school dropouts, movements after very long periods in a job are better rewarded in the United States whereas movements before 6 years in a job appear to be (marginally) better in France for this category. To summarize, short spells appear to be (slightly) the most profitable in France, the reverse being true in the

United States.

Other facts on wages are worthy of notice. We already mentioned some of them in our discussion of the French results. In particular, inter-industry wage differentials are less compressed in the top part of the wage distribution in France but are large in every education group in the United States.

Related to differences on wage determination that we just described, differences in the mobility processes between France and the United States must be stressed. First, in the United States, the mobility process always displays negative lagged dependence; after a move a worker tends to stay at the next period. This is not true in France. First, for the college educated workers there is no state dependence in the mobility process. But, more striking, there is positive state dependence in the mobility process for the CEP holders. Hence, a worker who just moved is more likely to move again, a consequence, as noted above, of repeated employment of low-education workers in sequences of short-term contracts. However, in the United States, workers tend to move early in a job (negative sign on the seniority coefficient in the mobility equation); a feature of the American labor market. But, this is not so for the two education groups in France where the CEP holders tend to move more often at longer tenures (and mildly so for the college-educated).

Finally, the comparison of the variance-covariance matrices of individual effects and of the variance-covariance matrices of idiosyncratic effects across the two countries confirms previous findings. First, the U.S. data source (the PSID) because of its survey structure captures initial conditions much better than the French data source (the DADS-EDP, of administrative origin). In particular the former has much better initial variables whereas imputations had to be performed in 1976 for the latter. Second, concentrating on the correlation of individual effects in the three main equations, participation and wage are highly positively correlated in both countries. But, when mobility equation is involved, signs are similar in the two countries for both groups of education but the estimates are imprecise in France. Finally, high-mobility individuals are clearly low-wage and low-participation individuals in the United States, stressing again the different role played by mobility in the two countries.

6.2 Returns to Seniority as an "Incentive Device"?

A natural question arising from the above comparison can be formulated as follows. Are the different features that seem to prevail in each country related ? Or, put differently, are the small estimated returns to seniority in France related to the patterns of mobility as estimated above, in particular to the relatively low job-to-job transition rates, as well to the relatively high risk of losing one's job ? Whereas, in the United States, are the large estimated returns to seniority related to this country patterns of mobility as estimated in BFKT and discussed just above, in particular the relatively high job-to-job transition rates, the low unemployment rate and the relatively high probability of exit out of unemployment ?

In this subsection, we show that these features are indeed part of a system. An equilibrium search model with wage-tenure contracts is shown to be a good tool for understanding and summarizing this system . The properties of the wage profiles at the stationary equilibrium are contrasted using the respective characteristics of the two labor markets.

The characteristics that matter for both our estimates and this model are the following. In France, the unemployment rate is muc larger than in the US (9.4% vs. 5,7% in March 2004 according to OECD data sources). Consequently, the job offer arrival rate can be assumed to be larger in the US than in France. Indeed, Jolivet, Postel-Vinay and Robin (2004), using a job search model, have estimated the job arrival rates for the US (PSID, 1993-1996) and several European countries (ECHP, 1994-2001). The estimated job arrival rate is more than three times larger on the US labor market than on the French one (1.7114 per annum vs. 0.5614).

The job search model used in this endeavor was developed recently by Burdett and Coles (2003). In particular, this model generates an unique equilibrium wage-tenure contract. We show that this wage-tenure contract is such that the slope of the wage function with respect to job tenure, for the first months or years, is an increasing function of the job offer arrival rate. Hence, it is an increasing function of the realized mobility on the labor market.

We start by summarizing the important aspects of the model. In Burdett and Coles (2003), the individuals are risk adverse. Let λ denote the job offers arrival rate and δ is the arrival rate of new workers into the labor force and the outflow rate of workers out from the labor market. Let p denote the instantaneous revenue received by firms for each worker employed and b is the instantaneous benefit received by each unemployed worker ($p > b > 0$).

The equilibrium is unique and is such that the optimal wage-tenure contract selected by a firm offering the lower starting wage satisfies

(19) $$\frac{dw}{dt} = \frac{\delta}{\sqrt{p-w_2}} \, \frac{p-w}{u'(w)} \int_{w}^{w_2} \frac{u'(s)}{\sqrt{p-s}} \, ds$$

with the initial condition $w(0) = w_1$ and where w_1, w_2 are such that

(20) $$\left(\frac{\delta}{\lambda+\delta}\right)^2 = \frac{p-w_2}{p-w_1},$$

(21) $$u(w_1) = u(b) - \frac{\sqrt{p-w_1}}{2} \int_{w_1}^{w_2} \frac{u'(s)}{\sqrt{p-s}} \, ds,$$

where $[w_1; w_2]$ is the support of the distribution of wages paid by the firms ($w_1 < b$ and $w_2 < p$).

Let us assume that the utility function is CRRA, $u(w) = \frac{w^{1-\sigma}}{1-\sigma}$ ($\sigma > 0$). Burdett and Coles (2003) show that the optimal wage-tenure contract, namely the baseline salary contract, is such that there exists a tenure such that, from this tenure on, this (baseline salary) contract is identical to the contract offered by a high-wage firm with a higher entry wage.

$$\frac{d^2 w}{d t^2} = \left(\frac{d w}{d t}\right)^2 \frac{1}{p-w}\left[\frac{\sigma p}{w} - (\sigma+1)\right] - \delta \frac{\sqrt{p-w}}{\sqrt{p-w_2}} \frac{d w}{d t} \tag{22}$$

with the initial conditions $w(0) = w_1$ and

$$\frac{d w(0)}{d t} = \frac{\delta}{\sqrt{p-w_2}} \frac{p-w_1}{u'(w_1)} \int_{w_1}^{w_2} \frac{u'(s)}{\sqrt{p-s}} \, d s \tag{23}$$

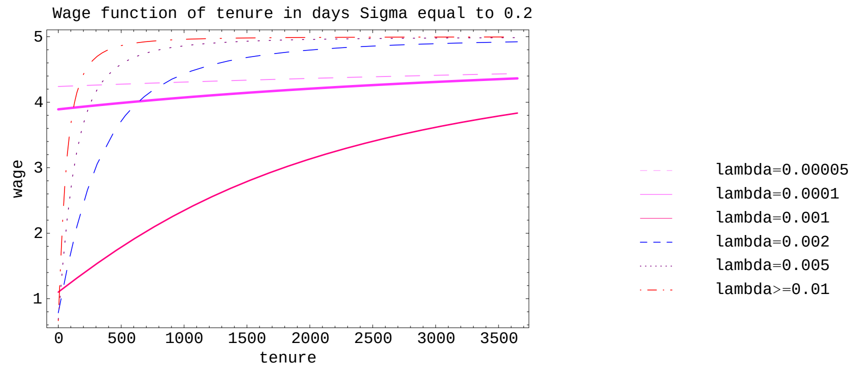
The differential equation 22 is highly non linear and have to be solved numerically. This can done by setting $(\lambda, \delta, \sigma, p)$ to some values and using, for instance, the procedure NDSolve of Mathematica.

In order to study the behavior of the wage-tenure contract curve with respect to the values of the job offers arrival rate, we have used the same parameter values as Burdett and Coles (see their section 5.2). Hence, we have set $p = 5$, $\frac{\delta}{\lambda} = 0.1$ and $b = 4.6$. For each value of the relative risk aversion coefficient ($\sigma \in \{0.2, 0.4, 0.8, 1.4\}$), we solve the system of equations (22)-(23) numerically for a set a values of the job offers arrival rate. The results are depicted in Figure 6.2 for $\sigma = 0.2$, in Figure 6.2 for $\sigma = 0.4$, in Figure 6.2 for $\sigma = 0.8$ and in Figure 6.2 for $\sigma = 1.4$. The Figures present these wage contract curves for the first 10 years of seniority. For all values of the relative risk aversion coefficient, we see that wage increases much more rapidly, in particular during the first year, for larger job offers arrival rates.

Using the values of the job offers arrival rates (per year) estimated by Jolivet, Postel-Vinay and Robin (2004) for France and the US, the U.S. situation corresponds to the curve where $\lambda = 0.005$ and the French labor market to the curve where $\lambda = 0.001$. And, for all relative risk aversion coefficients, the equilibrium wage-tenure contract curves are such that the high mobility country (the United States) has much higher returns to seniority than the low mobility country (France).

Two points are worth mentioning at this stage. First, we take - as firms appear to be doing - institutions that affect mobility as given. For instance, the housing market is much more fluid in the United States than in France (because, for instance, of strong regulations and transaction costs). Or, subsidies and government interventions preventing firm to go bankrupt seem more prevalent in France, dampening the forces of “creative destruction

”in this country. And firms must react within this environment. Therefore, French firms face a workforce that is mostly stable with little incentives to move, even after an involuntary separation. Second, as a recent paper by Wasmer argues (Wasmer, 2003), it is likely that French firms will invest in firm-specific human capital for this exact reason. In contrast, American firms face a workforce that is very mobile. Therefore, following again Wasmer (2003), these firms should rely on general human capital. Now, does it mean that returns to seniority should be large in France and small in the United States ? Or, put differently, should French firms pay for something they get “by construction” (of the institutions). This is, we believe, the misconception that has plagued some of this research in the recent years. And, the above model gets it right. The optimal tenure contract when mobility is strong should be larger than when mobility is weak.


Wage function of tenure in days Sigma equal to 0.2
wage
tenure
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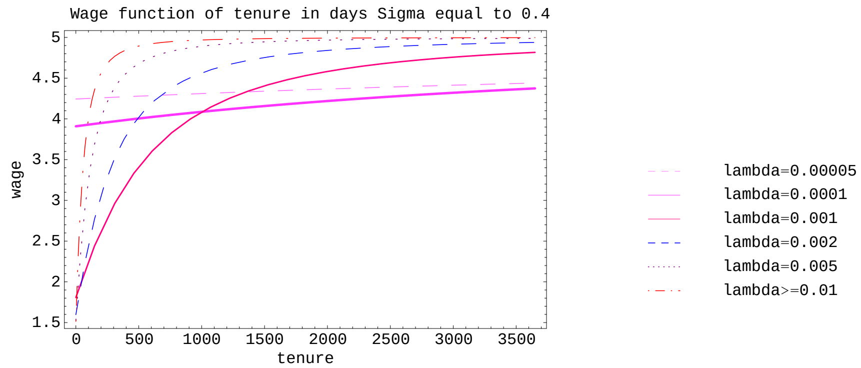
lambda=0.0001
lambda=0.001
lambda=0.002
lambda=0.005
lambda>=0.01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tenure
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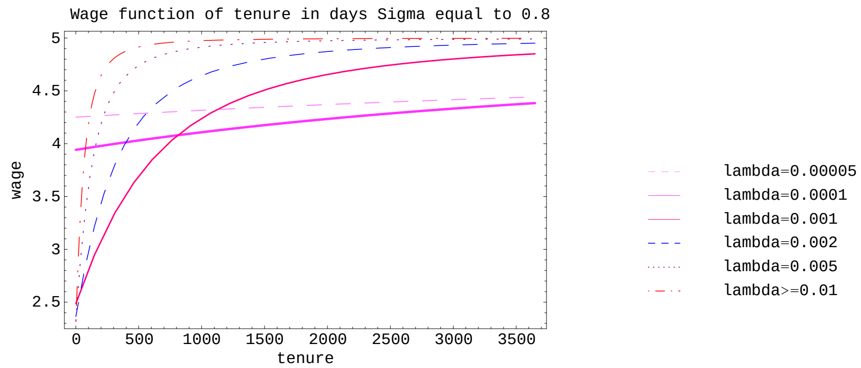
Wage function of tenure in days Sigma equal to 0.8
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tenure
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lambda=0.001
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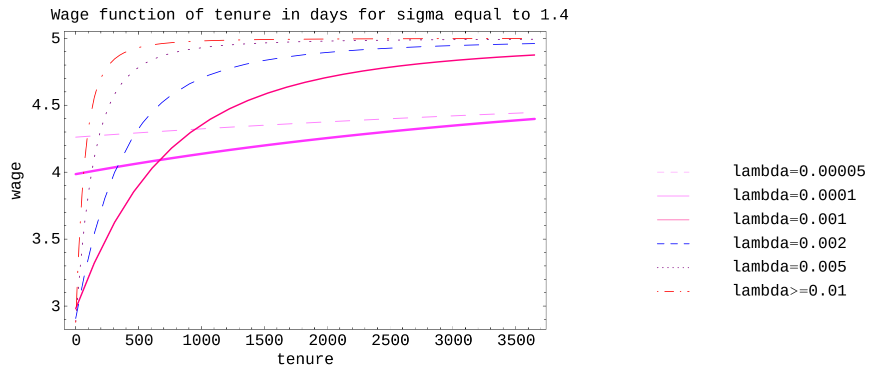
Wage function of tenure in days for sigma equal to 1.4
wage
tenure
lambda=0.00005
lambda=0.0001
lambda=0.001
lambda=0.002
lambda=0.005
lambda>=0.01

