Mobility and wage dynamics in the French labour market

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Mobilités et dynamiques salariales sur le marché du travail français

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Introduction

Le marché du travail français est caractérisé par une très forte proportion de contrats à durée indéterminée (Figure 1) et de façon corrélée, par une forte proportion de relations de long terme entre employeurs et employés (Figure 2). Malgré l'existence de ces relations pérennes entre employeurs et employés, la part de contrats de courte durée (Contrats à Durée Déterminée, missions d'intérim) ne cesse d'augmenter depuis leur introduction au début des années 1980 (Figure 1). En 2005, les contrats de court terme représentent 66% des embauches, et sont à l'origine de 60% des transitions de l'emploi vers le non-emploi. Outils de flexibilité des entreprises, ces contrats de court terme sont de plus en plus utilisés au détriment du salarié. Ils servent alors de variable d'ajustement protègeant ainsi les salariés employés en contrat à durée indéterminée. Cette polarisation croissante du marché du travail français oppose des contrats courts perçus comme outil de précarisation et des contrats à durée indéterminée synonyme de réussite d'intégration sur le marché du travail. Elle se traduit ainsi par la coexistence d'une forte proportion de relations de long terme entre salariés et employeurs et d'une part importante de changement d'employeurs dans les premiers temps de présence dans l'entreprise. Confortant ce constat, la fréquence des changements d'entreprises des travailleurs français est d'autant plus faible que l'expérience, mais aussi l'ancienneté dans l'entreprise, sont élevées. Par exemple, en moyenne sur 1991-2002, 13.7% des cadres ayant moins de 10 ans de carrière perdent leur emploi ou changent d'employeur. Parmi les cadres ayant 20 à 30 ans de carrière, cette proportion n'est plus que de 5.3% (Amossé (2003)). Cette mobilité diminue d'autant avec l'ancienneté que les salaires sont en moyenne plus élevés pour un temps plus grand passé dans l'entreprise (Pouget (2005b)). La probabilité de quitter l'entreprise est alors plus faible car les salaires alternatifs proposés le sont aussi. En France, la figure emblématique de cette faible mobilité associée à de très longues relations employeur employé est constituée par la Fonction Publique, qui représente, dans son acception la plus large, plus d'un emploi sur cinq (Pouget (2005a)). Le statut particulier de l'agent fonctionnaire est aujourd'hui débattu. En 2003, le rapport du Conseil d'Etat (Conseil d'Etat (2003)) pose par exemple le problème de l'évolution de la Fonction Publique : compte tenu de ses dépenses de personnel, soit au sens large 40% du budget de l'Etat, ce rapport indique que la Fonction Publique devrait faire preuve d'une efficacité accrue, et d'une meilleure adaptation aux exigences de la gestion des ressources humaines. Il souligne que la capacité concurrentielle de la France dépend tout autant de la maîtrise de ses dépenses publiques que de la performance de ses services publics. Se pose alors la question de la rémunération des fonctionnaires : il existerait une prime à l'emploi dans la Fonction Publique (Pouget (2005b)). Dans un contexte de fort déficit budgétaire, et de recherche d'efficience de la Fonction Publique, ce constat mérite approfondissement.

Figure 1.Part des contrats de long et de court terme au sein de la population active

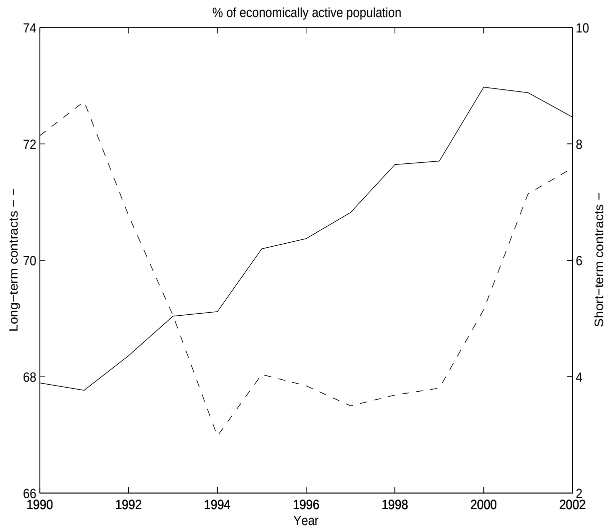
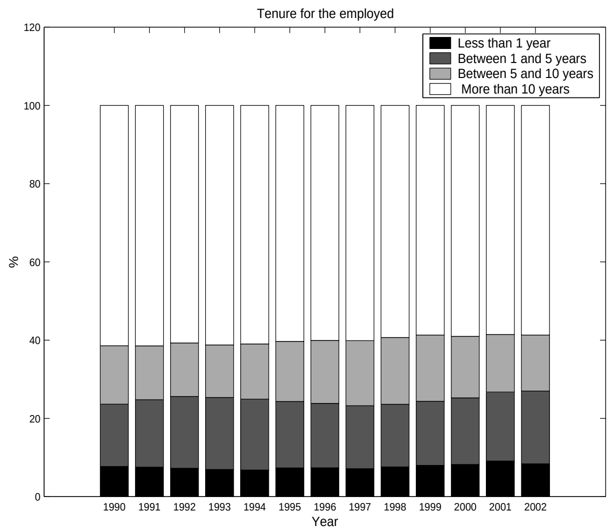


Figure 2. Répartition de l'ancienneté parmi les salariés



Ainsi, autour de ces faits brièvement présentés, s'articulent différentes questions qui sont abordées de façon détaillée par la suite :

a) d'une part, comment expliquer que les salaires croissent avec l'ancienneté et comment mesurer ce phénomène ?

b) d'autre part, compte tenu de la relation particulière qui lie l'agent fonctionnaire et son employeur, et de l'intérêt particulier que suscite la Fonction Publique dans un contexte budgétaire difficile, existe-t-il des différences de salaire effectives entre le secteur public et le secteur privé ? Cette question est d'autant plus cruciale que la maîtrise de la dépense publique est aujourd'hui difficile à atteindre. Le secteur public ne paie-t-il pas donc trop ses employés comparativement au secteur privé ?

c) enfin, à l'opposé des agents fonctionnaires, symbole d'une flexibilité accrue du marché du travail, les contrats courts, dont la proportion est en augmentation depuis leur introduction, constituent-ils un marchepied vers une relation de long terme avec l'entreprise ou plutôt un frein à une insertion durable ?

Salaires, mobilité et ancienneté

Qu'est-ce qui pourrait expliquer que les salaires augmentent avec l'ancienneté ?

