

The Returns to Seniority in France

(and Why they are Lower than in the United States)

Magali Beffy* Moshe Buchinsky† Denis Fougère‡
Thierry Kamionka§ Francis Kramarz¶

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Abstract

In this article, we estimate a joint model of participation, mobility, and wages in 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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* CREST-INSEE (magali.poncon-beffy@ensae.fr)

† UCLA, CREST and NBER (buchinsky@econ.ucla.edu)

‡ CNRS and CREST (fougere@ensae.fr)

§ CNRS and CREST (kamionka@ensae.fr)

¶ CREST-INSEE, CEPR and IZA(kramarz@ensae.fr): Corresponding author. We thank Pierre Cahuc, Jean Marc Robin, Alexandru Voicu, and seminar participants at Crest, Royal Holloway (DWP conference), Paris-I University, Warwick University, SOLE meetings, JMA conference for very helpful comments. In addition, Alexandru Voicu spotted a data error in an early version. Remaining errors are ours.

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 unemployed. 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 recognized 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 by Gibbs sampling and a Metropolis-Hastings algorithm. As our model contains censored endogenous variables, 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 Déclaration Annuelle de Données Sociales (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. While 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). In this model, contracts differ in the equilibrium slopes of the returns to tenure. Elements that determine these slopes include the job arrival rate, hence workers' mobility propensity, and risk aversion. 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). Therefore, the returns to seniority directly reflect the patterns of mobility in the two countries.

This paper is organized as follows. 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

Because we examine returns to experience and returns to seniority, we need to understand how mobility, participation, and wages are potentially related. Hence, as in BFKT and following Hyslop (1999) (who focuses on participation), the economic model that supports our approach is a structural choice model of firm-to-firm worker's movements with mobility costs paid by the worker. BFKT shows that under reasonable assumptions on this cost structure, this decision model generates first-order state dependence for participation and mobility processes (all conditions are spelled-out in great detail in BFKT). Therefore, the statistical model that we estimate follows directly from this structural choice model of participation and mobility. Wages, participation and mobility decisions are jointly modelled. Because the lagged mobility and participation decisions must be included in the participation and mobility equations, we follow Heckman (1981) and add two initial conditions equations.

This model translates into the following equations:

Initial Conditions

$$\begin{aligned}
 (1) \quad y_{i1} &= \mathbb{I}[X_{i1}^Y \delta_0^Y + \alpha_i^{Y,I} + v_{i1} > 0], \\
 (2) \quad w_{i1} &= y_{i1} \left(X_{i1}^W \delta^W + \theta_i^{W,I} + \epsilon_{i1} \right), \\
 (3) \quad m_{i1} &= y_{i1} \mathbb{I}[X_{i1}^M \delta_0^M + \alpha_i^{M,I} + u_{i1} > 0].
 \end{aligned}$$

Main Equations

$$(4) \quad \forall t > 1, \quad y_{it} = \mathbb{I}[y_{it}^* > 0],$$

where $y_{it}^* = \gamma^M m_{it-1} + \gamma^Y y_{it-1} + X_{it}^Y \delta^Y + \theta_i^{Y,I} + v_{it}$,

$$(5) \quad \forall t > 1, \quad w_{it} = y_{it} \left(X_{it}^W \delta^W + J_{it}^W + \theta_i^{W,I} + \epsilon_{it} \right),$$

$$(6) \quad \forall t > 1, \quad m_{it} = y_{it} \mathbb{I}[m_{it}^* > 0],$$

where $m_{it}^* = \gamma m_{it-1} + X_{it}^M \delta^M + \theta_i^{M,I} + u_{it}$; and y_{it} and m_{it} denote, respectively, participation and mobility, as previously defined.

The quantity y_{it} is an indicator function, equal to 1 if the individual i is employed at date t . Because m_{it}^* measures worker's i propensity to move between t and $t + 1$, the quantity m_{it} is an indicator function equal to 1 if the individual decides to be mobile between time t and time $t + 1$ and equal to 0 otherwise. As the above equation indicates, the observed mobility m_{it} is equal to 0 when the individual does not participate at time t . When the worker changes firm from time t to time $t + 1$, the mobility is set to 1. Finally, m_{it} is not observed (censored) whenever a worker participates at date t but does not participate at the next date, $t + 1$, because m_{it}^* can be positive or negative in this case.

The variable w_{it} denotes the logarithm of the annualized total real labor costs. The variable X_{it} denotes observable time-varying as well as the time-invariant characteristics for individuals at the different dates and J_{it}^W is a function that summarizes the worker's past career choices at date t (the exact specification will be detailed later).

θ^I denotes the random effects specific to the individuals. u , v and ϵ are the idiosyncratic 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:

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

Moreover, we assume that

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

where the variance-covariance matrix has the following form:

$$(8) \quad \Sigma_i^I = D_i \Delta_\rho D_i \quad \text{with}$$

$$(9) \quad \Delta_\rho = CC' \quad \text{where}$$

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

with

$$\cos_i = \cos(\eta_i), \quad \text{with } \eta_i \in [0; \pi],$$

and

$$(11) \quad D_i = \begin{pmatrix} \sigma_{i1} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{i2} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{i3} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{i4} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{i5} \end{pmatrix} \quad \text{with}$$

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

in order to make sure that Σ_i^I is positive definite symmetric whatever the value of the parameter $\eta' = (\eta_1, \dots, \eta_{10})$.¹

¹The γ_j terms are estimated separately in a factor analysis of individual data. The variables that enter this analysis are the sex, the

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:

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

It is worthwhile noting that the specification of the joint distribution of the person specific effects has direct implications for the correlation between the regressors and these random effects. To see this, consider an individual with seniority level $s_{it} = s$. Note that s_{it} can be written as:

$$s_{it} = (s_{it-1} + 1) \mathbb{I}[m_{it} = 0, y_{it} = 1]$$

This equation can be expanded by recursion up to entry in the firm. Since the seniority level of those currently employed depends on the sequence of past participation and mobility indicators, it must also be correlated with the person-specific effect of the wage equation θ_{wi} . This, in turn, is correlated with θ_{mi} and θ_{yi} , the person-specific effects in the mobility and participation equations, respectively. Similarly, experience and the J^W function are also correlated with θ_{wi} . Given that lagged values of participation and mobility, as well as the seniority level appear in both the participation and mobility equations, it follows that the regressors in these two equations are also correlated, albeit in a complex fashion, with the corresponding person-specific effects, namely θ_{mi} and θ_{yi} , respectively.

This reasoning applies also to the 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.

year of birth, the region where the individual lives (Ile de France versus other regions), the number of children, the marital status, the part-time status, and the unemployment rate in the department of work.

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 a Gibbs Sampling algorithm with Metropolis-Hastings steps for some of the parameters, in particular the correlation coefficients, 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 other parameters, 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:

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

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”, that is, we compute m_{it}^* and y_{it}^* based on (4)+(6), conditional on all the parameters.

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 Metropolis-Hastings algorithm. In this case, as we do not know how to draw in the posterior distribution, we draw, alternatively, the parameter using an other distribution and decide to keep or not the corresponding drawing according to a frequency such that the properties of the Markov chain (existence and characteristics of the stationary distribution) are the same. This the case, for the variance-covariance matrix when this matrix is such that some variance is fixed to one. In this case, is we consider an inverse-Wishart prior distribution for the matrix, the posterior distribution does not belong to this family.

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:

$$(14) \quad (\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \bar{\gamma}; \eta)$$

and \mathcal{P} denotes:

$$(15) \quad \mathcal{P} = (\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \bar{\gamma}; \eta; \theta^I)$$

where $\bar{\gamma} = (\gamma'_1, \dots, \gamma'_5)'$ and $\eta = (\eta_1, \dots, \eta_{10})'$.

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:

$$X_t = y_t y_{t-1} X_t^{11} + y_{t-1} (1 - y_t) X_t^{10} + y_t (1 - y_{t-1}) X_t^{01} + (1 - y_t) (1 - y_{t-1}) X_t^{00},$$

where

$$X_t^{11} = (y_t^*, y_t, w_t, m_{t-1}^*, m_{t-1}),$$

$$X_t^{10} = (y_t^*, y_t, m_{t-1}^*),$$

$$X_t^{01} = (y_t^*, y_t, w_t),$$

$$X_t^{00} = (y_t^*, y_t).$$

for the initial year we similarly define

$$X_1 = y_1 X_1^1 + (1 - y_1) X_1^0,$$

$$X_1^1 = (y_1^*, y_1, w_1),$$

$$X_1^0 = (y_1^*, y_1).$$

Since mobility at time T is never an explanatory variable in the model, the mobility equation does not require any completion at the end date of the sample.² Hence, for individual i , the contribution to the completed full conditional likelihood is:

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

$$\underline{X}_{i,t} = (X_{i1}, \dots, X_{it})$$

$$\mathcal{F}_{i,t-1} = (\underline{X}_{i,t-1})$$

with:

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

$$l(X_{it}^{01} | \mathcal{P}, \mathcal{F}_{i,t-1})^{(1-y_{i,t-1})y_{it}} l(X_{it}^{00} | \mathcal{P}, \mathcal{F}_{i,t-1})^{(1-y_{i,t-1})(1-y_{it})}$$

Thus, the full conditional likelihood is given by:

$$L(\underline{X}_T | \mathcal{P}) = \left(\frac{1}{V^w} \right)^{\sum_{i=1}^N \sum_{t=1}^T y_{it}} \left(\frac{1}{V^m} \right)^{\sum_{i=1}^N \sum_{t=1}^{T-1} y_{it}}$$

$$\prod_{i=1}^N (\mathbb{I}_{[y_{i1}^* > 0]})^{y_{i1}} (\mathbb{I}_{[y_{i1}^* \leq 0]})^{1-y_{i1}} \exp \left\{ -\frac{1}{2} (y_{i1}^* - m_{y_{i1}^*})^2 \right\} \exp \left\{ -\frac{y_{i1}}{2V^w} (w_{i1} - M_{i1}^w)^2 \right\}$$

$$\prod_{t=2}^T (\mathbb{I}_{[y_{it}^* \leq 0]})^{1-y_{it}} (\mathbb{I}_{[y_{it}^* > 0]})^{y_{it}} \exp \left\{ -\frac{1}{2} (y_{it}^* - m_{y_{it}^*})^2 \right\} \exp \left\{ -\frac{y_{it}}{2V^w} (w_{it}^* - M_{it}^w)^2 \right\}$$

$$\left((\mathbb{I}_{[m_{i,t-1}^* \leq 0]})^{1-m_{i,t-1}} (\mathbb{I}_{[m_{i,t-1}^* > 0]})^{m_{i,t-1}} \right)^{y_{i,t-1}y_{it}} \exp \left\{ -\frac{y_{i,t-1}}{2V^m} (m_{i,t-1}^* - M_{i,t-1}^m)^2 \right\}$$

with:

$$V^w = \sigma^2(1 - \rho_{yw}^2)$$

$$V^m = \frac{1 - \rho_{yw}^2 - \rho_{ym}^2 - \rho_{wm}^2 + 2\rho_{yw}\rho_{ym}\rho_{wm}}{1 - \rho_{yw}^2}$$

$$M_{it}^m = m_{m_{it}^*} + \underbrace{\frac{\rho_{y,m} - \rho_{w,m}\rho_{y,w}}{1 - \rho_{y,w}^2}}_a (y_{it}^* - m_{y_{it}^*}) + \underbrace{\frac{\rho_{w,m} - \rho_{y,m}\rho_{y,w}}{\sigma(1 - \rho_{y,w}^2)}}_b (w_{it} - m_{w_{it}})$$

$$M_{it}^w = m_{w_{it}} + \sigma\rho_{y,w}(y_{it}^* - m_{y_{it}^*})$$

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

and the residual correlations are parameterized by:

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

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

Finally, we define the various prior distributions as follows:

$$\begin{aligned} \delta_0^Y &\sim \mathcal{N}(m_{\delta_0^Y}, v_{\delta_0^Y}) & \delta_0^M &\sim \mathcal{N}(m_{\delta_0^M}, v_{\delta_0^M}) \\ \delta^Y &\sim \mathcal{N}(m_{\delta^Y}, v_{\delta^Y}) & \gamma^Y &\sim \mathcal{N}(m_{\gamma^Y}, v_{\gamma^Y}) \\ \gamma^M &\sim \mathcal{N}(m_{\gamma^M}, v_{\gamma^M}) & \delta^W &\sim \mathcal{N}(m_{\delta^W}, v_{\delta^W}) \\ \delta^M &\sim \mathcal{N}(m_{\delta^M}, v_{\delta^M}) & \gamma &\sim \mathcal{N}(m_{\gamma}, v_{\gamma}) \\ \sigma^2 &\sim \text{Inverse Gamma} \left(\frac{v}{2}, \frac{d}{2} \right) & \theta &\sim_{iid} \mathcal{U}[0, \pi] \\ \eta_j &\sim_{iid} \mathcal{U}[0, \pi] \text{ for } j = 1 \dots 10, \text{ and } \gamma_j &\sim_{iid} \mathcal{N}(m_{\gamma_j}, v_{\gamma_j}) \text{ for } j = 1 \dots 5 \end{aligned}$$

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 sources, the Déclarations Annuelles de Données Sociales (DADS) and the Echantillon Démographique Permanent (EDP) that are matched together. Our first source, the DADS, 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 the Institut National de la Statistique et des Etudes Economiques (INSEE) 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 covers the period 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 des Revenus kept information on the employing firm using the newly created SIREN number from the SIRENE system⁴. 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. In addition we also 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, as well as the location and industry of the employing establishment. The resulting data set has 13,770,082 total number of 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 French individuals. All individuals born in the first four days of the month of October of an even year are included in this sample. All questionnaires for these individuals from the 1968, 1975, 1982, and 1990 Censuses are gathered into the EDP. The exhaustive long-forms of the various Censuses were entered under electronic form only for this 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 questionnaires for these individuals. The INSEE regional agencies were in charge of this task. The usual socio-demographic variables are available in the EDP.⁵

For every individual, education measured as the highest diploma and the age at the end of school are col-

³Individuals 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).