7 Conclusion

In this article, we estimated returns to seniority in a structural framework in which participation, mobility and wages are jointly modelled. We include both state-dependence and unobserved correlated individual heterogeneity in the decisions. To estimate this complex structure, we use Bayesian techniques. The model is estimated using French longitudinal data sources for the period 1976-1995. Results presented for four groups of education show that returns to seniority are virtually zero, potentially negative for some low-education groups, slightly positive for college-educated workers (1% per year of seniority). A comparison with results obtained for the United States by BFKT using the exact same specification and similar estimation techniques (on the PSID) shows that returns to seniority are much lower in France and that returns to experience are virtually identical. Furthermore, unreported results (available from the authors) show that OLS estimates of the returns to seniority are much higher than those obtained for our system of equations. In addition, the same unreported results demonstrate that instrumental variables estimation following exactly Altonji's suggestions give results that look relatively similar to those obtained for our system of equations. Estimates are always lower than those obtained with OLS. However, Altonji's IV technique gives sometimes slightly higher estimates than those we obtain for our system (low education groups) and sometimes slightly lower estimates than those we obtain for our system (college-educated workers). This comparison for France stands in sharp contrast with that for the United States; results in BFKT show that Altonji's technique yields much lower returns to seniority than those obtained for the system of equations. Still, using Altonji's technique in both countries, our result still holds: returns to seniority are lower in France than in the United States.

Hence, modelling jointly mobility and participation with wages has non-trivial consequences that may vary across countries. In particular, the labor market institutions and state (high unemployment versus low unemployment, among other things) or other market institutions such as the housing market that may favor or discourage mobility are likely to have far-reaching effects on these mobility and participation processes. Techniques that do not deal directly with these questions are likely to give incomplete answers.

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A Mobility equation

A.1 *Parameter* γ

This parameter enters $m_{m_{it^*}}$ for $t = 2, ..., T-1$

$$m_{m_{it^*}} = \gamma m_{it-1} + X_{it}^M \delta^M + \Omega_i^I \theta^{M,I}$$

If we put apart this term in the full conditional likelihood, we get:

$$\begin{aligned}
\prod_{i=1}^{N}\prod_{t=2}^{T-1} \exp\left(-\frac{y_{it}}{2V^m}(m_{it}^* - M_{it}^m)^2\right) &= \exp\left(-\frac{1}{2V^m}\sum_{i=1}^{N}(\widetilde{\underline{m}_i^*}^{2,T-1} - \widetilde{\underline{M}_i^m}^{2,T-1})'(\widetilde{\underline{m}_i^*}^{2,T-1} - \widetilde{\underline{M}_i^m}^{2,T-1})\right) \\
&= \exp\left(-\frac{1}{2V^m}\sum_{i=1}^{N}(\widetilde{\underline{A}_i}^{2,T-1} - \gamma\widetilde{\underline{Lm}_i}^{2,T-1})'(\widetilde{\underline{A}_i}^{2,T-1} - \gamma\widetilde{\underline{Lm}_i}^{2,T-1})\right)
\end{aligned}$$

with:

- $M^m_{it} = m_{m^*_{it}} + \underbrace{\frac{\rho_{y,m} - \rho_{w,m}\rho_{y,w}}{1-\rho^2_{y,w}}}_{a}(y^*_{it} - m_{y^*_{it}}) + \underbrace{\frac{\rho_{w,m} - \rho_{y,m}\rho_{y,w}}{\sigma(1-\rho^2_{y,w})}}_{b}(w_{it} - m_{w_{it}})$
- $\widetilde{\underline{m}^*_i}^{2,T-1} = \begin{pmatrix} y_{i2}m^*_{i2} \\ ... \\ y_{iT-1}m^*_{iT-1} \end{pmatrix}$
- $\widetilde{\underline{M}^m_i}^{2,T-1} = \begin{pmatrix} y_{i2}M^m_{i2} \\ ... \\ y_{iT-1}M^m_{iT-1} \end{pmatrix}$
- $A_{it} = m^*_{it} - M^m_{it} + \gamma m_{it-1} = m^*_{it} - X^M_{it}\delta^M - \Omega^I_i\theta^{I,M} - a(y^*_{it} - m_{y^*_{it}}) - b(w_{it} - m_{w_{it}})$

By gathering squared and crossed terms, we get:

$$\begin{aligned} V^{post,-1}_{\gamma} &= V^{prior,-1}_{\gamma} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T-1}\right)'\widetilde{\underline{Lm}_i}^{2,T-1} \\ V^{post,-1}_{\gamma}M^{post}_{\gamma} &= V^{prior,-1}_{\gamma}M^{prior}_{\gamma} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T-1}\right)'\widetilde{\underline{A}_i}^{2,T-1} \end{aligned}$$

A.2 *Parameter* δ^M

We proceed the same way as before and we get with analogous notations:

$$\begin{aligned} V^{post,-1}_{\delta^M} &= V^{prior,-1}_{\delta^M} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{X}^M_i}^{2,T-1}\right)'\widetilde{\underline{X}^M_i}^{2,T-1} \\ V^{post,-1}_{\delta^M}M^{post}_{\delta^M} &= V^{prior,-1}_{\delta^M}M^{prior}_{\delta^M} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{X}^M_i}^{2,T-1}\right)'\widetilde{\underline{A}_i}^{2,T-1} \end{aligned}$$

with $A_{it} = m^*_{it} - M^m_{it} + \delta^M X^M_{it} = m^*_{it} - \gamma m_{it-1} - \Omega^I_i\theta^{I,M} - a(y^*_{it} - m_{y^*_{it}}) - b(w_{it} - m_{w_{it}})$

B Wage equation

B.1 *Parameter* δ^W

We have to take into account that δ^W enters both $m_{w_{it}}$ for $t = 1...T$ and M^m_{it} for $t = 1...T-1$.

Thus if we put apart these terms in the full conditional likelihood, we get:

$$
\begin{aligned}
& \prod_{i=1}^{N} \exp\left(-\frac{1}{2V^w}\sum_{t=1}^{T} y_{it}(w_{it}-M_{it}^w)^2\right)\exp\left(-\frac{1}{2V^m}\sum_{t=1}^{T-1} y_{it}(m_{it}^*-M_{it}^m)^2\right) \\
= & \prod_{i=1}^{N} \exp\left(-\frac{1}{2V^w}\sum_{t=1}^{T} y_{it}(A_{it}-X_{it}^W\delta^W)^2\right)\exp\left(-\frac{1}{2V^m}\sum_{t=1}^{T-1} y_{it}(B_{it}+bX_{it}^W\delta^W)^2\right)
\end{aligned}
$$

with:

- $w_{it} - M_{it}^w = A_{it} - X_{it}^W \delta^W$
- $m_{it}^* - M_{it}^m = B_{it} + bX_{it}^W \delta^W$

which is equivalent to:

- $A_{it} = w_{it} - \Omega_i^I \theta^{I,W} - \rho_{y,w}\sigma(y_{it}^* - m_{y_{it}^*}))$
- $B_{it} = m_{it}^* - m_{m_{it}^*} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - \Omega_i^I \theta^{I,W})$

If we use analogous notations as before, we get:

$$
\begin{aligned}
V_{\delta^W}^{post,-1} &= V_{\delta^W}^{prior,-1} + \frac{1}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{X}_i^W}^{1,T}\right)'\widetilde{\underline{X}_i^W}^{1,T} + \frac{b^2}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{X}_i^W}^{1,T-1}\right)'\widetilde{\underline{X}_i^W}^{1,T-1} \\
V_{\delta^W}^{post,-1}M_{\delta^W}^{post} &= V_{\delta^W}^{prior,-1}M_{\delta^W}^{prior} + \frac{1}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{X}_i^W}^{1,T}\right)'\widetilde{\underline{A}_i}^{1,T} - \frac{b}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{X}_i^W}^{1,T-1}\right)'\widetilde{\underline{B}_i}^{1,T-1}
\end{aligned}
$$

C Participation equation

C.1 *Parameter* γ^Y

We have to take into account that γ^Y enters both $m_{y_{it}^*}$ for $t = 2...T$, M_{it}^w for $t = 2...T$ and M_{it}^m for $t = 2...T-1$

Thus if we put apart these terms in the full conditional likelihood, we get:

$$
\begin{aligned}
& \prod_{i=1}^{N} \exp\left(-\frac{1}{2}\sum_{t=2}^{T}(y_{it}^*-m_{y_{it}^*})^2 - \frac{1}{2V^w}\sum_{t=2}^{T} y_{it}(w_{it}-M_{it}^w)^2 - \frac{1}{2V^m}\sum_{t=2}^{T-1} y_{it}(m_{it}^*-M_{it}^m)^2\right) \\
= & \prod_{i=1}^{N} \exp\left(-\frac{1}{2}\sum_{t=2}^{T}(A_{it}-\gamma^Y Ly_{it})^2 - \frac{1}{2V^w}\sum_{t=2}^{T} y_{it}(B_{it}+\rho_{y,w}\sigma\gamma^Y Ly_{it})^2 - \frac{1}{2V^m}\sum_{t=2}^{T-1} y_{it}(C_{it}+a\gamma^Y Ly_{it})^2\right)
\end{aligned}
$$

with:

- $y^*_{it} - m_{y^*_{it}} = A_{it} - \gamma^Y Ly_{it}$
- $w_{it} - M^w_{it} = B_{it} + \rho_{y,w}\sigma\gamma^Y Ly_{it}$
- $m^*_{it} - M^m_{it} = C_{it} + a\gamma^Y Ly_{it}$

which is equivalent to:

- $A_{it} = y^*_{it} - \gamma^M Lm_{it} - X^Y_{it}\delta^Y - \Omega^I_i\theta^{I,Y}$
- $B_{it} = w_{it} - m_{w_{it}} - \rho_{y,w}\sigma A_{it}$
- $C_{it} = m^*_{it} - m_{m^*_{it}} - b(w_{it} - m_{w_{it}}) - aA_{it}$