Des relations d'emploi durables et des salaires plus élevés en fonction de l'ancienneté seraient expliquées de façon évidente par l'existence d'un capital humain spécifique à l'entreprise. D'après Becker (1964) et Mincer (1974), les salariés investissent dans le capital spécifique à leur entreprise et de ce fait, avec une acquisition croissante de connaissances spécifiques, leur salaire augmenterait avec leur ancienneté dans l'entreprise. Ce capital humain spécifique, non transférable, serait valorisable pour le couple salarié - entreprise mais n'aurait aucune valeur monétaire en dehors. Parsons (1972) présente un modèle détaillé d'accumulation du capital humain spécifique qui explique la diminution de la probabilité de changer d'emploi en fonction de l'investissement en connaissances spécifiques à l'entreprise. Farber (1994b), à l'aide d'un modèle simple à vocation illustrative montre que si le capital humain spécifique s'accroît avec l'ancienneté, alors les taux de séparation sont élevés au début de la relation avec l'entreprise mais ils décroissent par la suite. De plus, en présence de capital spécifique, une rente est attribuée au salarié, augmentant ainsi son salaire par rapport au salaire alternatif qu'il pourrait obtenir. Sa probabilité de quitter l'entreprise en est diminuée d'autant.

L'existence d'une productivité spécifique au couple employeur - employé donné, inconnue *ex ante*, peut aussi expliquer cette croissance des salaires avec l'ancienneté (Jovanovic (1979a)). Le salarié apprend au fur et à mesure du temps passé dans l'entreprise sur la qualité de ses liens avec elle. Ce modèle permet ainsi d'expliquer les relations de long terme ainsi que les forts taux de séparation observés en début de poste. Il explique par ailleurs l'augmentation des salaires avec l'ancienneté, une composante essentielle des salaires étant le terme d'appariemment, supposé croissant avec le temps passé dans l'entreprise.

L'ensemble de ces faits pourrait aussi être expliqué par la présence d'une hétérogénéité individuelle inobservée. Une simple généralisation du modèle mover stayer de Blumen, Kogan, and MacCarthy (1955), avec la coexistence de deux types de travailleurs, ceux à faible et ceux à forte mobilité (ou ceux à forte et à faible habileté) conclut à l'existence de relations de long terme, à la diminution de la mobilité avec l'ancienneté, ainsi qu'à des salaires élevés aux anciennetés les plus grandes. En effet, les personnes les plus productives ont dès le début de leur carrière un salaire plus élevé. La probabilité qu'elles changent d'emploi est donc plus faible, la probabilité que leur soit offert un salaire alternatif plus élevé étant moins grande. Ces personnes changent alors d'emploi moins souvent, et ont au final une ancienneté plus élevée. Ceci expliquerait en particulier que la productivité des personnes dont l'ancienneté est élevée soit plus grande, et donc que leur salaire soit plus élevé.

Enfin l'entreprise peut tenir à fidéliser ses meilleurs salariés, et à récompenser leurs efforts. De ce fait, l'employeur crée une incitation pour l'employé, soit à rester, soit à fournir l'effort approprié, en différant une partie de son revenu dans le temps : s'établissent des contrats de travail implicites où les salaires augmentent avec le temps (see Blumen, Kogan, and MacCarthy (1955), Becker and Stigler (1974), Rosen (1976), Lazear and Rosen (1981), et plus récemment, Burdett and Coles (2003)). Dans les entreprises à fort capital spécifique, le revenu versé par l'employeur est implicitement différé dans le temps afin que l'employé ne quitte pas son entreprise ; ce profil de rémunération se rencontre aussi quand l'effort à fournir est important. La perspective d'une compensation financière incite le travailleur à fournir la quantité de travail appropriée. Cette structure de compensation différée permet enfin d'auto sélectionner les travailleurs aux compétences hétérogènes (Salop and Salop (1976)).

Se pose alors le problème de l'estimation du lien entre croissance du salaire et ancienneté ou capital spécifique. En effet, par analogie avec l'utilisation de l'expérience comme mesure du capital humain général (Mincer (1974) and Willis (1986)), l'ancienneté est utilisée comme mesure du capital spécifique à l'entreprise. Le logarithme du salaire est supposée dépendre de la même façon de l'ancienneté et de l'expérience. Bien que cette analogie implique certaines hypothèses (Farber (1994a)), un nombre élevé de papiers adoptent cette stratégie afin de tester l'existence de capital spécifique et d'estimer les rendements de l'ancienneté dans l'entreprise. Deux volets de la littérature s'opposent sur l'estimation de ces rendements : certaines études estiment que les rendements de l'ancienneté sont faibles voire négligeables ; d'autres en revanche estiment de substantiels rendements de l'ancienneté[1]. De telles dissensions existent en raison de la complexité de cette estimation : l'ancienneté comme l'expérience sont des variables endogènes, car participation au marché du travail, mobilité et salaires résultent de décisions des agents.

Les premiers articles à avoir traité de la mesure des rendements de l'ancienneté estiment en coupe des équations de salaire en fonction de l'expérience et de l'ancienneté. Abraham and Farber (1987) insistent sur le rôle de l'hétérogénéité inobservée et affirment que les salaires n'augmentent que peu avec l'ancienneté. Ils montrent que les rendements de l'ancienneté mesurés en coupe sont largement biaisés, du fait de la corrélation de l'ancienneté avec une variable omise représentant la qualité du travailleur, de l'emploi ainsi que la qualité de la relation employeur-employé. Pour ce faire, ils supposent que l'ancienneté observée à la date courante représente la moitié de la durée totale d'occupation de l'emploi. A partir de cette hypothèse, ils proposent deux méthodes : l'une repose sur l'utilisation de variables instrumentales[2], l'autre consiste à inclure la durée totale de l'emploi comme variable explicative supplémentaire du logarithme des salaires. Mais cette durée totale dans l'emploi n'est pas observée, et doit être simulée. Altonji and Shakotko (1987) utilisent aussi une approche instrumentale, à l'aide de la différence entre l'ancienneté courante et la moyenne de l'ancienneté[3], et concluent à la faible valeur des rendements de l'ancienneté. Altonji et Williams (1997) aboutissent à des conclusions similaires: ils reprennent les méthodes proposées par Altonji and Shakotko (1987) et par Topel (1991), et modifient certains traitements des données. Ces résultats ne sont pas neutres en ter-

[1] Pour une revue de la littérature précise, voir Cahuc and Zylberberg (1996).

[2] L'instrument utilisé est la différence entre l'ancienneté courante et la moitié de la durée totale de l'emploi

[3] Ils supposent que l'effet employeur-employé ne dépend pas du temps passé dans l'entreprise

mes de théorie économique : ils signifieraient que le capital humain est totalement transférable, qu'il n'existe pas de coûts de déplacement, et enfin, que les entreprises ne diffèrent pas une partie de la rémunération de leurs salariés dans le temps.

Topel (1991) adopte une approche légèrement différente en estimant les rendements de l'ancienneté en deux étapes. Dans un premier temps, il estime la croissance des salaires des personnes qui ne changent pas d'emploi. Ceci lui fournit une estimation de la somme des rendements de l'expérience et de l'ancienneté. Dans un second temps, il estime la croissance des salaires à partir des personnes qui débutent dans leur emploi: il obtient ainsi une estimation des rendements de l'expérience. Cette procédure en deux temps lui fournit une borne inférieure des rendements de l'ancienneté, qu'il estime substantiels.