⁴The SIRENE system is a directory identifying all French the firms and the corresponding establishment.

⁵Notice that no earnings or income variables have ever been asked in the French Censuses.

lected. Since the categories differ in the three Censuses, we first created eight education groups (identical to those used in Abowd, Kramarz, and Margolis, 1999), namely : No terminal degree, Elementary School, Junior High School, High School, Vocational-Technical School (basic), Vocational Technical School (advanced), Technical College and Undergraduate University, Graduate School and Other Post-Secondary Education. 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 apartment, type of city, location of the residence (region and department⁶). 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.⁷ 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 Paris 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

⁶A French "département" corresponds roughly a U.S. county. Several "département" form a region which is an administrative division.

⁷BFKT also presents estimates with a quartic specification in both experience and seniority. We come back to this issue later.

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,

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

Suppressing the i subscript, the variable d_{1t_l} equals 1 if the l th job lasted less than a year, and equals 0 otherwise. Similarly, $d_{2t_l} = 1$ if the l th job lasted between 1 and 5 years, and equals 0 otherwise, $d_{3t_l} = 1$ if the l th job lasted between 5 and 10 years, and equals 0 otherwise, $d_{4t_l} = 1$ if the l th job lasted more than 10 years and equals 0 otherwise. The quantity M_{it} denotes the number of job changes by the i th 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.⁸ Hence, at a start of a new job, two persons with exactly similar characteristics, but for one specific difference in their career – for instance, the first person had four jobs, each lasting 1 year whereas the second individual only had one job that lasted 4 years – will enter their new job with a potentially different starting wage.

Turning now to the mobility equation, most variables included in the wage equation are also present in the mobility equation with 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. Because job-specific variables cannot be defined for workers who have no job, seniority, the part-time status, and the employing industry, all present in the latter equation are now 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

⁸This 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.

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. 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, except functional form (i.e., the normality assumptions).

In the next paragraphs, we present our estimation results. Table 1 presents the estimation results for the wage equation for each education group. Table 2 presents the 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).⁹

In the next Section, Tables 6 to 9 show the results of a tight comparison between the United States and France. Because we estimate the same model as was estimated by BFKT, we are able to compare parameter estimates for high-school dropouts and college graduates in both countries. Table 6 presents estimates for the college graduates in the U.S. and France. Table 7 presents similar estimates for high-school dropouts. Table 8 compares the marginal and cumulative returns (at various points in the career) to experience and seniority for these two groups in our two countries. Finally, Table 9 presents estimates using two other methods – OLS and Altonji's – of the returns seniority and of the cumulative returns to seniority, for the two groups and the two countries.

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

In France, apart from those quitting the education system without any diploma¹⁰, 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.

Wage Equation: Since estimating returns to seniority is one of the main motivations for adopting the joint system estimation strategy, we first see (line 4, first four columns of Table 1) that these returns are small, 0.3%

⁹Descriptive Statistics are presented in Appendix Table B.1.

¹⁰With the possible confusion of missing response to the education question in the various Censuses.

per year (in the first years when the linear term is the dominating term). Returns to experience are twenty times larger than the returns to tenure. However, results of Table 1 also show that the timing of the mobilities in a career matters. First, time spent in a firm makes a difference (see panel “Number of Switches of Jobs that lasted:” – lines 15 to 18 – in the second part of the table). Moves after relatively short jobs are rewarded (5% if the change takes place at one year of seniority and 10% if it takes place after two to five years). Second, however, the part proportional to seniority at the end of the job shows that moves after two years in a job are better compensated than moves after 5, essentially cancelling all the effects of the constant. Then, from 5 to 10 years of seniority, there is neither a penalty or a reward. But, after ten years in a job, workers lose almost 2% per year of seniority. Third, and finally, one must add to a component proportional to experience at exit of the last job. There, moves early in a work life have a small negative impact but later moves, after 10 years of experience, add a small bonus. Hence, workers displaced after 20 years in a single employing firm in which they entered early in their career face a 20% ($\exp(-0.34 + 0.12)$) wage loss in their new firm, even controlling for employment with our participation equation. Important to note though, mobility is very low in France, as Table B.1 shows: the average CEP worker moves once over the period. However, movements are not evenly distributed in the population. Hence, benefits of voluntary mobility as well as difficulties coming with involuntary moves are both confined to a relatively small fraction of the workers.

In this first table, one more fact is worthy of notice. 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 policies for a category that includes many workers at the bottom of the wage distribution.

Participation and Mobility Equations: Tables 2 and 3 present our estimates of the participation and mobility equations, respectively, for CEP workers (first four columns). Table 4 presents our estimates for the initial conditions, for the same CEP workers (again, first four columns). 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 analysis (Altonji and co-authors, Topel,...), we are able to distinguish state-dependence from heterogeneity. Unsurprisingly, past participation and past mobility favors participation. Perhaps more surprising, mobility in the previous year has no impact on mobility today. If optimal mobility entails regular moves after 3 or 4 years in a firm (as one might think, given the wage evidence), then mobility in the previous year should be associated with lower mobility today, as is indeed observed in the U.S. (see BFKT and the France-U.S. comparison of Table 7). This lack of negative lagged dependence is obviously a reflection of the French labor market institutions where some workers often go from short-term contracts to short-term contracts, irrespective of their “tastes” when others

stay longer in their jobs . Unfortunately, as already mentioned, our data sources do not tell us the nature of the contract. Finally, and in line with this discussion, after this first year seniority negatively affects mobility.

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 (first four columns). The results clearly show that those who participate are also high-wage workers (in terms of individual effects). Non-participation (non-employment) and mobility are negatively correlated in terms of individual effect but positively correlated when considering the idiosyncratic component. Therefore, high mobility workers are low-employment workers. But, a temporary shock on mobility “enhances ”participation. Finally, both the idiosyncratic and the individual effects of the mobility and wage equations are negatively correlated. Hence, high-wage workers tend to be relatively immobile. Because most of these effects are large and significant, joint estimation of these equations clearly has a strong effect on the estimated returns to seniority and experience.

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

One element that distinguishes education systems in Continental Europe, in France as well as in Germany, 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: The returns to seniority coefficient, presented in Table 1 (next four columns), for workers with a vocational technical education are very slightly negative and barely significant. Estimates for the J^W function are indeed very similar to those obtained for high-school dropouts. Focusing on the two components related to seniority, movements after one year in job brings a 3% increase in the next job. Movements after two years bring 13%. Then, each additional year decreases this number by 3% up to 5 years of seniority and 2% up to 10 years, at which point workers lose approximately 5%. Then, workers tend to lose much more, as was observed for high-school dropouts. In addition, the experience component is negative in the first 10 years on the labor market but positive thereof. For a (displaced) worker who had one job that lasted 20 years, a move entails a 16% wage loss.

Participation and Mobility Equations: The estimated coefficients for the participation and the mobility equations are virtually identical to those obtained for the previous group (see Tables 2 and 3, next four columns). Hence, mobility decreases with seniority with no negative lagged dependence.

Stochastic Components: Here again, results are virtually identical to those presented for the high-school

dropouts group. In particular, high-wage workers are also high-participation and low-mobility.

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: Results for this group, presented again in Table 1 (columns 9 to 12), display some differences with the two previous groups we presented. First, returns to experience are very large (larger than for all other groups) but the returns to seniority are essentially zero, even slightly negative (and lower than for all other groups). However, the estimates for the J^W function are very similar to those observed for the less educated workers (High-school dropouts or CAP workers). In particular, moves after short spells are rewarded and very long spells entail large wage losses (1.5% per year, for jobs that lasted at least 6 years). And early moves after entry in the labor market are also associated to small losses (0.5%).

Participation and Mobility Equations: Here again, results are very consistent with those obtained for the lower education groups. Interestingly though, the dependence of mobility on lagged mobility becomes marginally negative, a result that, we will see, is consistent with results for the US. Finally, as was true for the two previous education groups, workers are less and less mobile with experience and seniority.

Stochastic Components: As was observed previously, high-wage workers are also high-participation workers. But high-wage workers are only marginally low-mobility workers. Indeed, Table B.1 shows that mobility for Baccalauréat holders is highest among all four education groups, whereas tenure and experience have their lowest values. This group comprises a large number of relatively young individuals (when the CEP group included a relatively large fraction of mature individuals).

5.5 Results for University and Grandes Ecoles Graduates

Another element that distinguishes the French education system from other European 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 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 all other education groups (see Table 1, last four columns). Not because returns to experience differ

but mostly because returns to seniority are now quite sizeable, approximately 2.6% per additional year. Furthermore, the estimated J^W function is also specific to that group. More precisely, each move after short employment spells brings 20% for jobs lasting one year, between 12% and 20% for employment spells lasting between two and five years, around 20% for spells lasting between 6 and 10 years, and 2% per year of seniority for spells lasting more than 10 years (hence at least 20%). Hence, seniority gets really compensated for these very educated workers. By contrast moves very early in the career entail small, 1%, wage losses. And, indeed, moves after six years of experience also entail small wage losses (again 1% per year). But these losses cannot eliminate the gains from added seniority.

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. In France, because minimum wages compress the bottom of the wage distribution, wage inequality is confined mostly in the upper part of the distribution. Finally, for all other education groups, foreigners were compensated roughly as the nationals. Here, results vastly differ. Getting a higher education may be a solution for finding a job for those born abroad (Maghreb, Portugal,...). But, employment comes at a price. Even though we can not use the word discrimination, pay is lower for them, 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. Even though workers' mobility is negatively related to seniority, the effect is weaker than in other groups. And there is no relation between mobility and experience; all these elements constitute evidence that engineers and professionals careers entail job changes at all ages. Furthermore, and in contrast to all other groups, participation choices are mildly affected by having young children (having a very small child even favors participation). Indeed, members of this very educated group obviously select 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. In addition, we do find that high-wage workers are also low-mobility workers. And, individuals faced with a positive idiosyncratic wage shock are faced with a negative mobility shock. However, because seniority entails increasing wages for these very educated workers, such correlations – similar to those estimated for the other groups – have different implications on workers wages and mobility patterns than they have in the less educated groups.

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. In each Table, the first four columns show the U.S. numbers and the last four columns report their French equivalent.

The first difference to be noted is essentially in the estimated returns to seniority. They are large in the United States (a linear component around 5% per year for both low and high-education groups) and smaller in France (zero for the three least educated groups and 2.6% for the college-educated group). We discuss this fact in the next subsection extensively. Related to this, we see that returns to experience are larger in France than in the United States for high-school dropouts and approximately equal for college-educated workers. But the total of returns to experience and returns to seniority is much larger in the U.S. for both groups. However, 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 the U.S. than in France for both groups. For instance, for the college-educated workers, movements out of jobs that lasted more than 10 years (resp. between 6 and 10 years) appear to receive a 60% premium (resp. 40%) in their next job, the equivalent premia are lower in France, also because experience plays a negative role in this country and has virtually no effect in the United States. It is even worse for the high-school dropouts: after long tenures, French workers lose when moving when their American equivalent strongly gain.

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 (see the second part of Table 1, and BFKT for 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. However, in the United States as well as in France, workers tend to move early in a job (negative sign on the seniority coefficient in the mobility equation). However, in France because workers can on short-term or on long-term contracts (not observed in the data), we see a mixture of very short jobs (no negative duration dependence) and long jobs. By contrast, in the United States where there is no such distinction between contracts, short jobs (but not very short) are common.

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 it is a survey, captures initial conditions much better than the French data source (the DADS-EDP, of administrative origin). More precisely, individuals are directly interviewed in the PSID, and therefore much better personal characteristics (such as race, family income, spouse's employment status,...) can be obtained. In France, because the data is administrative, some variables are not available and personal characteristics are likely to be measured with some error. For instance, civil-status and nationality variables come from different sources that can be sometimes contradictory, even though the wage measures and seniority measures (after 1976, see just below) are clearly of much better quality in the DADS. In addition, no measure of family income and very little information on the spouse characteristics are available. In addition, imputations of seniority have to be performed in year 1976 for the French data (in practice, the conditional expectation of seniority is obtained using the "structure des salaires" survey, see AKM). Consequently, correlations between initial equations and the others are generally weaker for France. Second, concentrating on the correlation of individual effects in the three main equations, we see that a) high-wage workers are high-participation workers, b) high-mobility individuals are clearly low-wage workers in both countries but the effect is much stronger in the United States (for the college-educated workers most particularly), stressing again the different role played by mobility in the two countries, and c) high-participation workers also tend to be low-mobility and here again the effect is much stronger in the United States.