If we use analogous notations as before, we get:

$$V^{post,-1}_{\gamma^Y} = V^{prior,-1}_{\gamma^Y} + \sum_{i=1}^{N}\left(\underline{Ly}_i^{2,T}\right)'\underline{Ly}_i^{2,T} + \frac{\rho^2_{y,w}\sigma^2}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{Ly}_i}^{2,T}\right)'\widetilde{\underline{Ly}_i}^{2,T} + \frac{a^2}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Ly}_i}^{2,T-1}\right)'\widetilde{\underline{Ly}_i}^{2,T-1}$$

$$V^{post,-1}_{\gamma^Y}M^{post}_{\gamma^Y} = V^{prior,-1}_{\gamma^Y}M^{prior}_{\gamma^Y} + \sum_{i=1}^{N}\left(\underline{Ly}_i^{2,T}\right)'\underline{A}_i^{2,T} - \frac{\rho_{y,w}\sigma}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{Ly}_i}^{2,T}\right)'\widetilde{\underline{B}_i}^{2,T} - \frac{a}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Ly}_i}^{2,T-1}\right)'\widetilde{\underline{C}_i}^{2,T-1}$$

C.2 *Parameter* γ^M

We proceed the same way and we get:

$$V^{post,-1}_{\gamma^M} = V^{prior,-1}_{\gamma^M} + \sum_{i=1}^{N}\left(\underline{Lm}_i^{2,T}\right)'\underline{Lm}_i^{2,T} + \frac{\rho^2_{y,w}\sigma^2}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T}\right)'\widetilde{\underline{Lm}_i}^{2,T} + \frac{a^2}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T-1}\right)'\widetilde{\underline{Lm}_i}^{2,T-1}$$

$$V^{post,-1}_{\gamma^M}M^{post}_{\gamma^M} = V^{prior,-1}_{\gamma^M}M^{prior}_{\gamma^M} + \sum_{i=1}^{N}\left(\underline{Lm}_i^{2,T}\right)'\underline{A}_i^{2,T} - \frac{\rho_{y,w}\sigma}{V^w}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T}\right)'\widetilde{\underline{B}_i}^{2,T} - \frac{a}{V^m}\sum_{i=1}^{N}\left(\widetilde{\underline{Lm}_i}^{2,T-1}\right)'\widetilde{\underline{C}_i}^{2,T-1}$$

with:

- $A_{it} = y^*_{it} - \gamma^Y Ly_{it} - X^Y_{it}\delta^Y - \Omega^I_i\theta^{I,Y}$
- $B_{it} = w_{it} - m_{w_{it}} - \rho_{y,w}\sigma\left(A_{it}\right)$
- $C_{it} = m^*_{it} - m_{m^*_{it}} - b(w_{it} - m_{w_{it}}) - a\left(A_{it}\right)$

C.3 *Parameter* δ^Y

We proceed the same way and we get:

$$V_{\delta Y}^{post,-1} = V_{\delta Y}^{prior,-1} + \sum_{i=1}^{N} \left(\underline{X}_i^{Y\,2,T}\right)' \underline{X}_i^{Y\,2,T} + \frac{\rho_{y,w}^2 \sigma^2}{V^w} \sum_{i=1}^{N} \left(\widetilde{\underline{X}_i^{Y}}^{2,T}\right)' \widetilde{\underline{X}_i^{Y}}^{2,T} + \frac{a^2}{V^m} \sum_{i=1}^{N} \left(\widetilde{\underline{X}_i^{Y}}^{2,T-1}\right)' \widetilde{\underline{X}_i^{Y}}^{2,T-1}$$

$$V_{\delta Y}^{post,-1} M_{\delta Y}^{post} = V_{\delta Y}^{prior,-1} M_{\delta Y}^{prior} + \sum_{i=1}^{N} \left(\underline{X}_i^{Y\,2,T}\right)' \underline{A}_i^{2,T} - \frac{\rho_{y,w}\sigma}{V^w} \sum_{i=1}^{N} \left(\widetilde{\underline{X}_i^{Y}}^{2,T}\right)' \widetilde{\underline{B}}_i^{\,2,T} - \frac{a}{V^m} \sum_{i=1}^{N} \left(\widetilde{\underline{X}_i^{Y}}^{2,T-1}\right)' \widetilde{\underline{C}}_i^{\,2,T-1}$$

with:

- $A_{it} = y_{it}^* - \gamma^Y L y_{it} - \gamma^M L m_{it} - \Omega_i^I \theta^{I,Y}$
- $B_{it} = w_{it} - m_{w_{it}} - \rho_{y,w}\sigma\left(A_{it}\right)$
- $C_{it} = m_{it}^* - m_{m_{it}^*} - b(w_{it} - m_{w_{it}}) - a\left(A_{it}\right)$

D Initial equations

D.1 *Parameter* δ_0^M

δ_0^M only enters m_{i1}^*. We thus get:

$$V_{\delta_0^M}^{post,-1} = V_{\delta_0^M}^{prior,-1} + \frac{1}{V^m} \sum_{i=1}^{N} \left(\widetilde{X_{i1}^M}\right)' \widetilde{X_{i1}^M}$$

$$V_{\delta_0^M}^{post,-1} M_{\delta_0^M}^{post} = V_{\delta_0^M}^{prior,-1} M_{\delta_0^M}^{prior} + \frac{1}{V^m} \sum_{i=1}^{N} \left(\widetilde{X_{i1}^M}\right)' \widetilde{A}_{i1}$$

with:

- $A_{i1} = m_{i1}^* - \Omega_i^I \alpha^{I,M} - a(y_{i1}^* - m_{y_{i1}^*}) - b(w_{i1} - m_{w_{i1}})$

D.2 *Parameter* δ_0^Y

We proceed the same way and we get:

$$V_{\delta_0^Y}^{post,-1} = V_{\delta_0^Y}^{prior,-1} + \sum_{i=1}^{N} X_{i1}^{Y\prime} X_{i1}^{Y} + \left(\frac{\rho_{y,w}^2 \sigma^2}{V^w} + \frac{a^2}{V^m}\right) \sum_{i=1}^{N} \widetilde{X_{i1}^{Y}}' \widetilde{X_{i1}^{Y}}$$

$$V_{\delta_0^Y}^{post,-1} M_{\delta_0^Y}^{post} = V_{\delta_0^Y}^{prior,-1} M_{\delta_0^Y}^{prior} + \sum_{i=1}^{N} X_{i1}^{Y\prime} A_i - \sum_{i=1}^{N} \widetilde{X_{i1}^{Y}}' \left(\frac{\rho_{y,w}\sigma}{V^w} \widetilde{B}_i + \frac{a}{V^m} \widetilde{C}_i\right)$$

with:

- $A_i = y^*_{i1} - \Omega_i^E \alpha^{I,Y}$
- $B_i = w_{i1} - m_{w_{i1}} - \rho_{y,w}\sigma A_i$
- $C_i = m^*_{i1} - m_{m^*_{i1}} - b(w_{i1} - m_{w_{i1}}) - aA_i$

E Latent variables

E.1 Latent participation y^*_{it}

We seek for terms where y^*_{it} is.

1. For $t = 1...T-1$

   (a) If $y_{it} = 1$

$$y^*_{it} \sim \mathcal{NT}_{\mathbb{R}^+}(M^{Apost}, V^{Apost})$$
$$V^{Apost,-1}M^{Apost} = (\frac{\sigma\rho_{v,\epsilon}}{V^w} - \frac{ab}{V^m})(w_{it} - m_{w_{it}}) + \frac{a}{V^m}(m^*_{it} - m_{m^*_{it}}) + (\frac{\sigma^2\rho^2_{v,\epsilon}}{V^w} + \frac{a^2}{V^m} + 1)m_{y^*_{it}}$$
$$V^{Apost} = \frac{1}{1 + \frac{a^2}{V^m} + \frac{\sigma^2\rho^2_{v,\epsilon}}{V^w}}$$

   (b) If $y_{it} = 0$

$$y^*_{it} \sim \mathcal{NT}_{\mathbb{R}^-}(m_{y^*_{it}}, 1)$$

2. For $t = T$

   (a) If $y_{iT} = 1$

$$y^*_{iT} \sim \mathcal{NT}_{\mathbb{R}^+}(M^{Apost}, 1 - \rho^2_{v,\epsilon})$$
$$M^{Apost} = (1 - \rho^2_{v,\epsilon})\left(m_{y^*_{iT}}(1 + \frac{\sigma^2\rho^2_{v,\epsilon}}{V^w}) + \frac{\sigma\rho_{v,\epsilon}}{V^w}(w_{iT} - m_{w_{iT}})\right)$$

   (b) If $y_{iT} = 0$

$$y^*_{iT} \sim \mathcal{NT}_{\mathbb{R}^-}(m_{y^*_{iT}}, 1)$$

E.2 Latent mobility m_{it}^*

Two conditions must be checked: first, $t = 1...T-1$ and, $y_{it} = 1$. When these conditions are fulfilled, we distinguish between different cases:

1. If $y_{it+1} = 0$

$$m_{it}^* \sim \mathcal{N}(M_{it}^m, V^m) \quad \text{and} \quad m_{it} = \mathbb{I}(m_{it}^* > 0)$$

2. If $y_{it+1} = 1$

   (a) If $m_{it} = 1$

$$m_{it}^* \sim \mathcal{NT}_{\mathbb{R}^+}(M_{it}^m, V^m)$$

   (b) If $m_{it} = 0$

$$m_{it}^* \sim \mathcal{NT}_{\mathbb{R}^-}(M_{it}^m, V^m)$$

F Variance-Covariance Matrix of Residuals

We use the Hastings-Metropolis algorithm because our priors are not conjugate (the posterior does not belong to the same family of distributions as the prior).

G Variance-Covariance Matrices of Individual Effects $\Sigma_i^I|(...); z; y, w$

The parameters $\eta_j, j = 1...10$ and $\gamma_j, j = 1...5$ do not enter the full conditional likelihood. They only enter the prior distributions. Let us denote p the parameter we are interested in among $\eta_j, j = 1...10$ and $\gamma_j, j = 1...5$.

$$\begin{aligned} l(p|(-p), \theta^I) &= l(\theta^I|p)\pi^0(p) \\ &= \pi^0(p)\prod_{i=1}^N l(\theta_i^I|\Sigma_i^I(p)) \\ &\propto \pi^0(p)\prod_{i=1}^N \frac{1}{\sqrt{\det(\Sigma_i^I(p))}} \exp\left(-\frac{1}{2}\theta_i^{I\prime}\Sigma_i^{I,-1}(p)\theta_i^I\right) \end{aligned}$$

We face non conjugate distributions therefore we use the independent Hastings-Metropolis algorithm with the prior distribution as instrumental distribution.