Malgré les différences de méthodes et d'instruments utilisés, chacune des études précédemment citées est confrontée d'une part, au problème de l'endogénéité de l'ancienneté et de l'expérience, d'autre part, au problème de la prise en compte de l'hétérogénéité inobservée (à la fois individuelle et spécifique à l'entreprise) et enfin, au problème de la mesure des variables d'intérêt.

Plus récemment, Dustmann and Meghir (2005) exploitent l'exogénéité de certaines mobilités, due à la fermeture d'entreprises non anticipée par leurs salariés. Ainsi ils estiment de façon robuste les rendements de l'ancienneté spécifiques non seulement à l'entreprise mais aussi au secteur. Buchinsky, Fougère, Kramarz, and Tchernis (2006) ont une approche différente. Afin de tenir compte de l'endogénéité de l'expérience et de l'ancienneté, ils modélisent à la fois la participation, la mobilité et les salaires. L'ancienneté est donc une fonction des participations et des mobilités passées, de même pour l'expérience. Afin de contrôler pour d'autres sources de biais, ils intègrent des termes d'hétérogénéité individuelle inobservée dans chaque équation, et ils estiment leur modèle en panel et non en coupe. Pour les Etats-Unis, ils concluent à l'existence de forts rendements de l'ancienneté.

L'ensemble des études précédemment citées étudie le cas des Etats-Unis. Dans la première partie de cette thèse[4], je m'attacherai à étudier les rendements de l'ancienneté en France en adoptant la méthodologie proposée dans Buchinsky, Fougère, Kramarz, and Tchernis (2006). Ces rendements seront comparés à ceux obtenus pour les Etats-Unis, et une explication struc-

[4]Ce papier a été coécrit avec M. Buchinsky, D. Fougère, T. Kamionka et F. Kramarz.

turelle des différences obtenues sera apportée à l'aide du modèle développé par Burdett and Coles (2003).

Dans un deuxième temps[5], afin de tenir compte non seulement de l'hétérogénéité individuelle mais aussi d'une possible hétérogénéité entreprise, le modèle de Buchinsky, Fougère, Kramarz, and Tchernis (2006) est étendu en incorporant des effets entreprises inobservés. Ces effets permettent ainsi de capturer des politiques de rémunération différentes selon les entreprises.

Différence de salaires entre secteur public et secteur privé

Outre cette dépendance des salaires en fonction de l'ancienneté, essentielle afin d'appréhender la mobilité et les profils de salaire au cours d'une carrière, est abordée dans cette thèse la question de l'efficience du secteur public.

En raison de la part de l'emploi public dans l'emploi total (24.9% de l'emploi total en France en 2000, 13.4% au Royaume-Uni, 15.2% aux Etats-Unis), de la différence de fonctionnement entre les deux secteurs, et du poids des salaires de la fonction publique dans le budget de l'Etat dans un contexte de hausse structurelle des dépenses publiques (retraites, santé...), l'intérêt pour le secteur public va croissant. Se posent donc les questions des effectifs de la fonction publique et celles de la rémunération de ses agents fonctionnaires. Un manque de fonctionnaires induirait un service rendu de moindre qualité que ce soit au niveau de l'enseignement, des soins… Mais un nombre trop important de fonctionnaires nuit à l'efficience du service public et alourdit inutilement les finances publiques. Enfin, compte tenu de la part de l'emploi public dans l'emploi total, la politique salariale menée dans le secteur public peut affecter l'efficience du secteur privé. Pour l'ensemble de ces raisons, il est essentiel d'évaluer et de comprendre les différences de structure de salaires entre secteur public et secteur privé.

Quelle est la rémunération des fonctionnaires comparée à celles des salariés du secteur privé ? Si elles existent, à quoi sont dues les différences de rémunération constatées ?

Afin de répondre à cette question, il doit d'abord être décidé quels critères de comparaison retenir. Usuellement sont comparées les moyennes de salaires entre les deux secteurs, ou les moyennes de salaires conditionnellement à certaines variables explicatives (diplôme, sexe, expérience, nationalité). Mais cette comparaison des salaires peut-elle être réduite à une comparaison de moyennes ? Comme Belman and Heywood (2004) le soulignent, cette mesure est

[5]Ce papier a été coécrit avec T. Kamionka, F. Kramarz et C. Robert.

trop réductrice. D'autres aspects de la distribution des salaires sont aussi à considérer, d'où le développement des études utilisant les régressions quantiles afin de mesurer les différences de rémunération entre secteurs public et privé le long de la distribution de salaire (Poterba and Rueben (1994), Bargain and Melly (2008) and Disney and Gosling (1998)).

Par ailleurs, la décision de travailler et le secteur d'activité résultent du choix des agents. Les premiers papiers s'intéressant aux différences de salaires entre le secteur public et le secteur privé ne contrôlaient pas de la sélection des individus dans le secteur public. Or négliger les effets de sélection induit une image faussée des différences salariales entre secteur public et secteur privé (Goddeeris (1988), Venti (1987) and Van der Gaag and Vijverberg (1988)). Les individus se répartissent de façon non aléatoire entre les deux secteurs (Roy (1951)) : on peut penser qu'ils s'auto sélectionnent dans le secteur dont ils espèrent les meilleures perspectives salariales. Les individus peuvent aussi, comme le soulignent Bellante and Link (1981), rechercher une assurance plus grande dans le secteur public, donc accepter des salaires moindres en contrepartie d'une meilleure protection (de l'emploi et de ce fait du salaire). Contrôler de ce choix entre secteur public et secteur privé implique l'utilisation de variables qui expliquent le choix de secteur mais qui sont exclues des équations de salaires. Dustman and Van Soest (1998) soulignent l'influence des variables utilisées sur les résultats obtenus, en plus de l'influence de la spécification du modèle et des hypothèses d'exogénéité faites sur le nombre d'heures travaillées, le niveau d'éducation et l'expérience. Ils conseillent l'utilisation d'informations passées sur les parents. Outre le choix de secteur existe un autre processus de sélection, celui de la participation au marché du travail. Très peu d'études contrôlent de l'endogénéité de la participation, (Heitmueller (2006) pour l'Ecosse, Postel-Vinay and Turon (2007) pour le Royaume-Uni, et Cappellari (2002) pour l'Italie).

Dans la deuxième partie de cette thèse[6] sont estimés les salaires contrefactuels des salariés du secteur public s'ils travaillaient dans le secteur privé. A cette fin, et compte tenu des mises en garde précédentes, sont estimées une équation de participation, une équation de choix de secteur et enfin, une équation de salaire pour chacun des deux secteurs (dans l'esprit de Tunali, 1986). Extension de Heitmueller (2006) dans le cas de l'Ecosse, ou de Fougère and Pouget (2003), le modèle est estimé sur des données de panel et non en coupe. Il intègre par ailleurs des termes d'hétérogénéité individuelle inobservée, qui sont spécifiques à chaque équation. Compte

[6] Ce papier a été coécrit avec T. Kamionka.

tenu de l'importance de la transmission du statut d'une génération à l'autre (Audier (2000) et Fougère and Pouget (2003)), sont intégrées des variables de statut du père et de la mère comme variables explicatives du choix de secteur. Enfin, afin de ne pas se restreindre au seul critère des moyennes, la comparaison se fait sur les quantiles des deux distributions.