To summarize these results, Table 8 presents the estimated cumulative and marginal returns to both experience and seniority in the United States and in France at various points in time.¹¹ Cumulative returns to (real) experience are slightly larger in France for both education groups. Cumulative returns to tenure are much larger for both high-school dropouts and college-educated workers in the U.S. (even though the difference is slightly

¹¹In all panels, the specification includes a quadratic function of experience and seniority in the wage equation. BFKT compares for the U.S. the estimates with those when these functions are both quartic. Estimates of the cumulative returns to experience and seniority are very similar. Hence, we compare the quadratic version.

smaller for the latter group). Total growth follows the same pattern: larger growth in the U.S. for both groups of workers.

Robustness and Specification Checks: We tested various specifications to assess robustness of our results. Particularly important is the following test. Are returns to seniority always (i.e. using either OLS or Altonji's IV methodology) lower in France than in the United States (and returns to experience larger in the former than in the latter)? To answer this question, we estimated a wage regression using OLS. Then, we estimated the exact same equation using Altonji's methodology. The estimation, was done on both data sets (PSID and DADS-EDP). Results are reported in Table 9. We summarize now the resulting estimates. First, Table 9 shows that OLS estimates of the returns to seniority in France are higher than those obtained for our system of equations for the college workers (and equal for High-School dropouts). Furthermore, Altonji's method yields insignificant and lower returns to seniority in France. All these results point to low returns to seniority in France, whatever the estimation method. In the United States, the results are strikingly different, and indeed relatively homogeneous across techniques. Returns to seniority are larger in all specifications in the United States than they are in France. For both groups of education, Altonji's methodology yields the lowest returns to seniority (see the linear tenure effect but, most importantly, the cumulative returns). OLS linear estimates are slightly larger than those estimated by Altonji's method. But cumulative returns are clearly ordered: Altonji's method give the smallest returns (say at 20 years), our estimation technique based on a system of equations yields the largest, and OLS are exactly in between, for both groups and both countries.¹²

To summarize, all tests show that returns to seniority and experience are biased when endogeneity as well as career concerns are not taken care of. Irrespective of the method used to correct for this endogeneity, returns to seniority are much larger in the United States than in France, and more so for workers most likely to face high unemployment rates.

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 as 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

¹²BFKT also presents estimates of returns to experience and seniority without introducing the J^W function. Cumulative returns most often decrease without J^W . Similar unreported – but available from the authors – estimates for France for high-school dropouts and college-educated workers show a similar pattern: the linear component of returns to seniority is roughly equal to zero for the former and equal to 1% for the latter.

discussed 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 much 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 in the US than in French (1.71 per annum vs. 0.56).

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, returns to seniority is increasing in the mobility rate of workers in the economy.

We start by summarizing the important aspects of the model. In Burdett and Coles (2003), the individuals are risk adverse and we consider a continuous time scale. Let λ denote the job offers arrival rate and let δ be 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 ($p > b > 0$). Let u denote the instantaneous utility. $u(\cdot)$ is assumed, in particular, to be strictly increasing and strictly concave. A firm is assumed to offer the same wage contract to all new workers. There is no recall of workers.

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

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

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

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

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

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 has constant relative risk aversion (CRRA) and writes as $u(w) = \frac{w^{1-\sigma}}{1-\sigma}$ ($\sigma > 0$). 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.

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

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

$$(23) \quad \frac{dw(0)}{dt} = \frac{\delta}{\sqrt{p-w_2}} \frac{p-w_1}{u'(w_1)} \int_{w_1}^{w_2} \frac{u'(s)}{\sqrt{p-s}} ds.$$

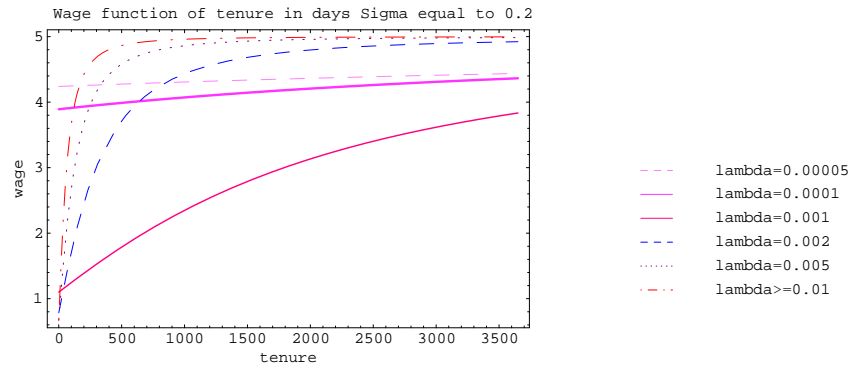
The differential equation (22) is highly non linear and have to be solved numerically. This can done by setting $(\lambda, \delta, \sigma, p)$ to some values and using, for instance, the procedure NDSolve of Mathematica.

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 (a) for $\sigma = 0.2$, in Figure (b) for $\sigma = 0.4$, in Figure (c) for $\sigma = 0.8$ and in Figure (d) 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 the larger job offers arrival rates.

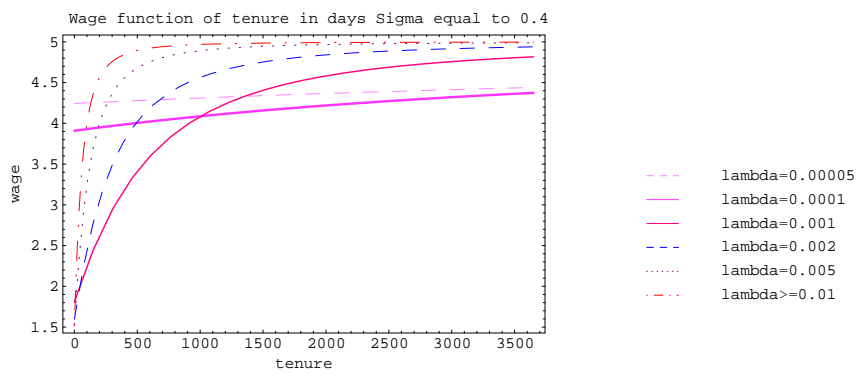
Using the values of the job offers arrival rates (per year) estimated by Jolivet, Postel-Vinay and Robin (2004) for France and the US, the U.S. situation corresponds to the curve where $\lambda = 0.005$ and the French labor market to the curve where $\lambda = 0.001$. And, for all relative risk aversion 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

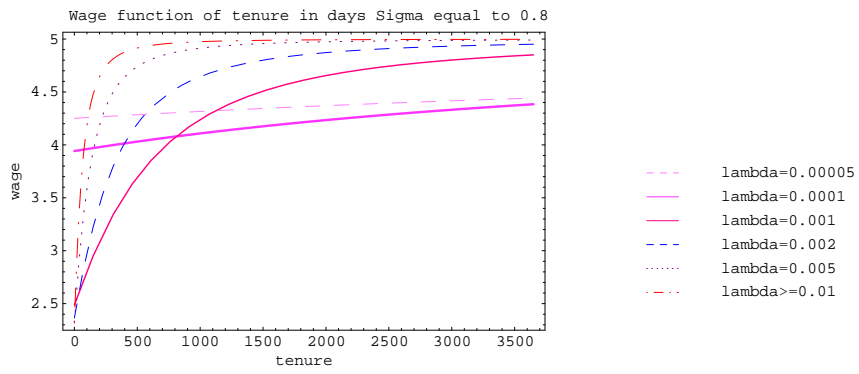
France (because, for instance, of strong regulations and transaction costs in the latter country). Or, subsidies and government interventions preventing firms to go bankrupt seem more prevalent in France, dampening the forces of “creative destruction ”in this country. And firms must react within this 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.



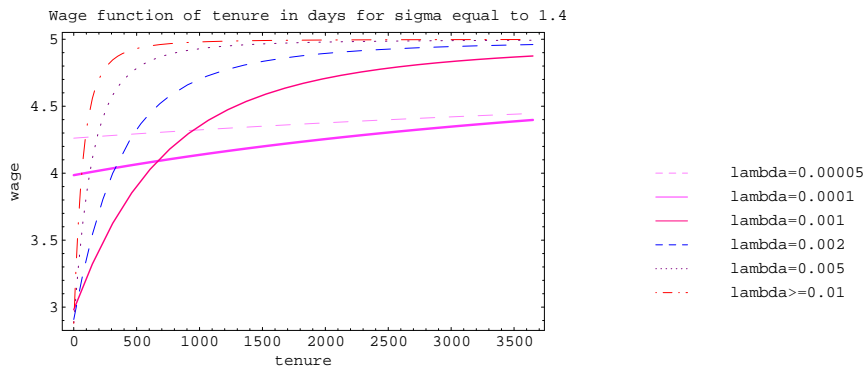
Wage-tenure contract curve (a)



Wage-tenure contract curve (b)



Wage-tenure contract curve (c)



Wage-tenure contract curve (d)

7 Conclusion

A central tenet of many theories in labor economics states that compensation should rise with to seniority. But, there has been and there still is much disagreement about the empirical evidence and the methods that try to assess these theories (see among others Altonji and Shakotko, 1987, and Topel, 1991 for the United States and AKM for France).

In this article, we reinvestigate the relations between wages, participation, and firm-to-firm mobility in the French context. We also take stock of the BFKT analysis that re-examined the American evidence using similar data sources as Topel and Altonji used in their work. To do this, we re-estimate 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, but positive for college-educated workers (2.5% per year of seniority). A very detailed 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, in both countries, our J^W function, a summary of career's influence on workers' wages, has strong impact on the estimates. Hence, career and past mobilities matter. Additional results show that OLS estimates of the cumulative returns to seniority are lower than those obtained for our system of equations. Furthermore, the same results demonstrate that instrumental variables estimation following exactly Altonji's suggestions give the smallest cumulative returns to seniority. These last two points hold both for the United States and for France. Finally, a comparison between the two countries also shows that, for all techniques – OLS, Altonji's, our system – returns to seniority are lower in France – a low firm-to-firm mobility country – than in the United States – a high firm-to-firm mobility country. One interpretation of these results – returns to seniority are directly related to patterns of mobility – is discussed using a theoretical framework borrowed from Burdett and Coles (2003). It shows that returns to seniority may play the role of an incentive device designed to counter excessive mobility.

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.

8 Bibliography

- Abowd J. M., Kramarz F. and D. N. Margolis (1999), "High Wage Workers and High Wage Firms", *Econometrica*, 67, 251-334.
- Abraham K.G. and H.S. Farber (1987), "Job Duration, Seniority, and Earnings", *American Economic Review*, vol. 77, 3, 278-297.
- Altonji J. G. and R. A. Shakotko (1987), "Do Wages Rise With Job Seniority ?", *Review of Economic Studies*, LIV, 437-459.
- Altonji J. G. and N. Williams (1992), "The Effects of Labor Market Experience, Job Seniority and Job Mobility on Wage Growth", NBER Working Paper Series 4133.
- Altonji J. G. and N. Williams (1997), "Do Wages Rise With Job Seniority ? A Reassessment", NBER Working Paper Series 6010.
- Becker G.S. (1964), *Human Capital*, Columbia Press.
- Buchinsky M., Fougère D., Kramarz F. and R. Tchernis (2002), "Interfirm Mobility, Wages, and the Returns to Seniority and Experience in the U.S.", CREST Working Papers 2002-29, Paris.
- Burdett K. and M. Coles (2003), "Equilibrium Wage-Tenure Contracts", *Econometrica*, vol. 71, 5, 1377-1404.
- Flinn Ch. J. (1986), "Wages and Job Mobility of Young Workers", *Journal of Political Economy*, vol. 94, S88-S110.
- Heckman J. J. (1981), "Heterogeneity and State Dependence", in *Studies in Labor Market*, Rosen S. ed., University of Chicago Press.
- Hyslop D. R. (1999), "State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women", *Econometrica*, 67, 1255-1294.
- Jolivet G., Postel-Vinay F. and J.-M. Robin (2004), "The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and the US", Mimeo Crest, Paris.
- Jovanovic B. (1979), "Firm-specific Capital and Turnover", *Journal of Political Economy*, vol. 87, 6, 1246-1260.
- Jovanovic B. (1984), "Matching, Turnover, and Unemployment", *Journal of Political Economy*, vol. 92, 1, 108-122.

- Lazear E. P. (1979), "Why is there mandatory retirement ?", *Journal of Political Economy*, vol. 87, 6, 1261-1284.
- Lazear E. P. (1981), "Agency, earnings profiles, productivity and hours restrictions", *American Economic Review*, vol. 71, 4, 606-620.
- Lazear E. P. (1999), "Personnel Economics: Past Lessons and Future Directions. Presidential Address to the Society of Labor Economics, San Francisco, May 1, 1998.", *Journal of Labor Economics*, vol.17, 2, 199-236.
- Lillard L. A. and R. J. Willis (1978), "Dynamic Aspects of Earnings Mobility", *Econometrica*, 46, 985-1012.
- Miller R.A. (1984), "Job Matching and Occupational Choice", *Journal of Political Economy*, vol. 92, 6, 1086-1120.
- Mincer J. (1974), "Progress in Human Capital Analysis of the distribution of earnings", NBER Working Paper 53.
- Postel-Vinay F. and J.M. Robin (2002), "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity", *Econometrica*, 70, 2295-2350.
- Salop J. and S. Salop (1976), "Self-Selection and Turnover in the Labor Market", *Quarterly Journal of Economics*, 90, 619-627.
- Topel R. H. (1991), "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority", *Journal of Political Economy*, 99, 145-175.
- Wasmer E. (2003), "Interpreting Europe and US labor markets differences : the specificity of human capital investments", CEPR discussion paper 3780.