$\star$

H Individual effects

The likelihood terms that include θ^I writes as:

$$\prod_{i=1}^{N} \exp\left(-\frac{1}{2}(y_{i1}^* - m_{y_{i1}^*})^2\right) \exp\left(-\frac{y_{i1}}{2V^w}(w_{i1} - M_{i1}^w)^2\right)$$
$$\prod_{t=2}^{T} \exp\left(-\frac{1}{2}(y_{it}^* - m_{y_{it}^*})^2\right) \exp\left(-\frac{y_{it}}{2V^w}(w_{it} - M_{it}^w)^2\right) \exp\left(-\frac{y_{it-1}}{2V^m}(m_{it-1}^* - M_{it-1}^m)^2\right)$$

with

$$\begin{aligned}
M_{it}^m &= m_{m_{it}^*} + a(y_{it}^* - m_{y_{it}^*}) + b(w_{it} - m_{w_{it}}) \\
M_{it}^w &= m_{w_{it}} + \sigma\rho_{v,\varepsilon}(y_{it}^* - m_{y_{it}^*})
\end{aligned}$$

The following notations are useful:

1. **First term**

$$\begin{aligned}
(y_{i1}^* - m_{y_{i1}^*})^2 &= (A_{i1} - \Omega_i^I \alpha^{I,Y})^2 \\
A_{i1} &= y_{i1}^* - XY_{i1}\delta_0^Y
\end{aligned}$$

2. **Second term**

$$\begin{aligned}
y_{i1}(w_{i1} - M_{w_{i1}})^2 &= y_{i1}(B_{i1} - \Omega_i^I \theta^{I,W} + \rho_{v,\varepsilon}\sigma\Omega_i^I \alpha^{I,Y})^2 \\
B_{i1} &= w_{i1} - XW_{i1}\delta^w - \rho_{v,\varepsilon}\sigma(y_{i1}^* - XY_{i1}\delta_0^Y) \\
\widetilde{B}_{i1} &= y_{i1}B_{i1} \\
\widetilde{\Omega}_{i1}^I &= y_{i1}\Omega_i^I
\end{aligned}$$

3. **Third term**

$$
\begin{aligned}
&(y_{it}^* - m_{y_{it}^*})^2 = (C_{it} - \Omega_i^I \theta^{Y,I})^2 \\
&C_{it} = y_{it}^* - XY_{it}\delta^Y - \gamma^Y y_{it-1} - \gamma^M m_{it-1}
\end{aligned}
$$

4. **Fourth term**

$$
\begin{aligned}
&y_{it}(w_{it} - M_{w_{it}})^2 = y_{it}(D_{it} - \Omega_i^I \theta^{W,I} + \rho_{v,\varepsilon}\sigma\Omega_i^I \theta^{Y,I})^2 \\
&D_{it} = w_{it} - XW_{it}\delta^w - \rho_{v,\varepsilon}\sigma C_{it} \\
&\widetilde{D}_{it} = y_{it} D_{it} \\
&\widetilde{\Omega}_{it}^I = y_{it}\Omega_i^I
\end{aligned}
$$

5. **Fifth term**

For $t > 1$

$$
\begin{aligned}
&y_{it}(m_{it}^* - M_{m_{it}^*})^2 = y_{it}(F_{it} + \Omega_i^I(-\theta_{M,I} + a\theta^{Y,I} + b\theta^{W,I}))^2 \\
&F_{it} = m_{it}^* - \gamma m_{it-1} - XM_{it}\delta^M - aC_{it} - b(w_{it} - XW_{it}\delta^w \\
&\widetilde{F}_{it} = y_{it} F_{it}
\end{aligned}
$$

For $t = 1$

$$
\begin{aligned}
&y_{i1}(m_{i1}^* - M_{m_{i1}^*})^2 = y_{i1}(G_{i1} + \Omega_i^I(-\alpha_{M,I} + a\alpha^{Y,I} + b\theta^{W,I}))^2 \\
&G_{i1} = m_{i1}^* - XM_{i1}\delta_0^M - aA_{i1} - b(w_{i1} - XW_{i1}\delta^w) \\
&\widetilde{G}_{i1} = y_{i1} G_{i1}
\end{aligned}
$$

The posterior distribution satisfies:

$$
\begin{aligned}
l(\theta^E|...) \quad \propto \quad & \exp\left(-\frac{1}{2}\theta^{I\prime}D^{I,-1}\theta^I\right) \\
& \exp\left(-\frac{1}{2}\sum_{i=1}^{n}(A_{i1}-\Omega_i^I\alpha^{Y,I})^2-\frac{1}{2V^w}\sum_i\left(\widetilde{B}_{i1}-\widetilde{\Omega}_{i1}^I(\theta^{W,I}-\rho_{v,\varepsilon}\sigma\alpha^{Y,I})\right)^2\right) \\
& \exp\left(-\frac{1}{2}\sum_i\sum_{t=2}^{T}(C_{it}-\Omega_i^I\theta^{Y,I})^2-\frac{1}{2V^w}\sum_i\sum_{t=2}^{T}\left(\widetilde{D}_{it}-\widetilde{\Omega}_{it}^I(\theta^{W,I}-\rho_{v,\varepsilon}\sigma\theta^{Y,I})\right)^2\right) \\
& \exp\left(-\frac{1}{2V^m}\sum_i(\widetilde{G}_{i1}+\widetilde{\Omega}_{i1}^I(-\alpha^{M,I}+a\alpha^{Y,I}+b\theta^{W,I}))^2\right) \\
& \exp\left(-\frac{1}{2V^m}\sum_i\sum_{t=2}^{T-1}\left(\widetilde{F}_{it}+\widetilde{\Omega}_{it}^I(-\theta^{M,I}+a\theta^{Y,I}+b\theta^{W,I})\right)^2\right)
\end{aligned}
$$

We define several projection operators: $P_1=(I_J,\underbrace{0_J,...,0_J}_{\text{4 matrices}})$ and we notice:

$$
\begin{aligned}
P_1\theta^I &= \alpha^{I,Y} \\
P_2\theta^I &= \alpha^{I,M} \\
P_3\theta^I &= \theta^{I,Y} \\
P_4\theta^I &= \theta^{I,W} \\
P_5\theta^I &= \theta^{I,M}
\end{aligned}
$$

Let us denote:

1. $E_1=\sum_{i=1}^n\Omega_i^{I\prime}\Omega_i^I$
2. $\widetilde{E_1}=\sum_{i=1}^n\widetilde{\Omega_{i1}^I}'\widetilde{\Omega_{i1}^I}$
3. $E_{2T}=\sum_{i=1}^n\underline{\Omega}_i^{I\prime}\underline{\Omega}_i^I$
4. $\widetilde{E_{2T}}=\sum_{i=1}^n\widetilde{\underline{\Omega}_i^I}'\widetilde{\underline{\Omega}_i^I}$
5. $\widetilde{E_{2,T-1}}=\sum_{i=1}^n\underline{\Omega}_i^{\widetilde{I,2,T-1}\prime}\underline{\Omega}_i^{\widetilde{I,2,T-1}}$

So we get for the variance-covariance matrix:

$$V^{-1} = D_0^{E,-1} + \left| \begin{array}{c|c|c|c|c} E_1 + (\frac{\rho_{v,\varepsilon}^2 \sigma^2}{V^w} + \frac{a^2}{V^m}) \widetilde{E_1} & -\frac{a}{V^m} \widetilde{E_1} & 0 & T_{41} & 0 \\ -\frac{a}{V^m} \widetilde{E_1} & \frac{1}{V^m} \widetilde{E_1} & 0 & T_{42} & 0 \\ 0 & 0 & E_{2T} + \frac{\rho_{v,\varepsilon}^2 \sigma^2}{V^w} \widetilde{E_{2,T}} + \frac{a^2}{V^m} \widetilde{E_{2,T-1}} & T_{43} & T_{53} \\ (-\frac{\rho_{v,\varepsilon} \sigma}{V^w} + \frac{ab}{V^m}) \widetilde{E_1} & -\frac{b}{V^m} \widetilde{E_1} & -\frac{\rho_{v,\varepsilon} \sigma}{V^w} \widetilde{E_{2T}} + \frac{ab}{V^m} \widetilde{E_{2T-1}} & \widetilde{E_1}(\frac{1}{V^w} + \frac{b^2}{V^m}) + \frac{1}{V^w} \widetilde{E_{2T}} + \frac{b^2}{V^m} \widetilde{E_{2T-1}} & T_{54} \\ 0 & 0 & -\frac{a}{V^m} \widetilde{E_{2T-1}} & -\frac{b}{V^m} \widetilde{E_{2T-1}} & \frac{1}{V^m} \widetilde{E_{2T-1}} \end{array} \right|$$

⋆

As for the posterior mean:

$$\begin{pmatrix} \sum_{i=1}^n \Omega_i^{I'} A_{i1} - \frac{\rho_{v,\varepsilon}\sigma}{V^w} \sum_{i=1}^n \widetilde{\Omega_{i1}^I}' \widetilde{B_{i1}} - \frac{a}{V^m} \sum_{i=1}^n \widetilde{\Omega_{i1}^I}' \widetilde{G_{i1}} \\ \frac{1}{V^m} \sum_{i=1}^n \widetilde{\Omega_{i1}^I}' \widetilde{G_{i1}} \\ \sum_{i=1}^n \underline{\Omega}_i^{I'} \underline{C}_i - \frac{\rho_{v,\varepsilon}\sigma}{V^w} \sum_{i=1}^n \widetilde{\underline{\Omega}_i^I}' \widetilde{\underline{D}_i} - \frac{a}{V^m} \sum_{i=1}^n \widetilde{\underline{\Omega}_{iT-1}^I}' \widetilde{\underline{F}_{iT-1}} \\ \frac{1}{V^w} \sum_{i=1}^n \widetilde{\Omega_{i1}^I}' \widetilde{B_{i1}} + \frac{1}{V^w} \sum_{i=1}^n \widetilde{\underline{\Omega}_i^I}' \widetilde{\underline{D}_i} - \frac{b}{V^m} \sum_{i=1}^n \widetilde{\Omega_{i1}^I}' \widetilde{G_{i1}} - \frac{b}{V^m} \sum_{i=1}^n \widetilde{\underline{\Omega}_{iT-1}^I}' \widetilde{\underline{F}_{iT-1}} \\ \frac{1}{V^m} \sum_{i=1}^n \widetilde{\underline{\Omega}_{iT-1}^I}' \widetilde{\underline{F}_{iT-1}} \end{pmatrix}$$