Les contrats courts, marche pied vers une relation durable ou outil de confinement

A l'opposé des agents fonctionnaires, tant leurs caractéristiques diffèrent, existe en France une proportion de contrats de court terme sans cesse croissante. Dans la littérature économique, ces contrats de court terme peuvent être considérés comme une première étape dans un processus d'intégration durable sur le marché du travail, ou bien comme une trappe à précarité. A l'aide de l'hétérogénéité de la productivité des travailleurs, ou du pouvoir de négociation dans un contexte d'information imparfaite (pour un synthèse détaillée sur la théorie insider-outsider, voir Lindbeck and Snower (1986)) peut être expliquée la dualité du marché du travail. Certains travailleurs seraient réduits à des relations de court terme en raison de leur faible productivité. Le contrat servirait de signal de l'habileté des travailleurs : ainsi une alternance d'emplois de court terme et de périodes de non-emploi seraient le signal d'une mauvaise productivité, les employeurs n'offriraient alors plus d'emploi durable (Katz (1986)). Mais l'existence de contrats de court terme pourrait être en revanche le fait de l'utilisation simultanée d'un emploi surprotégé et du travail temporaire (Cahuc and Postel-Vinay (2002) et Blanchard and Landier (2002)). D'un autre côté, les contrats de court terme peuvent être considérés comme des opportunités d'accumulation de capital humain général. Se succèderaient ainsi dans les premiers temps de la vie professionnelle des contrats courts qui permettent non seulement de trouver un meilleur appariement entreprise-salarié (Jovanovic (1979a)), mais aussi d'accéder à un meilleur salaire (aux Etats-Unis, les jeunes occupent sept emplois différents dans les dix premières années de leur vie active sur les dix en moyenne qu'ils occuperont sur l'ensemble de leur carrière, et ils connaissent une augmentation de salaire substantielle pendant ces premières années - voir Topel and Ward (1992)). Dans ce cas de figure, les contrats de court terme seraient plus une aide à l'intégration durable sur le marché du travail.

Afin d'étudier les différentes trajectoires observées sur le marché du travail, plusieurs types d'approche existent : modèles de durée, modèles de choix discrets. Les modèles de choix discret expliquent le statut de l'individu sur le marché du travail en fonction de son passé (et notamment des statuts occupés par le passé). C'est le cas d'études comme celles de Card and Sullivan (1988) ou Magnac (2000). Les modèles de durée quant à eux permettent de faire dépendre la probabilité de passer d'un état à l'autre selon le temps passé dans l'état précédemment occupé et de variables caractéristiques individuelles (Magnac and Robin (1994)). Un autre volet de la littérature repose sur les modèles *mover-stayer*, initialement introduits par Blumen, Kogan, and MacCarthy (1955) afin d'étudier la mobilité entre industries sur le marché du travail. Ce modèle repose sur un mélange de chaînes de Markov qui permet de prendre en compte l'hétérogénéité des dynamiques entre individus. Le modèle initial de Blumen, Kogan, and MacCarthy (1955) suppose l'existence de deux types d'individus : des individus faiblement mobiles d'une part, et des individus fortement mobiles d'autre part. Ces derniers seront dénommés " *movers* " contrairement aux premiers dénommés " *stayers* ". Dans la version de Kamionka (1996), ce modèle est étendu à quatre types afin de prendre en compte une hétérogénéité plus grande des trajectoires individuelles et une spécificité du marché du travail français, à savoir la coexistence de contrats de long terme et de contrats de court terme. Dans son modèle sont considérés quatre états, les emplois de long terme, les emplois de court terme, le chômage et enfin l'inactivité et quatre sous-chaînes de Markov : une première chaîne dégénérée typique des " *stayers* " en emploi de long terme, une deuxième chaîne elle aussi dégénérée typique des " stayers " en inactivité, et enfin deux chaînes de Markov, l'une de matrice de transition pleine caractéristique des " *movers* " dits " *secure* " (ils peuvent accèder à un emploi de long terme) ; la dernière restreinte des " *movers* " dits précaires car ils sont confinés à des épisodes d'emplois de court terme, de chômage et d'inactivité. C'est cette approche que je vais développer dans un dernier temps[7]. Le modèle de Kamionka (1996) n'intègre pas, si ce n'est par l'estimation sur des sous groupes, de variables caractéristiques individuelles. Afin d'y remédier, sont introduits des coefficients de mélange qui dépendent de caractéristiques individuelles afin de contrôler au mieux de l'hétérogénéité observée. Ce modèle permet d'étudier si certaines caractéristiques individuelles sont plus ou moins corrélées avec des parcours spécifiques sur le marché du travail, à savoir des trajectoires dites précaires ou des trajectoires dites " secure ". En raison du postulat fait sur la forme des matrices de transition des chaînes de markov, une étude de robustesse est menée. Bien que cette partition de la population semble naturelle dans le cas français, une approche à la Heckman and Singer (1984) a été menée, approche qui n'impose pas a priori la

[7]Ce papier a été coécrit avec E. Coudin et R. Rathelot.

nature de ces types. Sont donc estimées des transitions à l'aide d'un logit multinomial (Magnac (2000)) avec hétérogénéité inobservée (Brodaty (2007)).

Résumé des résultats essentiels

Le premier papier conclut à la faiblesse des rendements de l'ancienneté en France quel que soit le diplôme considéré à l'exception des diplômes du supérieur. Pour ces derniers, les rendements de l'ancienneté estimés sont de l'ordre de 2.6%. Les rendements de l'expérience sont bien plus élevés que ceux de l'ancienneté : de l'ordre de 5% pour les sans diplômes à 7.6% pour les bacheliers. Les estimations obtenues dans ce premier papier sont comparables à celles menées dans le papier de BFKT : les données et la méthode utilisée sont analogues. De ce fait, les estimations obtenues peuvent être comparées et la différence la plus nette constatée entre la France et les Etats-Unis concerne ces rendements de l'ancienneté. Aux Etats-Unis, ceux-ci sont élevés (de l'ordre de 5%) et significativement différents de 0, contrairement à la France où, exception faite des diplômés du supérieur, les rendements de l'ancienneté sont proches voire non statistiquement différents de 0. Une des explications possibles serait la différence des taux d'arrivée des offres entre les deux pays. Les simulations du modèle de Burdett and Coles (2003) réalisées montrent que, pour un taux journalier d'arrivée des offres de l'ordre de 0.0015[8], la pente du salaire est bien plus faible que celle obtenue avec un taux journalier d'arrivée des offres de l'ordre de 0.005 (taux estimé pour les Etats-Unis). Le manque de dynamisme du marché du travail français n'inciterait pas les entreprises à rémunérer l'ancienneté dans l'entreprise : en effet, la probabilité que le salarié reçoive une offre alternative plus élevée est faible en France. En revanche, aux Etats-Unis, les entreprises sont incitées à le faire si elles souhaitent conserver leurs salariés. Les résultats du deuxième papier confirment les estimations obtenues dans le premier. Malgré l'introduction d'une hétérogénéité entreprise inobservée, les estimations des rendements de l'ancienneté en France restent faibles, à la fois pour les hommes et pour les femmes, et quel que soit le niveau de diplôme considéré.