A Mobility equation

A.1 Parameter γ

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

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

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

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

with:

- $M_{it}^m = m_{m_{it}^*} + \underbrace{\frac{\rho_{y,m} - \rho_{w,m}\rho_{y,w}}{1 - \rho_{y,w}^2}}_a (y_{it}^* - m_{y_{it}^*}) + \underbrace{\frac{\rho_{w,m} - \rho_{y,m}\rho_{y,w}}{\sigma(1 - \rho_{y,w}^2)}}_b (w_{it} - m_{w_{it}})$
- $\widetilde{m}_i^{*2,T-1} = \begin{pmatrix} y_{i2} m_{i2}^* \\ \dots \\ y_{iT-1} m_{iT-1}^* \end{pmatrix}$
- $\widetilde{M}_i^m{}^{2,T-1} = \begin{pmatrix} y_{i2} M_{i2}^m \\ \dots \\ y_{iT-1} M_{iT-1}^m \end{pmatrix}$
- $A_{it} = m_{it}^* - M_{it}^m + \gamma m_{it-1} = m_{it}^* - X_{it}^M \delta^M - \Omega_i^I \theta^{I,M} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - m_{w_{it}})$

By gathering squared and crossed terms, we get:

$$V_\gamma^{post,-1} = V_\gamma^{prior,-1} + \frac{1}{V^m} \sum_{i=1}^N (\widetilde{Lm}_i^{2,T-1})' \widetilde{Lm}_i^{2,T-1}$$

$$V_\gamma^{post,-1} M_\gamma^{post} = V_\gamma^{prior,-1} M_\gamma^{prior} + \frac{1}{V^m} \sum_{i=1}^N (\widetilde{Lm}_i^{2,T-1})' \widetilde{A}_i^{2,T-1}$$

A.2 Parameter δ^M

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

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

with $A_{it} = m_{it}^* - M_{it}^m + \delta^M X_{it}^M = m_{it}^* - \gamma m_{it-1} - \Omega_i^I \theta^{I,M} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - m_{w_{it}})$

B Wage equation

B.1 Parameter δ^W

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

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:

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

C Participation equation

C.1 Parameter γ^Y

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

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

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

with:

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

which is equivalent to:

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

If we use analogous notations as before, we get:

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

C.2 Parameter γ^M

We proceed the same way and we get:

$$V_{\gamma^M}^{post,-1} = V_{\gamma^M}^{prior,-1} + \sum_{i=1}^N (\underline{L}m_i^{2,T})' \underline{L}m_i^{2,T} + \frac{\rho_{y,w}^2 \sigma^2}{Vw} \sum_{i=1}^N (\widetilde{\underline{L}m}_i^{2,T})' \widetilde{\underline{L}m}_i^{2,T} + \frac{a^2}{Vm} \sum_{i=1}^N (\underline{L}m_i^{2,T-1})' \underline{L}m_i^{2,T-1}$$

$$V_{\gamma^M}^{post,-1} M_{\gamma^M}^{post} = V_{\gamma^M}^{prior,-1} M_{\gamma^M}^{prior} + \sum_{i=1}^N (\underline{L}m_i^{2,T})' \underline{A}_i^{2,T} - \frac{\rho_{y,w} \sigma}{Vw} \sum_{i=1}^N (\widetilde{\underline{L}m}_i^{2,T})' \widetilde{\underline{B}}_i^{2,T} - \frac{a}{Vm} \sum_{i=1}^N (\underline{L}m_i^{2,T-1})' \underline{C}_i^{2,T-1}$$

with:

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

C.3 Parameter δ^Y

We proceed the same way and we get:

$$V_{\delta^Y}^{post,-1} = V_{\delta^Y}^{prior,-1} + \sum_{i=1}^N (\underline{X}_i^{Y2,T})' \underline{X}_i^{Y2,T} + \frac{\rho_{y,w}^2 \sigma^2}{Vw} \sum_{i=1}^N (\widetilde{\underline{X}}_i^{Y2,T})' \widetilde{\underline{X}}_i^{Y2,T} + \frac{a^2}{Vm} \sum_{i=1}^N (\underline{X}_i^{Y2,T-1})' \underline{X}_i^{Y2,T-1}$$

$$V_{\delta^Y}^{post,-1} M_{\delta^Y}^{post} = V_{\delta^Y}^{prior,-1} M_{\delta^Y}^{prior} + \sum_{i=1}^N (\underline{X}_i^{Y2,T})' \underline{A}_i^{2,T} - \frac{\rho_{y,w} \sigma}{Vw} \sum_{i=1}^N (\widetilde{\underline{X}}_i^{Y2,T})' \widetilde{\underline{B}}_i^{2,T} - \frac{a}{Vm} \sum_{i=1}^N (\underline{X}_i^{Y2,T-1})' \underline{C}_i^{2,T-1}$$

with:

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

D Initial equations

D.1 Parameter δ_0^M

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

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

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

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:

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

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

with:

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

E Latent variables

E.1 Latent participation y_{it}^*

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

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

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

$$y_{it}^* \sim \mathcal{NT}_{\mathbb{R}^+}(M^{Apost}, V^{Apost})$$

$$V^{Apost, -1} M^{Apost} = \left(\frac{\sigma \rho_{v,\epsilon}}{V^w} - \frac{ab}{V^m} \right) (w_{it} - m_{w_{it}}) + \frac{a}{V^m} (m_{it}^* - m_{m_{it}^*}) + \left(\frac{\sigma^2 \rho_{v,\epsilon}^2}{V^w} + \frac{a^2}{V^m} + 1 \right) m_{y_{it}^*}$$

$$V^{Apost} = \frac{1}{1 + \frac{a^2}{V^m} + \frac{\sigma^2 \rho_{v,\epsilon}^2}{V^w}}$$

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

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

2. For $t = T$

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

$$y_{iT}^* \sim \mathcal{NT}_{\mathbb{R}^+}(M^{Apost}, 1 - \rho_{v,\epsilon}^2)$$

$$M^{Apost} = (1 - \rho_{v,\epsilon}^2) \left(m_{y_{iT}^*} \left(1 + \frac{\sigma^2 \rho_{v,\epsilon}^2}{V^w} \right) + \frac{\sigma \rho_{v,\epsilon}}{V^w} (w_{iT} - m_{w_{iT}}) \right)$$

(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, $t = 1 \dots T - 1$ 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 $\Sigma_i^I | (\dots); z; y, w$

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

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

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

★

H Individual effects

The likelihood terms that include θ^I writes as:

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

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**

$$(y_{i1}^* - m_{y_{i1}^*})^2 = (A_{i1} - \Omega_i^I \alpha^{I,Y})^2$$

$$A_{i1} = y_{i1}^* - XY_{i1} \delta_0^Y$$

2. **Second term**

$$y_{i1}(w_{i1} - M_{w_{i1}})^2 = y_{i1}(B_{i1} - \Omega_i^I \theta^{I,W} + \rho_{v,\varepsilon} \sigma \Omega_i^I \alpha^{I,Y})^2$$

$$B_{i1} = w_{i1} - XW_{i1} \delta^w - \rho_{v,\varepsilon} \sigma (y_{i1}^* - XY_{i1} \delta_0^Y)$$

$$\tilde{B}_{i1} = y_{i1} B_{i1}$$

$$\tilde{\Omega}_{i1}^I = y_{i1} \Omega_i^I$$

3. **Third term**

$$(y_{it}^* - m_{y_{it}^*})^2 = (C_{it} - \Omega_i^I \theta^{Y,I})^2$$

$$C_{it} = y_{it}^* - XY_{it} \delta^Y - \gamma^Y y_{it-1} - \gamma^M m_{it-1}$$

4. **Fourth term**

$$y_{it}(w_{it} - M_{w_{it}})^2 = y_{it}(D_{it} - \Omega_i^I \theta^{W,I} + \rho_{v,\varepsilon} \sigma \Omega_i^I \theta^{Y,I})^2$$

$$D_{it} = w_{it} - XW_{it} \delta^w - \rho_{v,\varepsilon} \sigma C_{it}$$

$$\tilde{D}_{it} = y_{it} D_{it}$$

$$\tilde{\Omega}_{it}^I = y_{it} \Omega_i^I$$

5. **Fifth term**

For $t > 1$

$$y_{it}(m_{it}^* - M_{m_{it}^*})^2 = y_{it}(F_{it} + \Omega_i^I (-\theta_{M,I} + a\theta^{Y,I} + b\theta^{W,I}))^2$$

$$F_{it} = m_{it}^* - \gamma m_{it-1} - XM_{it} \delta^M - aC_{it} - b(w_{it} - XW_{it} \delta^w)$$

$$\tilde{F}_{it} = y_{it} F_{it}$$

For $t = 1$

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

The posterior distribution satisfies:

$$\begin{aligned}
l(\theta^E|\dots) &\propto \exp\left(-\frac{1}{2}\theta^{I'}D^{I,-1}\theta^I\right) \\
&\exp\left(-\frac{1}{2}\sum_{i=1}^n(A_{i1} - \Omega_i^I\alpha^{Y,I})^2 - \frac{1}{2V^w}\sum_i\left(\tilde{B}_{i1} - \tilde{\Omega}_{i1}^I(\theta^{W,I} - \rho_{v,\varepsilon}\sigma\alpha^{Y,I})\right)^2\right) \\
&\exp\left(-\frac{1}{2}\sum_i\sum_{t=2}^T(C_{it} - \Omega_i^I\theta^{Y,I})^2 - \frac{1}{2V^w}\sum_i\sum_{t=2}^T\left(\tilde{D}_{it} - \tilde{\Omega}_{it}^I(\theta^{W,I} - \rho_{v,\varepsilon}\sigma\theta^{Y,I})\right)^2\right) \\
&\exp\left(-\frac{1}{2V^m}\sum_i\left(\tilde{G}_{i1} + \tilde{\Omega}_{i1}^I(-\alpha^{M,I} + a\alpha^{Y,I} + b\theta^{W,I})\right)^2\right) \\
&\exp\left(-\frac{1}{2V^m}\sum_i\sum_{t=2}^{T-1}\left(\tilde{F}_{it} + \tilde{\Omega}_{it}^I(-\theta^{M,I} + a\theta^{Y,I} + b\theta^{W,I})\right)^2\right)
\end{aligned}$$

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

$$P_1\theta^I = \alpha^{I,Y}$$

$$P_2\theta^I = \alpha^{I,M}$$

$$P_3\theta^I = \theta^{I,Y}$$

$$P_4\theta^I = \theta^{I,W}$$

$$P_5\theta^I = \theta^{I,M}$$

Let us denote:

$$1. E_1 = \sum_{i=1}^n \Omega_i^{I'} \Omega_i^I$$

2. $\widetilde{E}_1 = \sum_{i=1}^n \widetilde{\Omega}_{i1}^I \widetilde{\Omega}_{i1}^I$
3. $E_{2T} = \sum_{i=1}^n \underline{\Omega}_i^I \underline{\Omega}_i^I$
4. $\widetilde{E}_{2T} = \sum_{i=1}^n \widetilde{\Omega}_i^I \widetilde{\Omega}_i^I$
5. $\widetilde{E}_{2,T-1} = \sum_{i=1}^n \widetilde{\Omega}_i^{I,2,T-1} \widetilde{\Omega}_i^{I,2,T-1}$

So we get for the variance-covariance matrix:

$$V^{-1} = D_0^{E,-1} + \begin{vmatrix} E_1 + (\frac{\rho_{v,\varepsilon}^2 \sigma^2}{Vw} + \frac{a^2}{V^m}) \widetilde{E}_1 & -\frac{a}{V^m} \widetilde{E}_1 & 0 & 0 & 0 & 0 \\ -\frac{a}{V^m} \widetilde{E}_1 & \frac{1}{V^m} \widetilde{E}_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & E_{2T} + \frac{\rho_{v,\varepsilon}^2 \sigma^2}{Vw} \widetilde{E}_{2,T} + \frac{a^2}{V^m} \widetilde{E}_{2,T-1} & 0 & 0 & 0 \\ (-\frac{\rho_{v,\varepsilon} \sigma}{Vw} + \frac{ab}{V^m}) \widetilde{E}_1 & -\frac{b}{V^m} \widetilde{E}_1 & -\frac{\rho_{v,\varepsilon} \sigma}{Vw} \widetilde{E}_{2T} + \frac{ab}{V^m} \widetilde{E}_{2T-1} & \widetilde{E}_1 (\frac{1}{Vw} + \frac{b^2}{V^m}) + \frac{1}{Vw} \widetilde{E}_{2T} + \frac{b^2}{V^m} \widetilde{E}_{2T-1} & 0 & 0 \\ 0 & 0 & -\frac{a}{V^m} \widetilde{E}_{2T-1} & -\frac{b}{V^m} \widetilde{E}_{2T-1} & \frac{1}{V^m} \widetilde{E}_{2T-1} & \frac{1}{V^m} \widetilde{E}_{2T-1} \end{vmatrix}$$