⋆

Table 1: Wage Equation

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Parameter:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Intercept	2.0073	0.0638	1.7819	2.2309	2.1197	0.0631	1.8879	2.3716	2.1436	0.0648	1.8955	2.3655	2.1846	0.0678	1.9322	2.4325
Experience	0.0495	0.0027	0.0380	0.0595	0.0570	0.0025	0.0457	0.0668	0.0859	0.0050	0.0681	0.1036	0.0674	0.0031	0.0553	0.0799
Experience squared	-0.0006	0.0000	-0.0008	-0.0004	-0.0008	0.0000	-0.0010	-0.0006	-0.0014	0.0001	-0.0018	-0.0009	-0.0011	0.0001	-0.0013	-0.0008
Seniority	0.0031	0.0018	-0.0046	0.0097	-0.0032	0.0018	-0.0110	0.0032	-0.0046	0.0041	-0.0225	0.0119	0.0094	0.0022	0.0001	0.0196
Seniority squared	-0.0002	0.0001	-0.0005	0.0001	0.0000	0.0001	-0.0002	0.0004	0.0002	0.0002	-0.0005	0.0009	-0.0002	0.0001	-0.0005	0.0002
Part Time	-0.5330	0.0123	-0.5768	-0.4836	-0.3941	0.0107	-0.4326	-0.3563	-0.6393	0.0170	-0.7005	-0.5806	-0.8471	0.0154	-0.9101	-0.7854
Individual and Family Characteristics:																
Sex	0.4848	0.0361	0.3764	0.6080	0.4486	0.0350	0.3331	0.5637	0.3363	0.0357	0.1892	0.4664	0.5211	0.0393	0.3876	0.6600
Married	0.0310	0.0145	-0.0240	0.0838	-0.0092	0.0123	-0.0518	0.0434	-0.0113	0.0213	-0.1041	0.0681	0.1918	0.0229	0.1085	0.2804
Lives in Couple	0.0412	0.0198	-0.0418	0.1205	-0.0229	0.0174	-0.0871	0.0393	-0.0308	0.0305	-0.1402	0.0856	-0.0040	0.0248	-0.0974	0.0859
Lives in region Ile de France	0.0895	0.0245	-0.0094	0.1773	0.1077	0.0222	0.0275	0.1810	0.1322	0.0281	0.0338	0.2557	0.1489	0.0189	0.0703	0.2163
Unemployment Rate	0.0353	0.0963	-0.3274	0.3882	0.1592	0.0942	-0.1783	0.4837	0.1560	0.0977	-0.1683	0.5420	0.1747	0.0951	-0.2355	0.5643
Nationality:																
Other than French	0.1277	0.0393	-0.0266	0.2638	0.0637	0.0466	-0.1143	0.2131	0.0508	0.0444	-0.1093	0.2235	-0.1034	0.0354	-0.2252	0.0110
Father other than French	0.0855	0.0851	-0.2189	0.4122	0.0644	0.0661	-0.1881	0.2883	0.0500	0.0684	-0.1821	0.3086	0.0108	0.0718	-0.2373	0.2552
Mother other than French	0.0658	0.0793	-0.2039	0.3260	0.0279	0.0658	-0.2098	0.2568	0.0158	0.0616	-0.2825	0.2488	0.0312	0.0702	-0.2161	0.2773
Cohort Effects:																
Born before 1929	0.1122	0.0621	-0.1132	0.3454	0.1044	0.0732	-0.1792	0.4504	0.0724	0.0827	-0.2522	0.4000	0.2454	0.0670	0.0021	0.5286
Born between 1930 and 1939	0.1687	0.0554	-0.0827	0.3711	0.1547	0.0606	-0.0556	0.3752	-0.0340	0.0747	-0.3405	0.2196	0.3615	0.0600	0.1531	0.6008
Born between 1940 and 1949	0.4048	0.0521	0.1794	0.5965	0.3314	0.0530	0.1372	0.5411	0.0387	0.0604	-0.2021	0.2974	0.4010	0.0521	0.2218	0.5953
Born between 1950 and 1959	0.5193	0.0508	0.3437	0.7162	0.4863	0.0480	0.3119	0.6634	0.3354	0.0512	0.1332	0.5371	0.5434	0.0510	0.3070	0.7258
Born between 1960 and 1969	0.4749	0.0677	0.2206	0.7024	0.4902	0.0511	0.2883	0.7254	0.4141	0.0450	0.2398	0.5868	0.6066	0.0599	0.3713	0.8314

(Continues on next page)

Table 1: Wage Equation (continued)

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Parameter:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Industry:																
Energy	-0.1447	0.0583	-0.3703	0.0821	0.1173	0.0533	-0.1135	0.3102	0.1136	0.0672	-0.1450	0.3856	0.1873	0.0524	0.0029	0.4110
Intermediate Goods	0.1564	0.0305	0.0361	0.2801	0.1695	0.0274	0.0647	0.2743	0.1909	0.0435	0.0113	0.3562	0.1285	0.0355	-0.0017	0.2731
Equipment Goods	0.1806	0.0305	0.0631	0.2969	0.1734	0.0271	0.0674	0.2882	0.1981	0.0416	0.0160	0.3681	0.2079	0.0333	0.0835	0.3266
Consumption Goods	0.0983	0.0290	-0.0130	0.2060	0.1432	0.0285	0.0345	0.2563	0.2217	0.0406	0.0619	0.3632	0.1166	0.0357	-0.0171	0.2605
Construction	0.1716	0.0311	0.0633	0.2843	0.2356	0.0264	0.1232	0.3453	0.3035	0.0485	0.0976	0.4766	0.1422	0.0426	-0.0121	0.3203
Retail and Wholesome Goods	0.0200	0.0252	-0.0741	0.1146	0.0841	0.0240	-0.0043	0.1768	0.1746	0.0330	0.0501	0.2985	0.1435	0.0322	0.0223	0.2855
Transport	0.0606	0.0339	-0.0761	0.1753	0.2148	0.0309	0.0793	0.3258	0.1937	0.0437	0.0361	0.3566	0.1271	0.0368	-0.0064	0.2732
Market Services	-0.0341	0.0237	-0.1292	0.0526	0.0993	0.0229	0.0002	0.1794	0.1511	0.0300	0.0489	0.2698	0.0986	0.0277	0.0002	0.1928
Insurance	0.0920	0.0643	-0.1553	0.3369	0.1254	0.0578	-0.0825	0.3406	0.1647	0.0578	-0.0447	0.3985	0.1779	0.0522	-0.0309	0.3790
Banking and Finance Industry	0.2280	0.0638	-0.0113	0.4626	0.1663	0.0549	-0.0515	0.3760	0.2634	0.0479	0.0902	0.4633	0.2186	0.0443	0.0471	0.3820
Non Market Services	-0.1098	0.0291	-0.2225	0.0038	-0.0336	0.0289	-0.1369	0.0790	-0.1326	0.0362	-0.2761	0.0174	-0.2934	0.0319	-0.4176	-0.1806
Job Switch variables in First Sample Year																
JC=job change in 1st year (yes=1)	0.0012	0.0127	-0.0441	0.0518	0.0139	0.0102	-0.0209	0.0514	0.0140	0.0224	-0.0762	0.1031	0.0002	0.0267	-0.0954	0.0961
Experience at *t-1* if *JC*=1	0.0000	0.0005	-0.0021	0.0018	0.0005	0.0007	-0.0024	0.0035	0.0017	0.0017	-0.0047	0.0084	-0.0003	0.0018	-0.0078	0.0070
Number of switches of jobs that lasted																
Up to 1 year	0.5643	0.0484	0.3624	0.7319	0.5788	0.0473	0.3925	0.7460	0.7158	0.0514	0.5199	0.9095	0.6290	0.0481	0.4185	0.8193
Between 2 and 5 years	0.5208	0.0514	0.3359	0.7023	0.5596	0.0489	0.3618	0.7765	0.6448	0.0551	0.4298	0.8442	0.6078	0.0508	0.4182	0.7926
Between 6 and 10 years	0.4411	0.0551	0.2052	0.6344	0.5207	0.0519	0.3372	0.7135	0.4469	0.0691	0.1840	0.7121	0.4796	0.0555	0.2683	0.6746
More than 10 years	0.4828	0.0556	0.2617	0.6865	0.4609	0.0543	0.2495	0.6423	0.3352	0.0755	0.0571	0.6265	0.4686	0.0568	0.2555	0.6855
Seniority at last job change that lasted																
Between 2 and 5 years	0.0052	0.0092	-0.0298	0.0367	0.0184	0.0067	-0.0105	0.0438	-0.0119	0.0131	-0.0601	0.0361	0.0397	0.0092	0.0051	0.0728
Between 6 and 10 years	-0.0053	0.0065	-0.0306	0.0189	-0.0017	0.0060	-0.0252	0.0200	-0.0158	0.0133	-0.0726	0.0316	0.0087	0.0057	-0.0215	0.0289
More than 10 years	-0.0078	0.0054	-0.0274	0.0114	-0.0214	0.0057	-0.0438	0.0007	-0.0325	0.0113	-0.0764	0.0100	-0.0072	0.0046	-0.0235	0.0101
Experience at last job change that lasted																
Up to 1 year	-0.0012	0.0005	-0.0030	0.0009	-0.0049	0.0005	-0.0067	-0.0029	-0.0048	0.0011	-0.0083	-0.0012	0.0003	0.0009	-0.0031	0.0035
Between 2 and 5 years	-0.0003	0.0012	-0.0044	0.0037	-0.0011	0.0011	-0.0053	0.0033	0.0056	0.0028	-0.0046	0.0173	-0.0062	0.0017	-0.0126	0.0009
Between 6 and 10 years	0.0002	0.0022	-0.0082	0.0088	-0.0032	0.0026	-0.0127	0.0063	0.0096	0.0065	-0.0120	0.0352	-0.0020	0.0026	-0.0111	0.0099
More than 10 years	0.0037	0.0031	-0.0086	0.0148	0.0128	0.0035	-0.0003	0.0262	0.0258	0.0079	-0.0064	0.0542	0.0079	0.0042	-0.0063	0.0227

Notes: Source : DADS-EDP from 1976 to 1996. 3,000 individuals randomly selected within 32,596; 12,405; 34,071; and 7,579 respectively.
Estimation by Gibbs Sampling. 80,000 iterations for the first three groups with a burn-in equal to 70,000; 30,000 iterations and 20,000 for the last

Table 2: Participation Equation

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Parameter:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Intercept	-1.1375	0.2254	-2.0040	-0.2941	-1.1732	0.2274	-1.9730	-0.2693	-0.8575	0.2244	-1.6982	0.0498	-0.7456	0.2288	-1.7444	0.1411
Experience	0.1717	0.0050	0.1534	0.1914	0.2954	0.0055	0.2755	0.3147	0.3986	0.0059	0.3777	0.4203	0.1435	0.0053	0.1248	0.1654
Experience squared	-0.0031	0.0001	-0.0035	-0.0028	-0.0055	0.0001	-0.0058	-0.0050	-0.0079	0.0001	-0.0083	-0.0074	-0.0033	0.0001	-0.0038	-0.0029
Local Unemployment Rate	7.2233	0.3014	6.0385	8.1602	8.7965	0.3535	7.5332	10.1660	6.2470	0.2813	5.0410	7.5074	6.3682	0.5105	4.1896	8.1078
Lagged Variables:																
Lagged Mobility γ^M	1.4515	0.0184	1.3928	1.5274	1.1894	0.0187	1.1203	1.2550	0.8826	0.0177	0.8172	0.9528	1.0206	0.0200	0.9467	1.1010
Lagged Participation γ^Y	0.1456	0.0098	0.1148	0.1835	0.1191	0.0098	0.0803	0.1574	0.0885	0.0095	0.0560	0.1207	0.1880	0.0094	0.1524	0.2284
Individual and Family Characteristics:																
Sex (equal to 1 for men)	0.1815	0.0421	0.0343	0.3041	0.0921	0.0408	-0.0629	0.2414	-0.0919	0.0411	-0.2231	0.0440	0.3057	0.0471	0.1688	0.4835
Children between 0 and 3	-0.3850	0.0333	-0.5048	-0.2624	-0.2215	0.0284	-0.3345	-0.1140	-0.2355	0.0335	-0.3653	-0.1158	0.0638	0.0323	-0.0653	0.1925
Children between 3 and 6	-0.3068	0.0311	-0.4193	-0.1866	-0.2696	0.0286	-0.3853	-0.1625	-0.2880	0.0367	-0.4132	-0.1473	-0.0295	0.0324	-0.1673	0.1063
Lives in Couple	-0.1690	0.0398	-0.3186	-0.0076	-0.2717	0.0406	-0.4244	-0.1234	-0.1940	0.0435	-0.3471	-0.0452	0.0595	0.0489	-0.1300	0.2304
Married	-0.1219	0.0268	-0.2191	-0.0227	-0.1913	0.0298	-0.2889	-0.0705	-0.2298	0.0301	-0.3426	-0.1197	0.0421	0.0354	-0.0936	0.1648
Lives in region Ile de France	0.0929	0.0361	-0.0324	0.2221	0.1006	0.0377	-0.0416	0.2509	0.0566	0.0257	-0.0382	0.1457	5.8202	0.2312	5.0749	6.4415
Nationality:																
Other than French	-0.2676	0.0471	-0.4200	-0.1047	-0.3383	0.0518	-0.5219	-0.1432	-0.2124	0.0479	-0.3719	-0.0462	-0.2358	0.0441	-0.3837	-0.0788
Father other than French	-0.0174	0.1726	-0.5539	0.6346	-0.2033	0.1028	-0.5343	0.1511	-0.0865	0.0973	-0.4581	0.2226	-0.0171	0.1254	-0.3995	0.4122
Mother other than French	-0.0907	0.1483	-0.6944	0.3956	0.0759	0.1144	-0.3143	0.5599	-0.0574	0.0888	-0.3750	0.2653	0.0851	0.1125	-0.2942	0.4720
Cohort Effects:																
Born before 1929	-2.7065	0.0598	-2.9093	-2.4886	-3.5956	0.1139	-3.9867	-3.1516	-3.4916	0.1193	-3.9338	-3.0827	-2.5766	0.0943	-2.9706	-2.2175
Born between 1930 and 1939	-2.3839	0.0710	-2.6506	-2.1372	-3.4876	0.0876	-3.9045	-3.2078	-4.4233	0.1119	-4.8957	-4.0327	-2.4421	0.0865	-2.7478	-2.0839
Born between 1940 and 1949	-1.9668	0.0710	-2.2632	-1.7182	-3.0691	0.0743	-3.3482	-2.7519	-3.8498	0.0899	-4.1460	-3.5430	-2.2836	0.0717	-2.5334	-1.9232
Born between 1950 and 1959	-1.3753	0.0637	-1.6339	-1.1501	-2.0515	0.0579	-2.2560	-1.8423	-2.0363	0.0560	-2.2784	-1.7976	-2.0120	0.0613	-2.2404	-1.7859
Born between 1960 and 1969	-0.6219	0.0911	-0.9140	-0.2750	-0.8117	0.0498	-1.0466	-0.6440	-0.9218	0.0385	-1.0643	-0.7779	-1.5498	0.0719	-1.8007	-1.2745