Quant au troisième papier qui traite de l'efficience du service public, plusieurs résultats sont à souligner. Tout d'abord un modèle structurel simple confirme que l'attractivité du secteur public augmente en cas de situation économique défavorable, ce qui est dans la lignée des résultats de Fougère and Pouget (2003). Ce résultat se retrouve dans les estimations du modèle forme réduite. Par ailleurs, une prime à l'emploi dans la fonction publique existe mais ceci n'est plus vrai pour le haut de la distribution des salaires. Quant aux femmes, elles ont un avantage com-

[8]Les taux fournis ici ont été estimés par Jolivet, Postel-Vinay, and Robin (2004).

paratif à travailler dans le secteur public quelle que soit leur position sur l'échelle des salaires. A l'inverse, les hommes bénéficient d'une prime à l'emploi dans la fonction publique seulement en bas de la distribution. Enfin, le troisième papier montre que les différences de structures des salaires entre secteur public et secteur privé sont la combinaison de trois effets :

- la moyenne brute des logs de salaires qui est plus élevée dans le secteur public que dans le secteur privé

- les rendements de certaines variables explicatives, comme le sexe ou le diplôme, qui diffèrent entre les deux secteurs. Les différentiels hommes-femmes sont par exemple plus forts dans le secteur privé que dans le secteur public, mais les diplômes sont généralement mieux rémunérés dans le secteur privé.

- enfin, l'habilité inobservée des salariés du secteur public qui serait légèrement inférieure s'ils travaillaient dans le secteur privé. Dans le cas des salariés du secteur privé, deux cas de figures se présentent : une partie d'entre eux auraient une productivité inobservée bien inférieure dans le secteur public, l'autre en revanche en aurait une légèrement supérieure. Pour ces derniers ainsi que pour les salariés du secteur public, ceci pourrait être interprété en terme de capital humain transférable.

Enfin, dans le quatrième papier, sont étudiées les trajectoires des 30-49 ans sur le marché du travail. L'ensemble des estimations de ce quatrième papier repose sur un mélange de chaînes de Markov dont les coefficients de mélange dépendent de caractéristiques observables. Deux de ces chaînes de Markov sont dégénérées, la troisième est supposée de matrice de transition pleine et la dernière, de matrice de transition contrainte (à savoir avec des 0 sur la première ligne et la première colonne pour signifier l'impossibilité d'accès à des emplois stables). Les résultats principaux obtenus à partir de ce modèle sont les suivants:

- La proportion de personnes confinées dans des trajectoires précaires, i.e. qui ne peuvent pas accéder à un emploi stable de type contrats à durée indéterminée, est estimée et de l'ordre de 5%. De simples statistiques descriptives qui ne prennent pas en compte la partialité des observations fournissent une proportion de 13%.

- Par ailleurs, à l'équilibre, les personnes confinées dans des trajectoires précaires auront trois à quatre fois plus de chance de se retrouver au chômage que des individus mobiles non confinés dans ces trajectoires.

- Enfin, les contraintes imposées sur les matrices de transition sont justifiées à posteriori par une étude de robustesse n'imposant pas à priori la nature des types considérés. L'estimation du modèle de Magnac (2000) avec une hétérogénéité inobservée du type d'Heckman and Singer (1984) confirme l'existence de *stayers* en emploi stable et en inactivité ainsi que celle de deux types de *movers* : des *movers* en situation difficile sur le marché du travail avec de faibles probabilités d'accès à un emploi stable, et des *movers* avec, en revanche, des probabilités élevées.

Chapitre 1

The returns to seniority in France
(and Why they are lower than in the United States?)

1. Introduction

In the past two decades, enormous progress has been made in the analysis of the wage structure. However, there is still significant disagreement about wage growth, a key issue in labor economics. In particular, the respective roles of general human capital, as measured by experience, and firm-specific human capital, as measured by tenure, are still generally debated. In general, experience and tenure increase simultaneously except when a worker moves from one firm to another, or becomes unemployed. Hence, studying the nature of participation and firm-to-firm mobility (or in short mobility), which, in turn, determine experience and seniority (or tenure), respectively, should be central to the study of wages. This will allow us to better identify these two components of human capital accumulation, which, in turn, will better serve us in assessing the respective roles of general (transferable) human capital and specific (non-transferable) human capital.

The role and relative importance of job tenure and experience on wage growth has been studied extensively. The results are generally mixed, especially for the U.S. Some authors concluded that experience matters more than seniority in wage growth (e.g. Altonji and Shakotko (1987), Altonji and Williams (1992) and Altonji and Williams (1997)), while others concluded that both experience and tenure are important factors of wage growth (e.g. Topel (1991), Buchinsky, Fougère, Kramarz, and Tchernis (2006) BFKT, hereafter). Indeed, identifying the relative roles of tenure and experience is a somewhat complex issue to study. In fact, it seems that various studies uncovered a number of crucial difficulties and provided varying solutions that potentially affect the ultimate estimates.[1]

Empirically, it is generally agreed that there exists a positive correlation between seniority and wages. Several economic theories have offered some explanations for the interdependence between wage growth and job tenure. First, the role of specific job tenure on the dynamics of wages has been studied by various human capital theories, starting with the seminal work of Becker (1964) and Mincer (1974). The central point of this theory is the increase in earnings that stems from individual's investment in human capital. The structure of wages can also be described by job matching theory (Jovanovic (1979a), Miller (1984), and Jovanovic (1984)). This theory attempts to provide explanations for both mobility of workers across firms and the

[1] Few such issues are: the definition of the variables, issues about the errors in measured seniority, the estimation methods that are used, the methods controlling for unobserved heterogeneity components in the model, and the exogeneity assumptions that are made.

observed patterns of significant decreases in the job separation rate as job-tenure increases. The key assumption for these types of models is that there exists a specific productivity level for any worker-occupation match. While the worker's wage depends on this productivity, it is, a priori, unknown. Indeed, the specific human capital investment will be larger when the match is less likely to be terminated (see Jovanovic (1979a)). Finally, a job matching model typically predicts an increase in the worker's wage with job seniority.

Alternatively, the dynamic of wage changes can be explained by deferred compensation theories. The key element of these theories is the existence of a contract between the firm and an employee, which is chosen so that the worker's choice of effort and/or quit decision will be optimal (see Salop and Salop (1976), or Lazear (1979), Lazear (1981) and Lazear (1999)). These theories predict that workers starting in a firm will be paid below their marginal product, whereas workers with long tenure in the firm will be paid above their marginal product.

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 contracts that make wages increase with tenure. Some of these models are able to characterize both workers' mobility and the existing positive relation between wage and tenure. For instance, the Burdett-Coles model allows the specificities of the wage-tenure contract to depend heavily on workers' preferences, as well as on labor market characteristics such job offer arrival rate.