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As for the posterior mean:

$$\begin{pmatrix} \sum_{i=1}^n \Omega_i^I A_{i1} - \frac{\rho_{v,\varepsilon} \sigma}{Vw} \sum_{i=1}^n \widetilde{\Omega}_{i1}^I B_{i1} - \frac{a}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{i1}^I G_{i1} \\ \frac{1}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{i1}^I G_{i1} \\ \sum_{i=1}^n \Omega_i^I C_i - \frac{\rho_{v,\varepsilon} \sigma}{Vw} \sum_{i=1}^n \widetilde{\Omega}_i^I D_i - \frac{a}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{iT-1}^I F_{iT-1} \\ \frac{1}{Vw} \sum_{i=1}^n \widetilde{\Omega}_{i1}^I B_{i1} + \frac{1}{Vw} \sum_{i=1}^n \widetilde{\Omega}_i^I D_i - \frac{b}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{i1}^I G_{i1} - \frac{b}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{iT-1}^I F_{iT-1} \\ \frac{1}{V^m} \sum_{i=1}^n \widetilde{\Omega}_{iT-1}^I F_{iT-1} \end{pmatrix}$$

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Table 1: Wage Equation

Parameter:	CEP (High-School Dropouts)			CAP-BEP (Vocational High-School, Basic)			Baccalauréat Degree (High-School Graduates)			College and Grandes Ecoles Graduates						
	Mean	StDev.	Max.	Min.	Max.	StDev.	Min.	Max.	Mean	StDev.	Max.	Min.	Max.			
Intercept	2.3537	0.0573	2.1497	2.6336	2.5619	0.0519	2.3516	2.7377	2.7754	0.0496	2.5940	2.9488	2.5562	0.0607	2.3243	2.7822
Experience	0.0504	0.0035	0.0372	0.0658	0.0590	0.0033	0.0461	0.0702	0.0764	0.0051	0.0589	0.0959	0.0537	0.0035	0.0410	0.0667
Experience squared	-0.0005	0.0001	-0.0007	-0.0003	-0.0006	0.0001	-0.0008	-0.0004	-0.0009	0.0001	-0.0013	-0.0005	-0.0008	0.0001	-0.0010	-0.0005
Seniority	0.0027	0.0030	-0.0091	0.0143	-0.0046	0.0029	-0.0153	0.0064	-0.0062	0.0049	-0.0238	0.0104	0.0264	0.0027	0.0157	0.0375
Seniority squared	-0.0002	0.0001	-0.0006	0.0000	-0.0002	0.0001	-0.0005	0.0002	-0.0001	0.0001	-0.0007	0.0004	-0.0004	0.0001	-0.0007	-0.0001
Part Time	-0.5199	0.0118	-0.5628	-0.4718	-0.4432	0.0107	-0.4814	-0.4039	-0.6559	0.0134	-0.7058	-0.5996	-0.8207	0.0149	-0.8821	-0.7675
Individual and Family Characteristics:																
Sex (equal to 1 for men)	0.5242	0.0352	0.3823	0.6427	0.4111	0.0344	0.2675	0.3037	0.3811	0.0383	0.2580	0.5179	0.5480	0.0398	0.4039	0.7134
Married	-0.0059	0.0139	-0.0571	0.0460	0.0216	0.0116	-0.0231	0.0002	-0.0070	0.0175	-0.0703	0.0597	0.1960	0.0216	0.1115	0.2884
Lives in Couple	0.0101	0.0185	-0.0601	0.0940	-0.0078	0.0170	-0.0734	0.0714	-0.0106	0.0245	-0.1212	0.0883	0.0178	0.0234	-0.0616	0.1023
Lives in region Ile de France	0.0787	0.0230	-0.0050	0.1694	0.0668	0.0211	-0.0181	0.0661	0.1022	0.0239	0.0202	0.1863	0.1358	0.0195	0.0665	0.2066
Unemployment Rate	0.0055	0.0945	-0.3572	0.3613	0.1361	0.0935	-0.2546	0.4865	0.1902	0.0961	-0.1473	0.5523	0.1523	0.0952	-0.2323	0.5208
Nationality:																
Other than French	0.0764	0.0404	-0.0566	0.2074	0.0550	0.0452	-0.0882	0.2141	0.0240	0.0450	-0.1402	0.1871	-0.0752	0.0339	-0.1853	0.0685
Father other than French	0.1064	0.0827	-0.1842	0.4998	0.0460	0.0705	-0.1948	0.3752	0.0856	0.0694	-0.1673	0.3289	-0.0183	0.0691	-0.3441	0.2372
Mother other than French	0.1250	0.0790	-0.1737	0.4833	0.0176	0.0715	-0.2286	0.3060	-0.0010	0.0609	-0.2397	0.2301	0.0551	0.0640	-0.2171	0.2820
Cohort Effects:																
Born before 1929	0.0873	0.0667	-0.1728	0.4053	0.0047	0.0753	-0.2561	0.2808	-0.0284	0.0835	-0.3641	0.2886	0.3720	0.0679	0.1175	0.6350
Born between 1930 and 1939	0.2579	0.0565	0.0538	0.4844	0.2006	0.0622	-0.0508	0.4324	-0.0411	0.0746	-0.3296	0.2236	0.4487	0.0604	0.2051	0.6857
Born between 1940 and 1949	0.5079	0.0535	0.2975	0.7440	0.3587	0.0526	0.1463	0.5545	0.1396	0.0587	-0.0627	0.3559	0.5208	0.0517	0.3259	0.7247
Born between 1950 and 1959	0.6393	0.0530	0.4305	0.8285	0.5828	0.0484	0.4076	0.7567	0.3839	0.0519	0.2163	0.5911	0.6085	0.0517	0.4162	0.8212
Born between 1960 and 1969	0.4583	0.0680	0.1732	0.7463	0.6027	0.0510	0.4159	0.7751	0.4775	0.0454	0.2967	0.7212	0.5722	0.0609	0.3319	0.8192

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Table 1: Wage Equation (continued)

Parameter:	CEP (High-School Dropouts)			CAP-BEP (Vocational High-School, Basic)			Baccalauréat Degree (High-School Graduates)			College and Grandes Ecoles Graduates					
	Mean	StDev.	Max.	Min.	Max.	Mean	StDev.	Max.	Min.	Max.	Mean	StDev.	Max.	Min.	Max.
Industry:															
Energy	0.1153	0.0654	0.3559	-0.1523	0.0099	0.0580	-0.1865	0.2248	0.1294	0.0677	-0.1100	0.3736	0.2386	0.0537	0.4528
Intermediate Goods	0.1317	0.0311	0.2558	0.0198	0.1856	0.0273	0.0920	0.2791	0.2055	0.0404	0.0264	0.3661	0.1364	0.0353	0.2816
Equipment Goods	0.1827	0.0308	0.3233	0.0722	0.1455	0.0270	0.0493	0.2546	0.2490	0.0370	0.1127	0.3943	0.2274	0.0326	0.3625
Consumption Goods	0.1411	0.0300	0.0284	0.0284	0.1452	0.0280	0.0273	0.2641	0.1865	0.0376	0.0154	0.3350	0.1349	0.0352	0.2534
Construction	0.0647	0.0322	0.0568	-0.0568	0.1537	0.0265	0.0505	0.2395	0.2773	0.0435	0.1239	0.4342	0.1341	0.0415	0.2765
Retail and Wholesome Goods	0.0954	0.0256	0.1820	-0.0202	0.0608	0.0241	-0.0388	0.1506	0.1758	0.0306	0.0649	0.3078	0.1664	0.0310	0.2826
Transport	0.1018	0.0348	0.0368	-0.0368	0.2387	0.0316	-0.0537	0.1930	0.1812	0.0397	0.0127	0.3325	0.1363	0.0379	0.2733
Market Services	0.0171	0.0253	0.0855	-0.0855	0.1028	0.0114	0.0228	-0.0843	0.1071	0.1637	0.0281	0.0518	0.0777	0.0266	0.1909
Insurance	0.1034	0.0737	0.1823	-0.1823	0.3736	0.0616	-0.2418	0.1956	0.2501	0.0506	0.0561	0.4389	0.1614	0.0555	0.3535
Banking and Finance Industry	0.2026	0.0612	-0.0741	0.4253	0.1510	0.0541	-0.0453	0.3643	0.2712	0.0430	0.1120	0.4406	0.2214	0.0425	0.3924
Non Market Services	-0.0573	0.0304	0.0607	-0.1841	-0.0902	0.0284	-0.1908	0.0247	-0.1539	0.0331	-0.2813	-0.0217	-0.3711	0.0315	-0.4887
Job Switch variables in First Sample Year															
JC=job change in 1st year	0.1077	0.0645	-0.1190	0.3638	0.0154	0.0652	-0.2382	0.2307	0.0401	0.0686	-0.1977	0.3012	0.1441	0.0741	0.3862
(yes=1)	-0.0049	0.0033	-0.0178	0.0072	-0.0083	0.0049	-0.0256	0.0082	-0.0059	0.0067	-0.0314	0.0188	-0.0030	0.0082	0.0274
Experience at $t-1$ if JC=1															
Number of switches of jobs that lasted															
Up to 1 year	0.0529	0.0146	-0.0051	0.1067	0.0301	0.0103	-0.0071	0.0649	0.0451	0.0129	-0.0113	0.0951	0.1829	0.0150	0.2384
Between 2 and 5 years	0.0985	0.0298	-0.0245	0.2012	0.1967	0.0237	0.1067	0.2941	0.1283	0.0329	0.0017	0.2478	0.0529	0.0300	0.1786
Between 6 and 10 years	-0.0164	0.0667	-0.2945	0.2278	0.1635	0.0592	-0.0600	0.3992	-0.0217	0.0806	-0.3041	0.2699	0.1731	0.0708	0.4239
More than 10 years	0.0585	0.0509	-0.1409	0.2493	-0.0619	0.0480	-0.2416	0.1354	0.0851	0.0717	-0.1828	0.3985	0.0582	0.0530	0.2796
Seniority at last job change that lasted															
Between 2 and 5 years	-0.0242	0.0093	-0.0603	0.0147	-0.0316	0.0081	-0.0626	-0.0032	-0.0344	0.0123	-0.0745	0.0124	0.0308	0.0102	0.0678
Between 6 and 10 years	-0.0025	0.0090	-0.0357	0.0327	-0.0199	0.0084	-0.0544	0.0137	-0.0156	0.0131	-0.0635	0.0341	0.0079	0.0101	0.0457
More than 10 years	-0.0167	0.0043	-0.0341	-0.0015	-0.0180	0.0047	-0.0365	-0.0011	-0.0145	0.0078	-0.0506	0.0140	0.0189	0.0042	0.0357
Experience at last job change that lasted															
Up to 1 year	-0.0055	0.0008	-0.0082	-0.0023	-0.0029	0.0007	-0.0056	-0.0005	-0.0059	0.0013	-0.0107	-0.0008	-0.0095	0.0012	-0.0045
Between 2 and 5 years	-0.0031	0.0010	-0.0071	0.0005	-0.0070	0.0010	-0.0107	-0.0032	-0.0036	0.0020	-0.0116	0.0041	-0.0039	0.0014	0.0015
Between 6 and 10 years	0.0016	0.0018	-0.0053	0.0085	-0.0106	0.0017	-0.0176	-0.0030	0.0003	0.0038	-0.0140	0.0140	-0.0096	0.0024	-0.0181
More than 10 years	0.0060	0.0021	-0.0017	0.0139	0.0094	0.0023	0.0007	0.0193	-0.0011	0.0042	-0.0203	0.0146	-0.0082	0.0027	0.0018

Notes: Source : DADS-EDP from 1978 to 1996. 3,000 individuals randomly selected within 32,596; 12,406; 34,071; and 7,579 respectively. Estimation by Gibbs Sampling. 80,000 iterations for the first group with a burn-in equal to 65,000; 80,000 iterations and 70,000 for the second group; 60,000 iterations and 50,000 for the two last groups. The equation also includes (unreported) year indicators.