Notes: Source : DADS-EDP from 1976 to 1996. 3,000 individuals randomly selected within 32,596; 12,405; 34,071; and 7,579 respectively.
Estimation by Gibbs Sampling. 80,000 iterations for the first three groups with a burn-in equal to 70,000; 30,000 iterations and 20,000 for the last

Table 3: Mobility Equation

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Parameter:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Intercept	2.0768	0.6692	-0.0527	4.6419	3.0425	0.9704	0.6321	6.2749	3.1823	0.6672	1.2765	5.0414	0.9000	0.4274	-0.7862	2.5078
Experience	0.5396	0.1034	0.2081	0.8046	0.5690	0.0957	0.3434	0.8461	0.4590	0.0960	0.1462	0.6643	0.0105	0.0087	-0.0255	0.0416
Experience squared	-0.0105	0.0020	-0.0162	-0.0050	-0.0087	0.0026	-0.0155	-0.0022	-0.0058	0.0029	-0.0128	0.0019	-0.0004	0.0002	-0.0012	0.0003
Seniority	0.2730	0.1401	0.0010	0.5424	-0.2201	0.1309	-0.4515	0.0958	-0.0769	0.0808	-0.2953	0.0828	0.0121	0.0088	-0.0172	0.0486
Seniority squared	-0.0076	0.0054	-0.0187	0.0036	0.0049	0.0067	-0.0106	0.0177	0.0024	0.0041	-0.0077	0.0118	-0.0006	0.0004	-0.0019	0.0006
Local Unemployment Rate	0.2215	1.0307	-3.4492	3.7278	0.1010	0.9814	-3.4842	3.8917	0.3052	0.9760	-3.5975	3.8724	0.6457	0.6962	-2.1651	3.2531
Part Time	0.3200	0.4890	-0.9670	1.3546	0.5539	0.3695	-0.4958	1.6576	0.0314	0.3861	-1.1603	0.9916	-0.4730	0.0410	-0.6090	-0.3154
Lagged Variables:																
Lagged Mobility γ	1.0420	0.3071	0.4791	1.7680	0.2436	0.2115	-0.2504	0.7045	-0.4555	0.2362	-0.9903	0.2676	0.0276	0.0415	-0.1055	0.1717
Individual and Family Characteristics:																
Sex	1.3045	0.6700	-0.2051	2.5813	0.4414	0.6360	-0.9448	1.7622	0.3018	0.4045	-0.8375	1.4962	-0.1397	0.0613	-0.3470	0.1009
Children between 0 and 3	0.4976	0.6191	-0.9096	2.4760	-0.1539	0.5621	-1.6982	0.9734	0.3433	0.8318	-1.4608	2.3896	0.0523	0.0479	-0.1435	0.2443
Children between 3 and 6	-0.3931	0.6255	-2.1820	1.1188	-0.3149	0.5039	-1.3369	0.9304	0.0606	1.0302	-1.8376	2.7593	0.0611	0.0472	-0.1025	0.2307
Married	-0.6253	0.6188	-1.9813	0.6223	0.0300	0.3454	-0.8544	0.9412	0.5566	0.9155	-0.9050	2.7615	0.1996	0.0559	-0.0066	0.4296
Lives in Couple	0.4495	0.9565	-1.8453	2.0857	1.0584	0.6827	-0.5039	2.6736	-0.0651	0.7481	-1.8414	1.7181	0.1060	0.0800	-0.1951	0.3884
Lives in region Ile de France	-0.0926	0.6084	-1.3876	1.3303	0.8778	1.0081	-1.3791	2.6800	0.8153	0.4044	-0.1589	1.8933	-0.1971	0.0520	-0.4330	-0.0044
Nationality																
Other than French	-0.0496	0.6347	-1.3465	2.0311	-0.0568	0.7453	-1.7824	1.3526	0.0634	0.6424	-1.1297	1.9631	0.0332	0.0592	-0.1551	0.2508
Father other than French	0.5663	0.7752	-1.5570	2.6507	0.3453	0.7850	-1.8083	2.4772	-0.1204	0.5706	-1.5624	1.3503	0.1121	0.1567	-0.5773	0.7734
Mother other than French	0.4739	0.7163	-1.9174	2.7725	0.0517	1.0513	-2.7990	3.0469	0.0315	0.7974	-1.5461	1.9293	-0.2494	0.1359	-0.7371	0.2586
Cohort Effects																
Born before 1929	0.1461	0.7316	-2.6363	2.8522	-0.1275	0.8861	-3.6205	2.5929	0.2812	1.0451	-3.0258	3.5326	1.1003	0.3911	-0.4400	2.8883
Born between 1930 and 1939	-1.4814	0.5522	-3.2903	0.5178	0.1245	0.8311	-2.6538	2.1118	-0.3355	0.9749	-2.8263	2.4097	0.7095	0.3652	-0.7969	2.4092
Born between 1940 and 1949	0.5822	0.6294	-1.2925	2.3450	0.7670	0.6169	-1.1350	2.5540	-0.0346	0.8542	-2.1876	2.7618	0.3894	0.3526	-0.8703	1.9306
Born between 1950 and 1959	0.8313	0.4838	-0.7063	2.5172	0.2643	0.7417	-1.3779	2.6224	0.3555	0.5637	-1.1589	2.2134	-0.0105	0.3492	-1.2434	1.4603
Born between 1960 and 1969	1.2615	0.6308	-0.9655	3.1850	1.0159	0.6511	-0.6204	3.0558	0.4400	0.6685	-1.3531	1.8718	-0.3265	0.3501	-1.5816	1.0114
Industry																
Energy	0.1766	1.0965	-2.1060	3.1748	0.0472	0.9691	-2.7353	2.6165	0.1984	0.8704	-2.4942	2.1947	0.8589	0.1870	0.1817	1.5324
Intermediate Goods	0.1045	0.7145	-2.0907	2.4042	0.7122	0.7796	-0.6720	3.6010	-0.3831	0.5566	-1.8946	1.2588	0.3333	0.1342	-0.1212	0.8148
Equipment Goods	0.8554	0.5105	-0.8460	2.1046	-0.5386	0.6105	-1.8450	1.5520	-0.1609	0.5349	-1.6593	1.5860	0.4401	0.1294	0.0164	0.8694
Consumption Goods	0.4125	0.6689	-0.9937	2.0925	0.0398	0.5209	-1.4037	1.6298	0.3966	0.8995	-1.8249	2.8584	0.3920	0.1356	-0.1227	0.9427
Construction	-0.0796	0.7332	-1.8977	1.6596	1.0926	0.7752	-1.1446	2.9628	0.1534	0.8276	-2.2654	2.0930	0.0672	0.1514	-0.4570	0.5819
Retail and Wholesome Goods	0.2220	0.6971	-1.7581	2.1362	0.6457	0.8289	-1.2875	2.6942	0.5952	0.8010	-1.2190	2.4780	0.3799	0.1308	-0.1194	0.8332
Transport	0.4409	0.7512	-1.7913	3.1346	-0.0717	0.7446	-1.8050	1.9270	0.6189	0.7810	-1.5800	2.5194	0.6788	0.1456	0.1993	1.2970
Market Services	-0.0385	0.5675	-1.4497	1.6268	0.4735	0.6478	-1.2049	2.1805	0.3704	0.4935	-1.0127	1.9475	0.3927	0.1206	-0.0458	0.8320
Insurance	0.0604	0.7887	-3.0204	2.3840	0.0165	1.0426	-2.8717	2.8364	0.1961	0.7115	-2.0789	2.2508	0.5749	0.1875	-0.0964	1.3216
Banking and Finance Industry	-0.3500	1.0847	-3.4689	3.8777	0.4177	0.9146	-1.9790	2.5866	0.9974	0.6082	-0.4458	2.8591	0.6638	0.1546	0.1394	1.1732
Non Market Services	0.2375	0.6835	-1.4936	1.9493	0.3045	0.9820	-1.8504	2.9131	0.2735	0.5716	-1.1924	1.7983	0.4756	0.1308	-0.0101	0.9290

Notes: Source : DADS-EDP from 1976 to 1996. 3,000 individuals randomly selected within 32,596; 12,405; 34,071; and 7,579 respectively.
Estimation by Gibbs Sampling. 80,000 iterations for the first three groups with a burn-in equal to 70,000; 30,000 iterations and 20,000 for the last