While the relation between wage growth and mobility (or job tenure) may result from (optimal) choices of the firm and/or the worker, it may also simply stem 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 be positive correlation between wages and job seniority, even though wages do not directly depend on job tenure (see, for instance Abraham and Farber (1987), Lillard and Willis (1978), and Flinn (1986)). This latter point illustrates the vital importance of being able to control for unobserved heterogeneity components. Furthermore, it highlights the need to control for the endogeneity of the mobility decisions, and consequently of measured job tenure.

Buchinsky, Fougère, Kramarz, and Tchernis (2006) develop a model in which costs that are induced by mobility generate state-dependence in the mobility decision, and similarly for the participation decision (as has already been demonstrated by Hyslop (1999)). It is well-known in the literature that, due to the problems raised above, the usual Ordinary Least-Squares (OLS) estimates of the returns to seniority will be biased. There are many ways to address this problem. One solution is the use of the instrumental variables framework as this is done by Altonji and Shakotko (1987). Alternatively, one can use panel data models that control for fixed effects (e.g. Abowd, Kramarz, and Margolis (1999)). Finally, one can take a more direct approach and jointly model the wages outcome, along with the mobility and participation decisions (e.g. BFKT).

In this paper, we adopt the latter approach. More specifically, we control for both state-dependence and (correlated) unobserved individual heterogeneity in the mobility and participation decisions. We also control for correlated unobserved individual heterogeneity in the wage equation. We use a Bayesian framework, similar to that used in BFKT, using Markov Chain Monte Carlo (MCMC) procedure that involve some Gibbs sampling steps combined with the Metropolis-Hastings algorithm. As our model contains limited dependent endogenous variables (i.e., participation and mobility), we also need to use some additional data augmentation steps.

We use data from the match of the French Déclaration Annuelle de Données Sociales (DADS) panel, providing us with observations on wages for the years 1976 through 1995, with the Echantillon Démographique Permanent (EDP) that provides time-variant and time-invariant personal characteristics. Because we use the exact same specification as in BFKT and relatively similar data sources, we place ourselves in a good position for comparing the returns to seniority in France and in the U.S. For the U.S, the estimates of the returns to seniority appear to be in line with those obtained by Topel (1991), and to a lesser extent with those of Altonji and Shakotko (1987), and Altonji and Williams (1992), Altonji and Williams (1997). In complete contrast, estimates obtained for France are much smaller than those obtained for the U.S. in any of the studies reported in the literature. In fact, some of the returns to seniority in France are virtually equal to zero. In comparison, the returns to experience are rather large and close to those estimated by BFKT.

We proceed then with an attempt to understand the rationale for the enormous differences between the U.S. and France. For this purpose, 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 rates of returns to tenure, i.e., the slope of the tenure profile. Elements that determine these slopes include: job arrival rate (and hence workers' propensity to move) 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 profile. Indeed, recent estimates show that the job arrival rate for the unemployed is about 1.71 per year in the U.S., while it is only 0.56 per year in France (Jolivet, Postel-Vinay, and Robin (2004)). Therefore, the returns to seniority may directly reflect the patterns of mobility in the two countries.

The remainder of the paper is organized as follows. Section 2 presents the statistical model. Section 3 explains the crucial parts of the estimation method employed here. Section 4 follows with description of the data sources. Section 5 provides the empirical results obtained for France, while Section 6 contrasts these results with those obtained by BFKT for the U.S. We also provide in this section a theoretical explanation of these differences supported by additional simulations. Finally, Section 7 briefly concludes.

2. The Statistical Model

The main goal of our study is to examine the returns to experience and seniority in France. To maximize comparability with previous research, and following BFKT, we posit a wage equation that is similar to Topel (1991) or to Altonji and Shakotko (1987), to Altonji and Williams (1992) or Altonji and Williams (1997). We differ from these authors by the way we deal with the obvious endogeneity of the participation and mobility decisions, which, in turn, define experience and tenure on the job. We follow here closely BFKT, extending on Hyslop (1999) (who focuses only on participation) by directly modeling participation and firm-to-firm mobility. The economic model that supports our approach is a structural dynamic choice model of firm-to-firm worker's mobility, with mobility costs. BFKT shows that under a set of plausible assumptions on this cost structure, this model generates first-order state dependence for the participation and mobility processes.

2.1. The structural model

In this section, we briefly summarize the structural model frow which the econometric model is derived. The observed log wage equation for individual i in job j at time t is given by:

$$w_{it} = w^*_{ijt}\mathbf{1}\left(y_{it}=1\right) \tag{2.1}$$

$$w^*_{ijt} = x'_{wit}\delta_0 + \epsilon_{ijt} \tag{2.2}$$

$$\epsilon_{ijt} = J^W_{ijt} + \alpha_{wi} + \eta_{it} \tag{2.3}$$

The function J^W_{ijt} is the sum of all discontinuous jumps in one's wage that resulted from all job changes until date t (see equation 2.11). This function generalizes the match effect introduced in the wage equation by either Topel or Altonji. Moreover it captures the initial conditions specific to the individual at the start of a new job. It enables to control for the quality of past matches, and to distinguish between displaced workers and workers who move directly from one job to another. The term α_{wi} is a person-specific correlated random effect, while η_{it} is a contemporaneous idiosyncratic error term.

A worker employed in period t receives a wage offer from his current firm. Given this offer, he decides either to quit or to stay at the end of period t. At the end of period t, he does not know with certainty the wage a new firm will offer him but he can form an expectation. For simplicity he receives with probability 1 an outside wage offer in the next period. He has no research cost, but he incurs the cost c_M at the beginning of period $t+1$ if he decides to move at the end of period t (due to his social network reconstruction). A non-participant pays a cost γ_1 at the beginning of period t to receive an offer during the period t. It is assumed $c_M > \gamma_1$ (see Hardman and Ioannides (2004)).

Each individual is supposed to maximize his discounted present value of the infinite lifetime intertemporally separable utility function under the period-by-period budget constraint:

$$\begin{aligned} U_t &= \sum_{s=t}^{\infty} \beta^{s-t}\mathbb{E}_t(u(C_s, y_s, X_s)) \\ C_t &= z_t + w_t y_t - c_M m_{t-1} - \gamma_1(1 - y_{t-1}) \end{aligned}$$

C_t denotes the consumption, z_t the non-labor income, $y_t = 1$ if the individual participates at t, $m_t = 1$ if the individual moves at the end of period t (i.e. between t and $t+1$).