Table 2: Participation Equation

Parameter:	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School Graduates)				College and Grandes Ecoles Graduates							
	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.				
Intercept	-1.2059	0.2264	-2.0459	-0.3083	-1.1824	0.2267	-2.1497	-0.3756	-0.8397	0.2241	-1.6846	0.0236	-0.8050	0.2304	-1.6848	0.1008
Experience	0.2211	0.0048	0.2034	0.2391	0.3273	0.0053	0.3085	0.3477	0.4304	0.0059	0.4090	0.4520	0.1777	0.0048	0.1583	0.1962
Experience squared	-0.0040	0.0001	-0.0044	-0.0037	-0.0061	0.0001	-0.0065	-0.0057	-0.0088	0.0001	-0.0092	-0.0084	-0.0040	0.0001	-0.0044	-0.0036
Local Unemployment Rate	7.4407	0.2864	6.3369	8.5610	8.6314	0.3401	7.3592	9.9501	6.4389	0.2804	5.4657	7.4100	6.4504	0.5114	4.3968	8.3073
Lagged Variables:																
Lagged Mobility γ^M	0.2041	0.0249	0.1008	0.2945	0.2081	0.0239	0.1248	0.2932	0.2445	0.0234	0.1322	0.3340	0.2665	0.0255	0.1764	0.3501
Lagged Participation γ	0.5192	0.0090	0.4845	0.5557	0.3961	0.0090	0.3600	0.4298	0.2595	0.0090	0.2244	0.2924	0.3414	0.0095	0.3067	0.3748
Individual and Family Characteristics:																
Sex (equal to 1 for men)	0.3000	0.0401	0.1684	0.4409	0.2096	0.0410	0.0607	-0.0732	-0.0796	0.0001	-0.2220	0.0433	0.3530	0.0450	0.1985	0.5176
Children between 0 and 3	-0.3319	0.0308	-0.4431	-0.2223	-0.1685	0.0273	-0.2773	-0.1853	-0.2517	0.0313	-0.3738	-0.1253	0.1060	0.0319	-0.0313	0.2170
Children between 3 and 6	-0.3387	0.0286	-0.4392	-0.2343	-0.2828	0.0271	-0.4028	0.1343	-0.4096	0.0353	-0.5338	-0.2655	-0.0304	0.0313	-0.1529	0.0842
Lives in Couple	-0.0546	0.0355	-0.1870	0.0854	-0.0060	0.0413	-0.1718	-0.1273	-0.2256	0.0420	-0.4316	-0.0312	0.0499	0.0461	-0.1381	0.2058
Married	-0.1070	0.0250	-0.1953	-0.0134	-0.2155	0.0274	-0.3142	-0.3363	-0.2101	0.0299	-0.3197	-0.1104	0.1099	0.0365	-0.0149	0.2283
Lives in region Ile de France	0.0659	0.0329	-0.0535	0.1876	0.1177	0.0371	0.0000	0.2511	0.0109	0.0247	-0.0846	0.1019	6.0465	0.1858	5.4092	6.5468
Nationality:																
Other than French	-0.3225	0.0454	-0.5021	-0.1568	-0.5103	0.0548	-0.7210	-0.3363	-0.2459	0.0522	-0.4212	-0.0396	-0.2613	0.0427	-0.4071	-0.1207
Father other than French	0.2813	0.1729	-0.2755	0.9149	0.2403	0.1149	-0.1324	0.6890	0.0532	0.0981	-0.3228	0.3805	0.1492	0.1303	-0.2729	0.5721
Mother other than French	-0.0161	0.1435	-0.5881	0.4719	0.0175	0.1233	-0.3805	0.4627	-0.1245	0.0808	-0.3920	0.2040	-0.1337	0.1200	-0.5597	0.2487
Cohort Effects:																
Born before 1929	-2.4810	0.0593	-2.7504	-2.2294	-3.3449	0.1126	-3.7576	-2.9619	-3.0419	0.1168	-3.4641	-2.6370	-2.5581	0.0934	-2.9179	-2.2146
Born between 1930 and 1939	-2.2575	0.0680	-2.5083	-2.0230	-3.1446	0.0836	-3.4547	-2.8658	-3.9734	0.1107	-4.3943	-3.6214	-2.5230	0.0862	-2.8828	-2.1666
Born between 1940 and 1949	-1.9738	0.0721	-2.2276	-1.7232	-2.9346	0.0777	-3.2263	-2.6812	-3.7966	0.0825	-4.1040	-3.5131	-2.3254	0.0700	-2.6082	-2.0824
Born between 1950 and 1959	-1.3127	0.0653	-1.5676	-1.0413	-1.7896	0.0593	-1.9957	-1.5794	-1.9638	0.0551	-2.1896	-1.7852	-1.9746	0.0622	-2.2054	-1.7624
Born between 1960 and 1969	-0.4090	0.0901	-0.7298	-0.0476	-0.6373	0.0503	-0.8121	-0.4662	-0.8580	0.0365	-0.9947	-0.7301	-1.4472	0.0710	-1.7185	-1.1838

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 group with a burn-in equal to 65,000; 80,000 iterations and 70,000 for the second group; 60,000 iterations and 50,000 for the two last groups. The equation also includes (unreported) year indicators.

Table 3: Mobility Equation

Parameter:	CEP (High-School Dropouts)			CAP-BEP (Vocational High-School, Basic)			Baccalauréat Degree (High-School Graduates)			College and Grandes Ecoles				
	Mean	StDev.	Max.	Mean	StDev.	Max.	Mean	StDev.	Max.	Mean	StDev.	Max.		
Intercept	-0.9936	0.3190	-2.0607	-1.0834	0.2773	-2.1074	-0.1132	0.2706	-1.5566	0.4488	-1.0982	0.4247	-2.5961	0.4947
Experience	-0.0119	0.0124	-0.0584	-0.0344	0.0107	-0.0826	0.0030	-0.0557	-0.0983	-0.0098	-0.0072	0.0090	-0.0373	0.0236
Experience squared	0.0001	0.0002	-0.0007	0.0006	0.0002	-0.0002	0.0013	0.0003	0.0002	0.0024	0.0003	0.0002	-0.0007	0.0011
Seniority	-0.0315	0.0089	-0.0603	-0.0315	0.0081	-0.0598	0.0008	-0.0335	-0.0783	0.0210	-0.0197	0.0080	-0.0462	0.0049
Seniority squared	0.0018	0.0004	0.0003	0.0032	0.0004	0.0005	0.0030	0.0017	0.0007	0.0036	0.0010	0.0003	0.0000	0.0022
Local Unemployment Rate	0.4218	0.7409	-2.1020	0.3087	0.6838	-2.2637	2.8675	-0.1282	0.6838	2.4090	0.0516	0.6968	-2.8736	2.9004
Part Time	0.4738	0.0452	0.2912	0.6054	0.0389	0.4430	0.7545	0.4737	0.0393	0.3181	0.6448	0.4497	0.3077	0.6004
Lagged Variables:														
Lagged Mobility γ	0.0150	0.0509	-0.1753	0.2228	0.0404	-0.1020	0.1900	-0.0638	0.0457	-0.2410	0.0979	-0.0161	0.0432	-0.1940
Individual and Family Characteristics:														
Sex	0.2164	0.0583	0.0099	0.4483	0.1942	0.0566	-0.0050	0.3919	0.1455	0.0556	-0.0331	0.3088	0.0932	0.0606
Children between 0 and 3	-0.3319	0.0308	-0.4431	0.2067	-0.0116	0.0436	-0.1583	0.1431	-0.0512	0.0594	-0.2485	0.2220	0.0042	0.0486
Children between 3 and 6	-0.3387	0.0286	-0.4392	0.1545	-0.0724	0.0446	-0.2665	0.0885	-0.1150	0.0693	-0.3834	0.1138	-0.0832	0.0473
Married	-0.1400	0.0506	-0.3126	0.0880	-0.0989	0.0699	-0.3476	0.1281	-0.2122	0.0772	-0.4918	0.0533	-0.1520	0.0561
Lives in Couple	-0.0055	0.0760	-0.3150	0.2829	-0.1666	0.0451	-0.3210	0.0063	-0.2443	0.0547	-0.4366	-0.0570	0.0781	-0.2862
Lives in region Ile de France	0.1744	0.0694	-0.0742	0.4067	0.0931	0.0618	-0.1074	0.3254	0.1122	0.0614	-0.1336	0.3622	0.2268	0.0503
Nationality														
Other than French	0.1540	0.0669	-0.0659	0.3914	0.0313	0.0803	-0.2119	0.3109	0.0035	0.0770	-0.2538	0.2508	-0.0358	0.0577
Father other than French	0.0417	0.2196	-0.8236	0.8865	0.0291	0.1316	-0.4380	0.5085	-0.0410	0.1322	-0.5067	0.4198	0.0162	0.1574
Mother other than French	0.2582	0.2082	-0.4319	1.0702	-0.1501	0.1447	-0.6825	0.3347	0.1056	0.1054	-0.2560	0.4953	0.0848	0.1466
Cohort Effects														
Born before 1929	-1.2194	0.3267	-2.5175	-0.0262	-0.9357	0.3015	-1.9970	0.0988	-1.9495	0.3715	-3.2924	-0.6306	-0.9637	0.3868
Born between 1930 and 1939	-1.1365	0.2856	-2.1678	0.1216	-0.7139	0.2333	-1.6084	0.0967	-1.1395	0.2640	-2.0043	-0.2303	-0.6508	0.3727
Born between 1940 and 1949	-0.7240	0.2466	-1.5697	0.3593	-0.4582	0.1866	-1.2629	0.2077	-0.9366	0.1816	-1.5296	-0.3493	-0.3260	0.3647
Born between 1950 and 1959	-0.6070	0.2169	-1.4110	0.2515	-0.2721	0.1496	-1.0042	0.2390	-0.5250	0.1230	-0.9590	-0.0832	0.0686	0.3625
Born between 1960 and 1969	-0.4095	0.2181	-1.1992	0.3931	-0.2520	0.1324	-0.7342	0.2528	-0.2829	0.0859	-0.6168	0.0319	0.4750	0.3680
Industry														
Energy	-0.0565	0.7367	-3.0659	2.2548	-1.2534	0.2465	-2.2500	-0.4472	-1.1784	0.2973	-2.1857	-0.0976	-0.7395	0.1920
Intermediate Goods	-0.3374	0.3187	-1.6399	0.9551	-0.1361	0.0986	-0.4907	0.2012	-0.0747	0.1433	-0.5886	0.5152	-0.3868	0.1262
Equipment Goods	0.3442	0.3134	-0.7644	1.5378	-0.2215	0.0977	-0.5730	0.1245	-0.0281	0.1354	-0.5356	0.4798	-0.4903	0.1232
Consumption Goods	0.5253	0.2945	-0.5168	1.7375	0.0385	0.1017	-0.3268	0.3856	-0.0535	0.1359	-0.5901	0.5204	-0.4103	0.1326
Construction	0.0887	0.2966	-1.2297	1.2266	0.2799	0.0917	-0.0506	0.6478	0.2324	0.1471	-0.4361	0.7247	-0.1671	0.1440
Retail and Wholesome Goods	0.3397	0.2743	-0.7272	1.3024	0.0454	0.0893	-0.2857	0.3716	0.1300	0.1209	-0.2720	0.5762	-0.4348	0.1227
Transport	0.4488	0.3799	-1.1288	1.9490	-0.2613	0.1069	-0.6548	0.1117	-0.3924	0.1432	-0.9237	0.1706	-0.7423	0.1430
Market Services	0.5872	0.2751	-0.5248	1.6170	0.1569	0.0861	-0.1231	0.5006	0.1053	0.1143	-0.3482	0.5286	-0.4290	0.1128
Insurance	0.6985	0.5764	-1.3449	3.2949	-0.0065	0.2297	-0.8253	0.8299	-0.0588	0.1743	-0.8918	0.5831	-0.3698	0.2003
Banking and Finance Industry	-0.7652	0.8214	-4.5648	2.0686	-0.5870	0.1863	-1.2710	0.0873	-0.2091	0.1408	-0.7437	0.3493	-0.6057	0.1468
Non Market Services	0.0160	0.4702	-2.1900	1.7453	-0.3484	0.1088	-0.7228	0.1118	-0.2473	0.1251	-0.7185	0.1817	-0.5744	0.1244

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 group with a burn-in equal to 65,000; 80,000 iterations and 70,000 for the second group; 60,000 iterations and 50,000 for the two last groups