Table 4: Initial Participation and Initial Mobility Equations

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Initial Participation	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Intercept	-1.1049	0.3721	-2.4940	0.4408	-1.3045	0.3763	-2.8871	0.1430	-2.1438	0.3995	-3.6831	-0.4294	-1.9636	0.4265	-3.6382	-0.4485
Experience	0.0040	0.0221	-0.0834	0.0769	0.1445	0.0225	0.0552	0.2399	0.1200	0.0259	0.0203	0.2389	0.0389	0.0161	-0.0287	0.1033
Experience squared	0.0008	0.0004	-0.0008	0.0026	-0.0032	0.0006	-0.0062	-0.0008	-0.0018	0.0007	-0.0044	0.0006	-0.0005	0.0005	-0.0025	0.0014
Local Unemployment Rate	1.4790	0.9500	-2.2326	4.9118	1.2546	0.9325	-2.3890	4.5763	1.5701	0.9367	-1.7036	4.8433	-0.1528	0.9771	-3.9408	3.4815
Sex (equal to 1 for men)	0.4185	0.0709	0.1629	0.6876	0.5403	0.0802	0.2358	0.8083	0.3556	0.1011	-0.0670	0.7427	0.5894	0.0963	0.2243	0.9477
Children between 0 and 3	-0.3160	0.1019	-0.6680	0.1912	-0.4859	0.1099	-0.8965	-0.0375	-0.0157	0.1578	-0.5814	0.5854	-0.1432	0.1294	-0.6354	0.3360
Children between 3 and 6	-0.2801	0.1060	-0.6742	0.1319	-0.4825	0.1211	-0.8922	0.0579	0.0617	0.1825	-0.8113	0.8010	-0.0381	0.1286	-0.5044	0.3912
Married	0.2048	0.0844	-0.1450	0.5288	0.4972	0.1048	0.1626	0.8706	0.2742	0.1288	-0.3065	0.8207	0.6459	0.1087	0.2514	1.0670
Lives in region Ile de France	0.0535	0.1132	-0.4016	0.4899	-0.0412	0.1299	-0.5100	0.4701	0.1329	0.1501	-0.4319	0.7393	4.7186	0.4037	3.6399	6.2068
Other than French	-0.0703	0.0836	-0.4245	0.2868	-0.1771	0.0904	-0.5200	0.1534	0.1094	0.1006	-0.2405	0.5141	0.2365	0.0819	-0.0870	0.5201
Father other than French	-0.5915	0.3110	-1.7487	0.3838	0.0976	0.1983	-0.6774	0.8976	-0.2553	0.3713	-1.9563	0.8891	0.0228	0.3773	-1.6193	1.3443
Mother other than French	-0.4983	0.3628	-1.9284	0.6361	-0.3194	0.2603	-1.5939	0.5597	-0.4690	0.4222	-2.3750	1.0202	-0.7449	0.3854	-2.0413	0.5517
Initial Mobility																
Intercept	1.9944	0.7532	-1.2206	4.3769	2.1904	0.7448	-1.0036	5.2922	1.5920	0.7982	-1.1914	4.8785	0.9666	0.5525	-1.0883	2.8413
Experience	0.4527	0.1945	-0.1077	1.0116	0.6157	0.2243	-0.0487	1.1835	0.7278	0.2355	-0.0083	1.3022	0.0010	0.0293	-0.1180	0.1438
Experience squared	-0.0064	0.0050	-0.0188	0.0080	0.0005	0.0062	-0.0151	0.0207	-0.0127	0.0070	-0.0292	0.0081	0.0000	0.0009	-0.0039	0.0036
Seniority	-0.1997	0.3000	-0.9412	0.5127	0.2121	0.3626	-0.7626	1.3041	0.4300	0.5427	-1.1973	1.6984	-0.0802	0.0404	-0.2312	0.0599
Seniority squared	0.0088	0.0186	-0.0351	0.0577	0.0215	0.0248	-0.0317	0.0831	0.0016	0.0311	-0.0553	0.1053	0.0031	0.0023	-0.0050	0.0114
Local Unemployment Rate	0.1037	0.9985	-3.8532	3.7983	0.1182	0.9891	-4.0237	3.9986	0.0949	1.0023	-4.1586	3.9986	0.0834	0.9994	-3.5987	4.0413
Sex (equal to 1 for men)	0.6616	0.7829	-1.3483	2.6187	0.9083	0.6783	-1.4747	2.9115	0.4784	0.7386	-2.0752	2.5779	-0.1453	0.1776	-0.7775	0.6063
Children between 0 and 3	0.3125	0.7709	-1.9758	2.5667	0.0804	0.9480	-2.2955	3.4939	0.3813	0.9485	-2.3097	3.2016	0.1331	0.1974	-0.6553	0.9201
Children between 3 and 6	0.1879	0.9866	-3.0787	2.8965	0.0173	0.8554	-2.3229	2.8490	-0.2035	0.9725	-3.3708	2.8145	0.0608	0.2055	-0.6983	0.8129
Married	0.0028	0.6643	-2.0263	2.2416	0.2060	0.8908	-1.9908	2.7565	0.0279	0.8504	-2.5028	3.2804	0.3996	0.1784	-0.2644	1.0338
Lives in region Ile de France	-0.0528	0.9751	-2.6563	4.1217	0.1092	1.0527	-2.6010	3.3143	0.1813	0.8262	-2.2608	3.0243	-0.3110	0.1447	-0.8127	0.2560
Other than French	0.3440	0.7863	-2.3366	2.2587	0.0603	0.7914	-2.3328	2.3200	0.3700	0.7290	-1.4243	3.7212	0.2506	0.1469	-0.3042	0.8513
Father other than French	0.0910	0.9335	-3.7647	3.4035	0.1031	0.9050	-2.5294	3.2658	0.0279	0.9765	-3.8312	3.4237	-0.4469	0.5608	-2.4698	1.4672
Mother other than French	0.0939	0.9584	-3.0027	3.8895	0.0801	0.9286	-3.0826	3.0646	0.0157	0.9880	-3.5231	3.6970	0.1315	0.6210	-2.0247	2.5181

Notes: Source : DADS-EDP from 1976 to 1996. 3,000 individuals randomly selected within 32,596; 12,405; 34,071; and 7,579 respectively.
Estimation by Gibbs Sampling. 80,000 iterations for the first three groups with a burn-in equal to 70,000; 30,000 iterations and 20,000 for the last

Table 5: Variance-Covariance Matrices (Individual and Idiosyncratic Effects)

	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
Individual Effects:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
ρ_{y0m0}	0.0105	0.0200	-0.0323	0.0600	0.0019	0.0245	-0.0464	0.0636	0.0188	0.0256	-0.0394	0.0844	-0.0076	0.0258	-0.0596	0.0550
ρ_{y0y}	0.2136	0.0250	0.1319	0.2537	0.0322	0.0190	-0.0130	0.0908	0.0426	0.0308	-0.0211	0.1018	0.1068	0.0147	0.0611	0.1372
ρ_{y0w}	0.1981	0.0169	0.1616	0.2370	-0.0069	0.0197	-0.0544	0.0323	0.0360	0.0249	-0.0086	0.0931	0.0521	0.0195	0.0073	0.0919
ρ_{y0m}	-0.0455	0.0270	-0.1002	0.0053	-0.0125	0.0202	-0.0598	0.0362	0.0147	0.0190	-0.0352	0.0694	-0.0016	0.0318	-0.0768	0.0556
ρ_{m0y}	0.0121	0.0321	-0.0492	0.0824	-0.0223	0.0263	-0.0622	0.0400	0.0067	0.0209	-0.0488	0.0438	0.0281	0.0255	-0.0437	0.0886
ρ_{m0w}	0.0070	0.0309	-0.0735	0.0720	-0.0296	0.0208	-0.0782	0.0154	0.0235	0.0179	-0.0162	0.0665	-0.0111	0.0193	-0.0524	0.0263
ρ_{m0m}	-0.0173	0.0205	-0.0685	0.0314	0.0298	0.0236	-0.0189	0.0810	-0.0271	0.0204	-0.0692	0.0238	-0.0006	0.0561	-0.0739	0.1096
ρ_{yw}	0.3627	0.0331	0.2924	0.4328	0.4020	0.0380	0.3471	0.4995	0.3193	0.0291	0.2603	0.3812	0.1454	0.0426	0.0630	0.2345
ρ_{ym}	-0.0204	0.0244	-0.0750	0.0325	-0.0225	0.0250	-0.0775	0.0404	-0.0260	0.0189	-0.0656	0.0206	-0.0322	0.0401	-0.1185	0.0419
ρ_{wm}	-0.0435	0.0348	-0.0993	0.0285	-0.0415	0.0404	-0.1146	0.0239	-0.0819	0.0239	-0.1409	-0.0309	-0.0100	0.0246	-0.0855	0.0382
Idiosyncratic Effects:																
σ^2	0.2846	0.0015	0.2786	0.2944	0.2722	0.0017	0.2650	0.2807	0.6563	0.0065	0.6365	0.6809	0.4026	0.0034	0.3934	0.4150
ρ_{wm}	0.1296	0.1240	-0.1575	0.4311	-0.0151	0.1306	-0.3385	0.3077	0.0296	0.0631	-0.1867	0.2046	0.1160	0.0135	0.0000	0.1718
ρ_{ym}	0.1277	0.2699	-0.4203	0.6082	0.1587	0.2627	-0.3142	0.6929	0.4225	0.2426	-0.3690	0.7210	-0.0506	0.0492	-0.2551	0.1005
ρ_{yw}	0.0552	0.0159	-0.0086	0.1136	-0.0403	0.0145	-0.1048	0.0209	0.0989	0.0320	-0.0187	0.1970	-0.0170	0.0211	-0.0975	0.0635

Notes: Source : DADS-EDP from 1976 to 1996. 3,000 individuals randomly selected within 32,596; 12,405; 34,071; and 7,579 respectively. Estimation by Gibbs Sampling. 80,000 iterations for the first three groups with a burn-in equal to 70,000; 30,000 iterations

Table 6: Comparison United-States vs France (College Graduates)

	College Graduates, United States				College or Grandes Ecoles Graduates, France			
Parameters:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Wage Equation:								
Experience	0.0580	0.0032	0.0518	0.0643	0.0674	0.0031	0.0553	0.0799
Experience squared	-0.0013	0.0001	-0.0015	-0.0012	-0.0011	0.0001	-0.0013	-0.0008
Seniority	0.0518	0.0029	0.0460	0.0576	0.0094	0.0022	0.0001	0.0196
Seniority squared	-0.0005	0.0001	-0.0007	-0.0004	-0.0002	0.0001	-0.0005	0.0002
Number of switches of jobs that lasted:								
Up to 1 year	0.2240	0.0172	0.1905	0.2572	0.6290	0.0481	0.4185	0.8193
Between 2 and 5 years	0.1648	0.0189	0.1274	0.2018	0.6078	0.0508	0.4182	0.7926
Between 6 and 10 years	0.3231	0.0683	0.1861	0.4572	0.4796	0.0555	0.2683	0.6746
More than 10 years	0.4717	0.0869	0.3031	0.6425	0.4686	0.0568	0.2555	0.6855
Seniority at last job change that lasted:								
Between 2 and 5 years	0.0567	0.0070	0.0432	0.0709	0.0397	0.0092	0.0051	0.0728
Between 6 and 10 years	0.0111	0.0097	-0.0079	0.0303	0.0087	0.0057	-0.0215	0.0289
More than 10 years	0.0062	0.0055	-0.0050	0.0166	-0.0072	0.0046	-0.0235	0.0101
Experience at last job change that lasted:								
Up to 1 year	-0.0071	0.0016	-0.0102	-0.0040	0.0003	0.0009	-0.0031	0.0035
Between 2 and 5 years	-0.0058	0.0016	-0.0090	-0.0027	-0.0062	0.0017	-0.0126	0.0009
Between 6 and 10 years	-0.0025	0.0025	-0.0073	0.0024	-0.0020	0.0026	-0.0111	0.0099
More than 10 years	-0.0026	0.0033	-0.0090	0.0036	0.0079	0.0042	-0.0063	0.0227
Participation Equation:								
Lagged Mobility γ^M	0.3336	0.1646	0.0111	0.6274	1.0206	0.0200	0.9467	1.1010
Lagged Participation γ^Y	2.0046	0.0944	1.8178	2.1978	0.1880	0.0094	0.1524	0.2284
Mobility Equation:								
Seniority	-0.0878	0.0074	-0.1024	-0.0734	0.0121	0.0088	-0.0172	0.0486
Seniority squared	0.0020	0.0003	0.0015	0.0026	-0.0006	0.0004	-0.0019	0.0006
Lagged Mobility γ	-0.9019	0.0552	-1.0133	-0.7953	0.0276	0.0415	-0.1055	0.1717
Individual Effects:								
ρ_{y0m0}	0.8040	0.0556	0.7024	0.9005	-0.0076	0.0258	-0.0596	0.0550
ρ_{y0y}	0.5716	0.0286	0.5190	0.6224	0.1068	0.0147	0.0611	0.1372
ρ_{y0w}	0.1335	0.0757	0.0169	0.2714	0.0521	0.0195	0.0073	0.0919
ρ_{y0m}	-0.6044	0.0773	-0.7595	-0.4892	-0.0016	0.0318	-0.0768	0.0556
ρ_{m0y}	0.2896	0.0429	0.2268	0.3845	0.0281	0.0255	-0.0437	0.0886
ρ_{m0w}	-0.1450	0.0884	-0.2586	0.0403	-0.0111	0.0193	-0.0524	0.0263
ρ_{m0m}	-0.4234	0.0789	-0.5691	-0.2668	-0.0006	0.0561	-0.0739	0.1096
ρ_{yw}	0.2174	0.0553	0.1066	0.3017	0.1454	0.0426	0.0630	0.2345
ρ_{ym}	-0.5061	0.0656	-0.6172	-0.3874	-0.0322	0.0401	-0.1185	0.0419
ρ_{wm}	-0.5352	0.0590	-0.6371	-0.4131	-0.0100	0.0246	-0.0855	0.0382
Idiosyncratic Effects:								
σ^2	0.2062	0.0023	0.2016	0.2104	0.4026	0.0034	0.3934	0.4150
ρ_{wm}	0.0013	-0.0111	0.0075	0.0161	0.1160	0.0135	0.0000	0.1718
ρ_{ym}	-0.0005	0.0113	-0.0217	0.0188	-0.0506	0.0492	-0.2551	0.1005
ρ_{yw}	-0.0496	0.0124	-0.0672	-0.0205	-0.0170	0.0211	-0.0975	0.0635