By virtue of Bellman's optimality, the value function at the beginning of period t, given past participation and past mobility, is given by

$$V_t(y_{t-1}, m_{t-1}; X_t) = \max_{y_t, m_t} \left(u(c_t, y_t; X_t) + \beta\mathbb{E}_t\left(V_{t+1}(y_t, m_t; X_{t+1})\right)\right)$$

When the individual does not participate at $t-1$ i.e. $y_{t-1}=0$ (and $m_{t-1}=0$):

$$V_t(0,0,X_t) = \max_{y_t,m_t}\left(V_t^0(0,0,X_t), V_t^1(0,0,X_t), V_t^2(0,0,X_t)\right)$$

with

$$V_t^0(0,0,X_t) = u(z_t-\gamma_1,0,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(0,0;X_{t+1})\right)$$

$$V_t^1(0,0,X_t) = u(z_t-\gamma_1+w_t,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,0;X_{t+1})\right)$$

$$V_t^2(0,0,X_t) = u(z_t-\gamma_1+w_t,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,1;X_{t+1})\right)$$

When the individual participates at $t-1$ ($y_{t-1}=1$) and does not move at the end of period $t-1$ ($m_{t-1}=1$)

$$V_t(1,0,X_t) = \max_{y_t,m_t}\left(V_t^0(1,0,X_t), V_t^1(1,0,X_t), V_t^2(1,0,X_t)\right)$$

with

$$V_t^0(1,0,X_t) = u(z_t,0,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(0,0;X_{t+1})\right)$$

$$V_t^1(1,0,X_t) = u(z_t+w_t,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,0;X_{t+1})\right)$$

$$V_t^2(1,0,X_t) = u(z_t+w_t,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,1;X_{t+1})\right)$$

When the individual participates at $t-1$ ($y_{t-1}=1$) and moves at the end of period $t-1$ ($m_{t-1}=1$)

$$V_t(1,0,X_t) = \max_{y_t,m_t}\left(V_t^0(1,0,X_t), V_t^1(1,0,X_t), V_t^2(1,0,X_t)\right)$$

with

$$V_t^0(1,1,X_t) = u(z_t-c_M,0,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(0,0;X_{t+1})\right)$$

$$V_t^1(1,1,X_t) = u(z_t+w_t-c_M,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,0;X_{t+1})\right)$$

$$V_t^2(1,1,X_t) = u(z_t+w_t-c_M,1,X_t) + \beta\mathbb{E}_t\left(V_{t+1}(1,1;X_{t+1})\right)$$

Buchinsky, Fougère, Kramarz, and Tchernis (2006) derive transitions from different reservation wages. When the individual does not participate at $t-1$, there are two reservations wages $w^*_{01,t}$ and $w^*_{02,t}$ implicitly defined by

$$V_t^0(0,0,X_t) \quad = \quad V_t^1(0,0,X_t|w^*_{01,t}) = V_t^2(0,0,X_t|w^*_{02,t}) \tag{2.4}$$

For each period t, as in Burdett (1978a), it is assumed that

$$\frac{d}{dw}V_t^2(1,m_t,X_t) \leq \frac{d}{dw}V_t^1(1,m_t,X_t) \quad m_t = 0,1$$

Under this assumption, and using (2.4), if $w^*_{01,t} > w^*_{02,t}$, there exists a wage value, $w^*_{03,t}$ such that

$$\begin{array}{rl} & V_t^1(0,0,X_t|w^*_{03,t}) = V_t^2(0,0,X_t|w^*_{03,t}) \\ w \leq w^*_{02,t}, & V_t^0(0,0,X_t|w) \geq \max\left(V_t^1(0,0,X_t|w), V_t^2(0,0,X_t|w)\right) \\ w^*_{02,t} \leq w \leq w^*_{03,t}, & V_t^2(0,0,X_t|w) \geq V_t^1(0,0,X_t|w) \geq V_t^0(0,0,X_t|w) \\ w^*_{03,t} \leq w, & V_t^1(0,0,X_t|w) \geq V_t^2(0,0,X_t|w) \geq V_t^0(0,0,X_t|w) \end{array}$$

Then the decision rule for a non-participant is:

1. If $w^*_{02} < w^*_{01}$, either the individual stays non-employed if $w < w^*_{02}$, or the individual accepts the offer and will move to another firm in the next period if $w^*_{02} < w < w^*_{03}$, or he accepts the offer and will stay in the firm another period if $w > w^*_{03}$

2. If $w^*_{02} > w^*_{01}$, either the individual stays non-employed if $w < w^*_{01}$, then the individual accepts the offer and will stay in the firm another period if $w > w^*_{01}$

When the individual participates at $t-1$ and does not move at the end of period $t-1$ (resp. when he participates at $t-1$ and moves at the end of period $t-1$), the same reasoning applies with $w^*_{12}, w^*_{11}, w^*_{13}$ (resp. $w^*_{22}, w^*_{21}, w^*_{23}$) instead of $w^*_{02}, w^*_{01}, w^*_{03}$.

Under some conditions, using Taylor expansions and the concavity of u, Buchinsky, Fougère, Kramarz, and Tchernis (2006) find[2]:

$$\begin{array}{ccc} w^*_{11,t} \approx w^*_{01,t} - \gamma_{11} & w^*_{12,t} \approx w^*_{02,t} - \gamma_{12} & w^*_{13,t} \approx w^*_{03,t} + \gamma_{13} \\ w^*_{21,t} \approx w^*_{01,t} - \gamma_{11} + \gamma_{21} & w^*_{22,t} \approx w^*_{02,t} - \gamma_{12} + \gamma_{22} & w^*_{23,t} \approx w^*_{03,t} + \gamma_{13} + \gamma_{23} \end{array}$$

Thus it can be derived for participation at date t denoted y_t,

$$y_t \;=\; \mathbf{1}\left(w_t > w^*_{02,t}(1-y_{t-1}) + w^*_{12,t}y_{t-1}(1-m_{t-1}) + w^*_{22,t}y_{t-1}m_{t-1}\right)$$

[2]For the specific conditions and detailed description see BFKT.

$$= \mathbf{1}\left(w_t > w^*_{02,t} - \gamma_{12} y_{t-1} + \gamma_{22} y_{t-1} m_{t-1}\right)$$

and for mobility at the end of period t denoted m_t,

$$\begin{aligned} s_t &= 1 - m_t = \mathbf{1}\left(w_t > y_{t-1}(1-m_{t-1}) w^*_{13,t} + y_{t-1} m_{t-1} w^*_{23,t} + (1-y_{t-1}) w^*_{03,t}\right) \\ &= \mathbf{1}\left(w_t > y_{t-1} w^*_{13,t} + \gamma_{23} y_{t-1} m_{t-1}\right) \end{aligned}$$

Generally the reservation wages are intractable, thus they are arbitrarily approximated by linear functions of the entire set of exogenous and predetermined covariates. Substituting the expressions and using the equations 2.1 yields the following participation and mobility equations at period t:

$$\begin{aligned} y_t &= \mathbf{1}\left(a_0 J^W_{it} + x'_{yt}\beta_0 + \beta_y y_{t-1} + \beta_m y_{t-1} m_{t-1} + \alpha_y + u_t > 0\right) \\ m_t &= \mathbf{1}(y_{t-1} = 1, y_t = 1)\mathbf{1}\left(a_1 J^W_{it} + x'_{mt}\lambda_0 + \lambda_m y_{t-1} m_{t-1} + \alpha_m + v_t > 0\right) \end{aligned}$$