Table 4: Initial Participation and Initial Mobility Equations

Initial Participation	CEP (High-School Dropouts)				CAP-BEP (Vocational High-School, Basic)				Baccalauréat Degree (High-School Graduates)				College and Grandes Ecoles Graduates			
	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.
Intercept	-2.8459	0.3998	-4.4209	-1.2872	-2.9903	0.4063	-4.4661	-1.4209	-3.2965	0.4107	-4.8259	-1.6793	-1.8846	0.4200	-3.6938	-0.2150
Experience	0.2003	0.0233	0.1096	0.2960	0.3312	0.0245	0.2181	0.4190	0.2898	0.0281	0.1905	0.3940	0.0428	0.0167	-0.0241	0.1168
Experience squared	-0.0010	0.0004	-0.0028	0.0007	-0.0045	0.0006	-0.0065	-0.0017	-0.0035	0.0007	-0.0061	-0.0003	-0.0007	0.0005	-0.0028	0.0014
Local Unemployment Rate	1.8225	0.9446	-2.0866	5.3900	1.5990	0.9471	-2.8114	4.7906	0.9676	0.9385	-2.8523	4.3225	-0.2731	0.9917	-3.7677	3.1575
Sex (equal to 1 for men)	0.7011	0.0761	0.4171	0.9858	0.5576	0.0817	0.2327	0.8446	0.4306	0.1069	0.0225	0.7779	0.5024	0.1001	0.1483	0.8873
Children between 0 and 3	-0.1709	0.1044	-0.5627	0.3006	-0.1886	0.1213	-0.6498	0.2391	0.0611	0.1642	-0.5658	0.6788	0.0136	0.1265	-0.4573	0.5252
Children between 3 and 6	-0.1679	0.1127	-0.6025	0.2895	-0.2899	0.1327	-0.7747	0.2075	0.0143	0.1931	-0.6440	0.7694	-0.0125	0.1312	-0.4876	0.4769
Married	0.0578	0.0910	-0.2656	0.4203	0.0305	0.1094	-0.3520	0.4622	-0.0696	0.1335	-0.5810	0.5318	0.4551	0.1067	0.0553	0.8785
Lives in region Ile de France	0.0160	0.1113	-0.3950	0.4059	0.0275	0.1391	-0.4451	0.6154	0.2574	0.1473	-0.2731	0.8070	4.6120	0.4169	3.7299	6.1850
Other than French	-0.2463	0.0876	-0.5905	0.0964	-0.2507	0.0987	-0.6461	0.0901	0.1400	0.1098	-0.2342	0.5515	0.2845	0.0854	-0.0502	0.5580
Father other than French	-0.0080	0.3362	-1.2229	1.3345	-0.0287	0.2417	-1.0755	0.7581	-0.6772	0.3976	-2.3310	0.5886	-0.1210	0.3964	-1.8075	1.2105
Mother other than French	-0.1357	0.3457	-1.6436	1.0800	-0.2486	0.3084	-1.8191	0.7796	-0.3021	0.4362	-2.0293	0.9482	-0.5356	0.3765	-2.1067	0.7331
Initial Mobility																
Intercept	-1.0043	0.5541	-3.5567	1.0965	-1.1277	0.5214	-3.7585	0.7110	-0.6695	0.6101	-3.3510	1.4467	-1.1251	0.5457	-3.1394	0.9738
Experience	0.0164	0.0381	-0.1176	0.1670	0.0800	0.0438	-0.1002	0.2379	0.0381	0.0565	-0.1590	0.2775	0.0030	0.0279	-0.1081	0.1122
Experience squared	-0.0001	0.0008	-0.0027	0.0026	-0.0012	0.0012	-0.0060	0.0038	-0.0006	0.0013	-0.0063	0.0040	-0.0001	0.0008	-0.0040	0.0027
Seniority	-0.4945	0.0437	-0.6556	-0.3266	-0.5516	0.0512	-0.7257	-0.3539	-0.5295	0.0735	-0.7890	-0.2591	0.1388	0.0403	-0.0198	0.2919
Seniority squared	0.0157	0.0026	0.0042	0.0255	0.0187	0.0038	0.0029	0.0301	0.0206	0.0043	0.0049	0.0368	-0.0058	0.0023	-0.0141	0.0028
Local Unemployment Rate	-0.1881	0.9895	-4.4757	3.9299	-0.1133	0.9912	-4.4792	4.4205	-0.0831	1.0065	-3.4719	3.6690	-0.1105	0.9974	-4.0807	3.6591
Sex (equal to 1 for men)	0.4416	0.1522	-0.1351	1.0065	0.2230	0.1706	-0.4682	0.8153	0.4696	0.2482	-0.5680	1.3473	0.0748	0.1764	-0.5819	0.8026
Children between 0 and 3	0.3233	0.1866	-0.3666	1.1331	-0.0474	0.2092	-0.7469	0.7188	-0.7832	0.3849	-2.4259	0.6247	-0.2102	0.2016	-0.9516	0.4958
Children between 3 and 6	0.1478	0.2152	-0.6293	0.8820	-0.3287	0.2487	-1.3511	0.5859	-0.7928	0.4742	-2.4296	0.9457	-0.2312	0.2094	-1.0546	0.5431
Married	-0.0472	0.1645	-0.7074	0.5208	0.3208	0.5807	-1.8336	2.4291	-0.2479	0.6237	-2.8261	1.8324	-0.1949	0.1716	-0.8382	0.3945
Lives in region Ile de France	-0.0098	0.2195	-0.8985	0.7789	0.5650	0.2378	-0.3138	1.3940	0.0095	0.2972	-1.1301	1.0360	0.2560	0.1510	-0.3512	0.8225
Other than French	0.1687	0.1607	-0.4254	0.8077	0.0575	0.1820	-0.6858	0.6537	-0.0978	0.2123	-0.8993	0.7121	-0.1333	0.1493	-0.6482	0.4311
Father other than French	-0.4096	0.5882	-2.6578	1.7066	0.1086	0.4143	-1.6320	1.5360	-1.1672	0.7540	-3.9754	1.9901	0.2762	0.5906	-1.9951	2.3810
Mother other than French	-0.4311	0.8170	-3.6439	2.4283	-0.0549	0.6113	-2.4960	2.1895	0.4172	0.9042	-2.9469	3.5456	0.1405	0.6861	-2.5378	2.5869

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 group with a burn-in equal to 65,000; 80,000 iterations and 70,000 for the second group; 60,000 iterations and 50,000 for the two last groups.

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						
	Mean	StDev.	Max.	Mean	StDev.	Max.	Mean	StDev.	Max.	Mean	StDev.	Max.				
$\rho_{y_0m_0}$	0.0254	0.0245	-0.0472	0.0771	-0.0143	0.0227	-0.0684	0.0403	0.0397	0.0244	-0.0076	0.0979	0.0214	0.0136	-0.0165	0.0674
ρ_{y_0y}	0.1458	0.0285	0.0742	0.2000	0.1238	0.0226	0.0726	0.1817	0.1199	0.0334	0.0503	0.1953	0.1364	0.0187	0.0852	0.1834
ρ_{y_0w}	0.0596	0.0357	-0.0066	0.1485	-0.0120	0.0205	-0.0565	0.0356	0.0576	0.0334	0.0022	0.1280	0.0525	0.0194	0.0087	0.1025
ρ_{y_0m}	0.0206	0.0193	-0.0414	0.0632	-0.0261	0.0164	-0.0587	0.0259	0.0422	0.0368	-0.0213	0.1294	-0.0311	0.0179	-0.0659	0.0101
ρ_{m_0y}	0.0087	0.0229	-0.0653	0.0545	-0.0025	0.0339	-0.0692	0.0544	0.0245	0.0226	-0.0304	0.0716	-0.0033	0.0353	-0.0775	0.0595
ρ_{m_0w}	0.0407	0.0301	-0.0079	0.1382	0.0202	0.0291	-0.0425	0.0879	-0.0168	0.0359	-0.1196	0.0410	0.0045	0.0110	-0.0278	0.0346
ρ_{m_0m}	-0.0312	0.0236	-0.0865	0.0281	0.0155	0.0203	-0.0345	0.0595	-0.0154	0.0156	-0.0541	0.0233	-0.0091	0.0173	-0.0491	0.0292
ρ_{yw}	0.2538	0.0369	0.1737	0.3272	0.1260	0.0214	0.0770	0.1738	0.2068	0.0216	0.1488	0.2500	0.1773	0.0200	0.1243	0.2185
ρ_{ym}	-0.0677	0.0185	-0.1291	-0.0241	-0.1013	0.0174	-0.1602	-0.0598	-0.0643	0.0202	-0.1114	-0.0092	-0.0287	0.0200	-0.0707	0.0231
ρ_{wm}	-0.1578	0.0282	-0.2188	-0.1027	-0.1897	0.0368	-0.2441	-0.0884	-0.0275	0.0175	-0.0814	0.0115	-0.0629	0.0214	-0.1099	-0.0089
Idiosyncratic Effects:																
σ^2	0.2669	0.0024	0.2591	0.2765	0.2653	0.0022	0.2571	0.2738	0.3964	0.0041	0.3828	0.4130	0.3728	0.0035	0.3640	0.3869
ρ_{wm}	-0.0595	0.0133	-0.1085	0.0000	-0.0574	0.0113	-0.1033	0.0000	-0.0553	0.0140	-0.1174	0.0004	-0.0835	0.0134	-0.1350	0.0000
ρ_{ym}	0.1455	0.0573	-0.0299	0.3588	0.1097	0.0538	-0.0921	0.2544	0.0383	0.0500	-0.1185	0.2012	0.2026	0.0499	-0.0427	0.3431
ρ_{yw}	0.0171	0.0160	-0.0436	0.0677	-0.0099	0.0161	-0.0708	0.0542	0.0161	0.0195	-0.0512	0.0790	0.0373	0.0222	-0.0571	0.1140

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 group with a burn-in equal to 65,000; 80,000 iterations and 70,000 for the second group; 60,000 iterations and 50,000 for the two last groups.

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

Parameters:	College Graduates, United States				College or Grandes Ecoles Graduates, France			
	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.
Wage Equation:								
Experience	0.0580	0.0032	0.0518	0.0643	0.0537	0.0035	0.0410	0.0667
Experience squared	-0.0013	0.0001	-0.0015	-0.0012	-0.0008	0.0001	-0.0010	-0.0005
Seniority	0.0518	0.0029	0.0460	0.0576	0.0264	0.0027	0.0157	0.0375
Seniority squared	-0.0005	0.0001	-0.0007	-0.0004	-0.0004	0.0001	-0.0007	-0.0001
Number of switches of jobs that lasted:								
Up to 1 year	0.2240	0.0172	0.1905	0.2572	0.1829	0.0150	0.1198	0.2384
Between 2 and 5 years	0.1648	0.0189	0.1274	0.2018	0.0529	0.0300	-0.0704	0.1786
Between 6 and 10 years	0.3231	0.0683	0.1861	0.4572	0.1731	0.0708	-0.1087	0.4239
More than 10 years	0.4717	0.0869	0.3031	0.6425	0.0582	0.0530	-0.1644	0.2796
Seniority at last job change that lasted:								
Between 2 and 5 years	0.0567	0.0070	0.0432	0.0709	0.0308	0.0102	-0.0080	0.0678
Between 6 and 10 years	0.0111	0.0097	-0.0079	0.0303	0.0079	0.0101	-0.0290	0.0457
More than 10 years	0.0062	0.0055	-0.0050	0.0166	0.0189	0.0042	0.0004	0.0357
Experience at last job change that lasted:								
Up to 1 year	-0.0071	0.0016	-0.0102	-0.0040	-0.0095	0.0012	-0.0135	-0.0045
Between 2 and 5 years	-0.0058	0.0016	-0.0090	-0.0027	-0.0039	0.0014	-0.0094	0.0015
Between 6 and 10 years	-0.0025	0.0025	-0.0073	0.0024	-0.0096	0.0024	-0.0181	-0.0013
More than 10 years	-0.0026	0.0033	-0.0090	0.0036	-0.0082	0.0027	-0.0196	0.0018
Participation Equation:								
Lagged Mobility γ^M	0.3336	0.1646	0.0111	0.6274	0.2665	0.0255	0.1764	0.3501
Lagged Participation γ^Y	2.0046	0.0944	1.8178	2.1978	0.3414	0.0095	0.3067	0.3748
Mobility Equation:								
Seniority	-0.0878	0.0074	-0.1024	-0.0734	-0.0197	0.0080	-0.0462	0.0049
Seniority squared	0.0020	0.0003	0.0015	0.0026	0.0010	0.0003	0.0000	0.0022
Lagged Mobility γ	-0.9019	0.0552	-1.0133	-0.7953	-0.0161	0.0432	-0.1940	0.1412
Individual Effects:								
ρ_{y0m0}	0.8040	0.0556	0.7024	0.9005	0.0214	0.0136	-0.0165	0.0674
ρ_{y0y}	0.5716	0.0286	0.5190	0.6224	0.1364	0.0187	0.0852	0.1834
ρ_{y0w}	0.1335	0.0757	0.0169	0.2714	0.0525	0.0194	0.0087	0.1025
ρ_{y0m}	-0.6044	0.0773	-0.7595	-0.4892	-0.0311	0.0179	-0.0659	0.0101
ρ_{m0y}	0.2896	0.0429	0.2268	0.3845	-0.0033	0.0353	-0.0775	0.0595
ρ_{m0w}	-0.1450	0.0884	-0.2586	0.0403	0.0045	0.0110	-0.0278	0.0346
ρ_{m0m}	-0.4234	0.0789	-0.5691	-0.2668	-0.0091	0.0173	-0.0491	0.0292
ρ_{yw}	0.2174	0.0553	0.1066	0.3017	0.1773	0.0200	0.1243	0.2185
ρ_{ym}	-0.5061	0.0656	-0.6172	-0.3874	-0.0287	0.0200	-0.0707	0.0231
ρ_{wm}	-0.5352	0.0590	-0.6371	-0.4131	-0.0629	0.0214	-0.1099	-0.0089
Idiosyncratic Effects:								
σ^z	0.2062	0.0023	0.2016	0.2104	0.3728	0.0035	0.3640	0.3869
ρ_{wm}	0.0013	-0.0111	0.0075	0.0161	-0.0835	0.0134	-0.1350	0.0000
ρ_{ym}	-0.0005	0.0113	-0.0217	0.0188	0.2026	0.0499	-0.0427	0.3431
ρ_{yw}	-0.0496	0.0124	-0.0672	-0.0205	0.0373	0.0222	-0.0571	0.1140