Table 7: Comparison United-States vs France (High-School Dropouts)

	High-School Dropouts United States				CEP Graduates France			
Parameters:	**Mean**	**StDev.**	**Min.**	**Max.**	**Mean**	**StDev.**	**Min.**	**Max.**
Wage Equation:								
Experience	0.0283	0.0027	0.0229	0.0334	0.0495	0.0027	0.0380	0.0595
Experience squared	-0.0007	0.0000	-0.0007	-0.0006	-0.0006	0.0000	-0.0008	-0.0004
Seniority	0.0517	0.0034	0.0455	0.0580	0.0031	0.0018	-0.0046	0.0097
Seniority squared	-0.0005	0.0001	-0.0008	-0.0003	-0.0002	0.0001	-0.0005	0.0001
Number of switches of jobs that lasted:								
Up to 1 year	0.0923	0.0144	0.0635	0.1203	0.5643	0.0484	0.3624	0.7319
Between 2 and 5 years	0.0958	0.0219	0.0526	0.1386	0.5208	0.0514	0.3359	0.7023
Between 6 and 10 years	0.1229	0.1027	-0.0569	0.3076	0.4411	0.0551	0.2052	0.6344
More than 10 years	0.2457	0.1078	0.0474	0.4606	0.4828	0.0556	0.2617	0.6865
Seniority at last job change that lasted:								
Between 2 and 5 years	0.0293	0.0084	0.0127	0.0456	0.0052	0.0092	-0.0298	0.0367
Between 6 and 10 years	0.0213	0.0109	0.0003	0.0422	-0.0053	0.0065	-0.0306	0.0189
More than 10 years	0.0350	0.0053	0.0238	0.0444	-0.0078	0.0054	-0.0274	0.0114
Experience at last job change that lasted:								
Up to 1 year	0.0009	0.0012	-0.0015	0.0033	-0.0012	0.0005	-0.0030	0.0009
Between 2 and 5 years	-0.0007	0.0016	-0.0038	0.0024	-0.0003	0.0012	-0.0044	0.0037
Between 6 and 10 years	0.0007	0.0030	-0.0049	0.0060	0.0002	0.0022	-0.0082	0.0088
More than 10 years	-0.0090	0.0029	-0.0150	-0.0035	0.0037	0.0031	-0.0086	0.0148
Participation Equation:								
Lagged Mobility γ^M	0.5295	0.1258	0.3043	0.7836	1.4515	0.0184	1.3928	1.5274
Lagged Participation γ^Y	1.7349	0.0660	1.5999	1.8530	0.1456	0.0098	0.1148	0.1835
Mobility Equation:								
Seniority	-0.0812	0.0115	-0.1007	-0.0605	0.2730	0.1401	0.0010	0.5424
Seniority squared	0.0018	0.0003	0.0011	0.0024	-0.0076	0.0054	-0.0187	0.0036
Lagged Mobility γ	-0.7190	0.0738	-0.8544	-0.5807	1.0420	0.3071	0.4791	1.7680
Individual Effects:								
ρ_{y0m0}	-0.1020	0.1146	-0.2589	0.1067	0.0105	0.0200	-0.0323	0.0600
ρ_{y0y}	0.7548	0.0566	0.6525	0.8747	0.2136	0.0250	0.1319	0.2537
ρ_{y0w}	0.3447	0.0351	0.2732	0.4142	0.1981	0.0169	0.1616	0.2370
ρ_{y0m}	0.0278	0.2007	-0.2908	0.2281	-0.0455	0.0270	-0.1002	0.0053
ρ_{m0y}	0.1972	0.0746	0.0260	0.2971	0.0121	0.0321	-0.0492	0.0824
ρ_{m0w}	0.0646	0.0505	-0.0061	0.1794	0.0070	0.0309	-0.0735	0.0720
ρ_{m0m}	-0.0573	0.1666	-0.2619	0.2194	-0.0173	0.0205	-0.0685	0.0314
ρ_{yw}	0.2958	0.0282	0.2292	0.3560	0.3627	0.0331	0.2924	0.4328
ρ_{ym}	-0.2100	0.1053	-0.3832	-0.0429	-0.0204	0.0244	-0.0750	0.0325
ρ_{wm}	-0.2744	0.0799	-0.4083	-0.1348	-0.0435	0.0348	-0.0993	0.0285
Idiosyncratic Effects:								
σ^2	0.2448	0.0064	0.2331	0.2539	0.2846	0.0015	0.2786	0.2944
ρ_{wm}	-0.0055	0.0074	-0.0185	0.0072	0.1296	0.1240	-0.1575	0.4311
ρ_{ym}	0.0029	0.0077	-0.0117	0.0160	0.1277	0.2699	-0.4203	0.6082
ρ_{yw}	-0.0346	0.0072	-0.0497	-0.0183	0.0552	0.0159	-0.0086	0.1136

Table I.1a: Descriptive Statistics

	CEP (High-School Dropouts)		CAP (Occupational degrees)		Baccalauréat (High-School Graduates)		Grandes Ecoles, College Graduates	
Variable	Mean	St Error	Mean	St Error	Mean	St Error	Mean	St Error
Participation	0.5045	0.5000	0.5953	0.4908	0.4604	0.4984	0.4700	0.4991
Wage	4.0874	0.8093	4.1948	0.7426	4.1573	0.9801	4.7006	1.1599
Mobility	0.8374	0.3690	0.8411	0.3656	0.7727	0.4191	0.7176	0.4502
Tenure	7.6476	7.8048	6.0996	6.9759	4.1165	6.1718	6.2467	7.7694
Experience	24.7733	11.4711	17.3792	10.6656	11.7819	9.9945	15.7837	9.6285
Lives in Couple	0.0648	0.2461	0.0607	0.2388	0.0661	0.2484	0.0551	0.2281
Married	0.6347	0.4815	0.5645	0.4958	0.3540	0.4782	0.5706	0.4950
Children between 0 and 3	0.0863	0.2809	0.1329	0.3395	0.1019	0.3025	0.1225	0.3279
Children between 3 and 6	0.0898	0.2859	0.1152	0.3192	0.0749	0.2633	0.1096	0.3125
Number of Children	1.3196	1.3771	1.0769	1.2186	0.5873	0.9889	0.9830	1.4218
Lives in Region Ile de France	0.1196	0.3245	0.0869	0.2817	0.1531	0.3600	0.2088	0.4064
Lives in Paris	0.1182	0.3228	0.0834	0.2765	0.1532	0.3602	0.2707	0.4443
Lives in Town	0.2033	0.4024	0.2270	0.4189	0.2417	0.4281	0.2251	0.4176
Rural	0.6785	0.4670	0.6896	0.4627	0.6051	0.4888	0.5043	0.5000

Notes: Source : DADS-EDP from 1976 to 1996. 32,596; 12,405; 34,071; and 7,579 individuals respectively.

Table I.1b: Descriptive Statistics (continued)

	CEP (High-School Dropouts)		CAP (Occupational degrees)		Baccalauréat (High-School Graduates)		Grandes Ecoles, College Graduates	
Variable	Mean	St Error	Mean	St Error	Mean	St Error	Mean	St Error
Part Time	0.1846	0.3880	0.1521	0.3591	0.2394	0.4267	0.2137	0.4100
local Unemployment Rate	8.1940	3.6354	8.4130	3.4429	8.2858	3.5824	8.9162	2.7771
Agriculture	0.0416	0.1997	0.0401	0.1962	0.0209	0.1429	0.0130	0.1133
Energy	0.0096	0.0977	0.0149	0.1210	0.0125	0.1110	0.0219	0.1463
Intermediate Goods	0.1014	0.3018	0.0991	0.2988	0.0484	0.2147	0.0634	0.2436
Equipment Goods	0.1139	0.3176	0.1260	0.3319	0.0665	0.2491	0.1277	0.3337
Consumption Goods	0.1128	0.3164	0.0738	0.2614	0.0546	0.2272	0.0555	0.2289
Construction	0.0870	0.2819	0.1158	0.3200	0.0375	0.1901	0.0357	0.1856
Retail and Wholesome Goods	0.1603	0.3669	0.1429	0.3499	0.1561	0.3630	0.0939	0.2917
Transport	0.0615	0.2402	0.0602	0.2378	0.0704	0.2557	0.0531	0.2242
Market Services	0.2098	0.4072	0.2256	0.4180	0.3161	0.4650	0.3383	0.4731
Insurance	0.0082	0.0900	0.0088	0.0934	0.0187	0.1356	0.0156	0.1238
Banking and Finance Industry	0.0157	0.1241	0.0242	0.1536	0.0557	0.2294	0.0452	0.2077
Non Market Services	0.0713	0.2573	0.0631	0.2432	0.1358	0.3426	0.1306	0.3370
Born before 1929	0.2380	0.4258	0.0515	0.2210	0.0452	0.2078	0.0956	0.2941
Born between 1930 and 1939	0.2132	0.4096	0.1171	0.3215	0.0480	0.2137	0.1314	0.3378
Born between 1940 and 1949	0.2290	0.4202	0.2032	0.4024	0.1048	0.3063	0.2867	0.4522
Born between 1950 and 1959	0.2329	0.4227	0.3099	0.4625	0.2123	0.4089	0.3266	0.4690
Born between 1960 and 1969	0.0646	0.2459	0.2787	0.4483	0.4476	0.4973	0.1580	0.3648
Born after 1970	0.0222	0.1475	0.0398	0.1954	0.1421	0.3492	0.0017	0.0417

Notes: Source : DADS-EDP from 1976 to 1996. 32,596; 12,405; 34,071; and 7,579 individuals respectively.