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

Parameters:	High-School Dropouts				CEP Graduates			
	United States		France		United States		France	
	Mean	StDev.	Min.	Max.	Mean	StDev.	Min.	Max.
Wage Equation:								
Experience	0.0283	0.0027	0.0229	0.0334	0.0504	0.0035	0.0372	0.0658
Experience squared	-0.0007	0.0000	-0.0007	-0.0006	-0.0005	0.0001	-0.0007	-0.0003
Seniority	0.0517	0.0034	0.0455	0.0580	0.0027	0.0030	-0.0091	0.0143
Seniority squared	-0.0005	0.0001	-0.0008	-0.0003	-0.0002	0.0001	-0.0006	0.0000
Number of switches of jobs that lasted:								
Up to 1 year	0.0923	0.0144	0.0635	0.1203	0.0529	0.0146	-0.0051	0.1067
Between 2 and 5 years	0.0958	0.0219	0.0526	0.1386	0.0985	0.0298	-0.0245	0.2012
Between 6 and 10 years	0.1229	0.1027	-0.0569	0.3076	-0.0164	0.0667	-0.2545	0.2278
More than 10 years	0.2457	0.1078	0.0474	0.4606	0.0585	0.0509	-0.1409	0.2493
Seniority at last job change that lasted:								
Between 2 and 5 years	0.0293	0.0084	0.0127	0.0456	-0.0242	0.0093	-0.0603	0.0147
Between 6 and 10 years	0.0213	0.0109	0.0003	0.0422	-0.0025	0.0090	-0.0357	0.0327
More than 10 years	0.0350	0.0053	0.0238	0.0444	-0.0167	0.0043	-0.0341	-0.0015
Experience at last job change that lasted:								
Up to 1 year	0.0009	0.0012	-0.0015	0.0033	-0.0055	0.0008	-0.0082	-0.0023
Between 2 and 5 years	-0.0007	0.0016	-0.0038	0.0024	-0.0031	0.0010	-0.0071	0.0005
Between 6 and 10 years	0.0007	0.0030	-0.0049	0.0060	0.0016	0.0018	-0.0053	0.0085
More than 10 years	-0.0090	0.0029	-0.0150	-0.0035	0.0060	0.0021	-0.0017	0.0139
Participation Equation:								
Lagged Mobility γ^M	0.5295	0.1258	0.3043	0.7836	0.2041	0.0249	0.1008	0.2945
Lagged Participation γ^Y	1.7349	0.0660	1.5999	1.8530	0.5192	0.0090	0.4845	0.5557
Mobility Equation:								
Seniority	-0.0812	0.0115	-0.1007	-0.0605	-0.0315	0.0089	-0.0603	0.0018
Seniority squared	0.0018	0.0003	0.0011	0.0024	0.0018	0.0004	0.0003	0.0032
Lagged Mobility γ	-0.7190	0.0738	-0.8544	-0.5807	0.0150	0.0509	-0.1753	0.2228
Individual Effects:								
ρ_{y0m0}	-0.1020	0.1146	-0.2589	0.1067	0.0254	0.0245	-0.0472	0.0771
ρ_{y0y}	0.7548	0.0566	0.6525	0.8747	0.1458	0.0285	0.0742	0.2000
ρ_{y0w}	0.3447	0.0351	0.2732	0.4142	0.0596	0.0357	-0.0066	0.1485
ρ_{y0m}	0.0278	0.2007	-0.2908	0.2281	0.0206	0.0193	-0.0414	0.0632
ρ_{m0y}	0.1972	0.0746	0.0260	0.2971	0.0087	0.0229	-0.0653	0.0545
ρ_{m0w}	0.0646	0.0505	-0.0061	0.1794	0.0407	0.0301	-0.0079	0.1382
ρ_{m0m}	-0.0573	0.1666	-0.2619	0.2194	-0.0312	0.0236	-0.0865	0.0281
ρ_{yw}	0.2958	0.0282	0.2292	0.3560	0.2538	0.0369	0.1737	0.3272
ρ_{ym}	-0.2100	0.1053	-0.3832	-0.0429	-0.0677	0.0185	-0.1291	-0.0241
ρ_{wm}	-0.2744	0.0799	-0.4083	-0.1348	-0.1578	0.0282	-0.2188	-0.1027
Idiosyncratic Effects:								
σ^2	0.2448	0.0064	0.2331	0.2539	0.2669	0.0024	0.2591	0.2765
ρ_{wm}	-0.0055	0.0074	-0.0185	0.0072	-0.0595	0.0133	-0.1085	0.0000
ρ_{ym}	0.0029	0.0077	-0.0117	0.0160	0.1455	0.0573	-0.0299	0.3588
ρ_{yw}	-0.0346	0.0072	-0.0497	-0.0183	0.0171	0.0160	-0.0436	0.0677

Table 8: Estimated Cumulative and Marginal Returns to Experience and Seniority: U.S. and France

	Cumulative Returns			Marginal Returns (in %)		
	Years of Experience			Years of Experience		
	5	10	15	5	10	15
Panel A: USA						
HS Dropouts	0.101 (0.005)	0.246 (0.012)	0.472 (0.022)	2.661 (0.286)	1.959 (0.248)	1.256 (0.215)
College Graduates	0.256 (0.015)	0.446 (0.029)	0.567 (0.040)	4.455 (0.285)	3.109 (0.253)	1.763 (0.231)
Panel B: France						
HS Dropouts	0.240 (0.017)	0.458 (0.031)	0.652 (0.045)	4.575 (0.314)	4.112 (0.285)	3.648 (0.265)
College Graduates	0.249 (0.016)	0.459 (0.030)	0.630 (0.042)	4.587 (0.303)	3.808 (0.263)	3.030 (0.241)

	Cumulative Returns			Marginal Returns (in %)		
	Years of Seniority			Years of Seniority		
	5	10	15	5	10	15
Panel A: USA						
HS Dropouts	0.266 (0.029)	0.347 (0.040)	0.392 (0.050)	4.721 (0.216)	4.314 (0.169)	3.906 (0.156)
College Graduates	0.236 (0.014)	0.449 (0.025)	0.637 (0.034)	4.485 (0.247)	4.001 (0.209)	3.517 (0.205)
Panel B: France						
HS Dropouts	0.006 (0.014)	-0.002 (0.027)	-0.025 (0.039)	-0.021 (0.269)	-0.307 (0.257)	-0.594 (0.267)
College Graduates	0.122 (0.012)	0.225 (0.023)	0.307 (0.031)	2.245 (0.225)	1.849 (0.199)	1.453 (0.207)

Notes: Sources: PSID for the U.S. and DADS-EDP for France. Estimates from BFKT and this paper. Bayesian estimation methods.

Table 9: Comparison of Estimates (OLS, IV à la Altonji)

	U.S.		France	
	HS Dropouts	College	HS Dropouts	College
Altonji-Williams				
Linear tenure	0.046 (0.006)	0.037 (0.006)	-0.004 (0.003)	-0.001 (0.003)
Linear experience	0.055 (0.011)	0.058 (0.014)	0.036 (0.004)	0.051 (0.004)
<i>Cumulative Returns to Tenure</i>				
2 years	0.062 (0.010)	0.043 (0.008)	-0.008 (0.005)	-0.002 (0.007)
5 years	0.112 (0.017)	0.078 (0.014)	-0.020 (0.014)	-0.005 (0.017)
10 years	0.131 (0.019)	0.092 (0.015)	-0.042 (0.029)	-0.013 (0.035)
15 years	0.131 (0.018)	0.090 (0.016)	-0.064 (0.046)	-0.022 (0.056)
20 years	0.146 (0.019)	0.099 (0.020)	-0.088 (0.066)	-0.034 (0.080)
OLS				
Linear tenure	0.058 (0.006)	0.040 (0.005)	0.001 (0.002)	0.021 (0.002)
Linear experience	0.059 (0.010)	0.059 (0.008)	0.037 (0.003)	0.039 (0.004)
<i>Cumulative Returns to Tenure</i>				
2 years	0.099 (0.009)	0.068 (0.007)	0.003 (0.004)	0.041 (0.005)
5 years	0.197 (0.015)	0.136 (0.012)	0.013 (0.009)	0.096 (0.012)
10 years	0.273 (0.016)	0.189 (0.013)	0.042 (0.020)	0.171 (0.026)
15 years	0.300 (0.017)	0.208 (0.015)	0.087 (0.032)	0.226 (0.041)
20 years	0.328 (0.017)	0.223 (0.018)	0.147 (0.046)	0.260 (0.059)
System				
Linear tenure	0.052 (0.003)	0.052 (0.003)	0.003 (0.003)	0.026 (0.003)
Linear experience	0.028 (0.003)	0.058 (0.003)	0.050 (0.004)	0.054 (0.004)

Notes: Sources: PSID for the U.S., DADS-EDP for France

The panel labeled Altonji-Williams reports estimates using instrumental variables for tenure (diff. with average tenure in the job) as in Altonji-Williams

Table B.1: Descriptive Statistics

Variable	CEP (High-School Dropouts)		CAP (Occupational degrees)		Baccalauréat (High-School Graduates)		Grandes Ecoles, College Graduates	
	Mean	St Error	Mean	St Error	Mean	St Error	Mean	St Error
Participation	0.5045	0.5000	0.5860	0.4926	0.4604	0.4984	0.4700	0.4991
Wage	4.0874	0.8093	4.1991	0.7463	4.1573	0.9801	4.7006	1.1599
Mobility	0.0752	0.2637	0.0938	0.2916	0.1232	0.3287	0.0952	0.2935
Tenure	7.6476	7.8048	5.9895	6.9210	4.1165	6.1718	6.2467	7.7694
Experience	24.7733	11.4711	17.4464	10.7499	11.7819	9.9945	15.7837	9.6285
Lives in Couple	0.0648	0.2461	0.0613	0.2399	0.0661	0.2484	0.0551	0.2281
Married	0.6347	0.4815	0.5650	0.4958	0.3540	0.4782	0.5706	0.4950
Children between 0 and 3	0.0863	0.2809	0.1317	0.3381	0.1019	0.3025	0.1225	0.3279
Children between 3 and 6	0.0898	0.2859	0.1142	0.3180	0.0749	0.2633	0.1096	0.3125
Number of Children	1.3196	1.3771	1.0712	1.2158	0.5873	0.9889	0.9830	1.4218
Lives in Region Ile de France	0.1196	0.3245	0.1124	0.3160	0.1531	0.3600	0.2088	0.4064
Lives in Paris	0.1182	0.3228	0.1120	0.3153	0.1532	0.3602	0.2707	0.4443
Lives in Town	0.2033	0.4024	0.2167	0.4120	0.2417	0.4281	0.2251	0.4176
Rural	0.6785	0.4670	0.6714	0.4697	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 B.1: Descriptive Statistics (continued)

Variable	CEP (High-School Dropouts)		CAP (Occupational degrees)		Baccalauréat (High-School Graduates)		Grandes Ecoles, College Graduates	
	Mean	St Error	Mean	St Error	Mean	St Error	Mean	St Error
Part Time	0.1846	0.3880	0.1528	0.3598	0.2394	0.4267	0.2137	0.4100
Local Unemployment Rate	8.1940	3.6354	8.3736	3.4322	8.2858	3.5824	8.9162	2.7771
Agriculture	0.0424	0.2016	0.0379	0.1909	0.0216	0.1454	0.0130	0.1133
Energy	0.0095	0.0969	0.0164	0.1272	0.0117	0.1076	0.0219	0.1463
Intermediate Goods	0.1007	0.3009	0.0960	0.2946	0.0489	0.2157	0.0634	0.2436
Equipment Goods	0.1122	0.3157	0.1305	0.3368	0.0691	0.2536	0.1277	0.3337
Consumption Goods	0.1127	0.3162	0.0741	0.2620	0.0551	0.2281	0.0555	0.2289
Construction	0.0884	0.2840	0.1159	0.3201	0.0387	0.1930	0.0357	0.1856
Retail and Wholesome Goods	0.1611	0.3676	0.1436	0.3507	0.1554	0.3623	0.0939	0.2917
Transport	0.0606	0.2385	0.0629	0.2428	0.0699	0.2550	0.0531	0.2242
Market Services	0.2083	0.4061	0.2222	0.4158	0.3082	0.4617	0.3383	0.4731
Insurance	0.0079	0.0886	0.0080	0.0893	0.0197	0.1390	0.0156	0.1238
Banking and Finance Industry	0.0155	0.1234	0.0213	0.1445	0.0558	0.2296	0.0452	0.2077
Non Market Services	0.0748	0.2630	0.0661	0.2484	0.1396	0.3466	0.1306	0.3370
Born before 1929	0.2380	0.4258	0.0540	0.2261	0.0452	0.2078	0.0956	0.2941
Born between 1930 and 1939	0.2132	0.4096	0.1215	0.3268	0.0480	0.2137	0.1314	0.3378
Born between 1940 and 1949	0.2290	0.4202	0.2013	0.4010	0.1048	0.3063	0.2867	0.4522
Born between 1950 and 1959	0.2329	0.4227	0.3084	0.4618	0.2123	0.4089	0.3266	0.4690
Born between 1960 and 1969	0.0646	0.2459	0.2758	0.4469	0.4476	0.4973	0.1580	0.3648
Born after 1970	0.0222	0.1475	0.0390	0.1935	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.