2.2. Specification of the General Model

Therefore, the statistical model that we estimate derive from this structural choice model of participation and mobility, whereby the wage equation is estimated jointly with the participation and mobility equations. The equations for participation, mobility, and log-wage are given, respectively, by

$$y_{it} = \mathbf{1}\left(y^*_{it} > 0\right), \quad \text{where} \tag{2.5}$$

$$y^*_{it} = \gamma^M m_{it-1} + \gamma^Y y_{it-1} + X^Y_{it}\delta^Y + \theta^{Y,I}_i + v_{it},$$

$$m_{it} = y_{it+1} y_{it}\mathbf{1}\left(m^*_{it} > 0\right), \quad \text{where} \tag{2.6}$$

$$m^*_{it} = \gamma\, m_{it-1} + X^M_{it}\delta^M + \theta^{M,I}_i + u_{it}, \quad \text{and}$$

$$w_{it} = X^W_{it}\delta^W + J^W_{it} + \theta^{W,I}_i + \epsilon_{it}, \text{ if } \quad y_{it} = 1 \tag{2.7}$$

for all years for which $t > 1$, for $i = 1, ..., n$.

y_{it} is the usual indicator function. $y_{it} = 1$ if the individual participates, 0 otherwise. The quantity y^*_{it} is the latent variable measuring the value of participation at time t. Similarly, m^*_{it}

is a latent variable measuring worker's i value of moving between t and $t+1$, and m_{it} is an indicator function, denoting whether or not the individual moved at the end of time t. Note that by definition, observed mobility m_{it} is equal to 0 when the individual does not participate at time t. Finally, note that m_{it} is not observed (censored) whenever a worker participates at date t but does not participate at $t+1$. The variable w_{it} denotes the logarithm of the hourly total real labor costs.

The terms $\theta^{Y,I}$, $\theta^{M,I}$, and $\theta^{W,I}$ denote the correlated random effects specific to the individuals, while u, v and ϵ are idiosyncratic error terms. In principle, there are J firms and N individuals in the panel of length T, but our panel is unbalanced in the sense that we do not observe all individuals in all time periods.

Note that because lagged mobility and lagged participation must be included in the participation and mobility equations, one needs to control for the well-known initial conditions in the first period. We follow Heckman (1981) and we add for $t=1$ the following participation, mobility, and wages equations, respectively

$$y_{i1} = \mathbf{1}\left(X_{i1}^{Y}\delta_0^{Y} + \alpha_i^{Y,I} + v_{i1} > 0\right) \tag{2.8}$$

$$m_{i1} = y_{i1}\mathbf{1}\left(X_{i1}^{M}\delta_0^{M} + \alpha_i^{M,I} + u_{i1} > 0\right), \quad \text{and} \tag{2.9}$$

$$w_{i1} = X_{i1}^{W}\delta^{W} + \theta_i^{W,I} + \epsilon_{i1} \text{ if } y_{i1} = 1 \tag{2.10}$$

The wage equation is standard for most of its components and includes, in particular, a quadratic function of experience and seniority.[3] It also includes the following individual characteristics: gender, 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 effects. We also include information on the job characteristics: an indicator function for part-time work, and 14 indicators for the industry of the employing firm. In addition we include a complete set of year dummy variables.

Finally, following the specification adopted in BFKT, we include the function J_{it}^{W}, that captures the sum of all wage changes that resulted from job changes (i.e., moves between one

[3]BFKT also presents estimates with a quartic specification in both experience and seniority. This issue is addressed further below.

firm and another) prior to the current date t. This term allows us to control for discontinuous jumps 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,

$$J_{it}^{W} = \left(\phi_0^s + \phi_0^e e_{i0}\right) d_{i1} + \sum_{l=1}^{K_{it}} \left[\sum_{j=1}^{4} \left(\phi_{j0} + \phi_j^s s_{t_l - 1} + \phi_j^e e_{t_l - 1}\right) d_{jit_l} \right]. \tag{2.11}$$

Suppressing the i subscript, the variable d_{1t_l} equals 1 if the lth job lasted less than a year, and equals 0 otherwise. Similarly, $d_{2t_l} = 1$ if the lth job lasted between 1 and 5 years, and equals 0 otherwise, $d_{3t_l} = 1$ if the lth job lasted between 5 and 10 years, and equals 0 otherwise, $d_{4t_l} = 1$ if the lth job lasted more than 10 years and equals 0 otherwise. The quantity K_{it} denotes the number of job changes by the ith individual, up to time t (not including the individual's first sample year). If an individual changed jobs in his/her first sample then $d_{i1} = 1$, otherwise $d_{i1} = 0$. The quantities e_t and s_t denote the experience and seniority in year t, respectively.[4] Hence, at the start of a new job, two individuals with identical characteristics, but with different career paths enter their new job with potentially different starting wages.

Turning now to *the mobility equation*, most of the variables that are 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 the ages of 0 and 3, and for having children between the ages of 3 and 6 are included in the mobility equation, but are not present in the wage equation.

The specification of *the participation equation* is very similar to that of the mobility equation. Nevertheless, 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 mobility equation, are excluded from the participation equation.

Finally, the initial mobility and participation equations are simplified versions of these equations, that is, all the variables that appear in the general participation and mobility equation are also included in the corresponding initial conditions, except for the lagged dependent variables.

Note the specification above introduces multiple exclusion restrictions. For instance, the

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

industry affiliation is included in both wage and mobility equations but is excluded (for obvious reasons) from the participation equation. Conversely, the children variables are not present in the wage equation but are included in the two other equations. This restriction is often used in empirical applications. Furthermore, following Buchinsky, Fougère, Kramarz, and Tchernis (2006), the J_{it}^{W} function is included in the wage equation but not in the participation and mobility equations. When the J_{it}^{W} function is included in the mobility and participation equations, its coefficients are non significantly different from zero. Therefore, we adopted a similar specification to maximize comparability. Unfortunately, there appears to be no set of exclusion restrictions that would guarantee convincing identification of the *initial* conditions equations, except functional form (i.e., the normality assumptions).

2.3. Stochastic Assumptions

The vector of individual specific effects, including those from the initial condition equations, is given by

$$\theta_i^I = \left(\alpha_i^{Y,I}, \alpha_i^{M,I}, \theta_i^{Y,I}, \theta_i^{W,I}, \theta_i^{M,I}\right)$$

$$\theta_i^I | \Sigma_i^I \sim_{\text{i.i.d. a priori}} \mathcal{N}\left(0, \Sigma_i^I\right),$$

We assume that individuals are independent, but their various individual effects may not have the same distribution. Namely, we assume that θ_i^I follows the distribution given by

$$\begin{aligned} \theta_i^I &\sim N(f\left(x_{i1}, ..., x_{iT}\right), \Sigma_i^I), \quad \text{where} \\ \Sigma_i^I &= D_i \Delta_\rho D_i, \\ D_i &= \text{diag}\left(\sigma_{yi}, \sigma_{mi}, \sigma_{wi}\right), \quad \text{and} \\ \{\Delta_\rho\}_{j,l} &= \rho_{\theta_j^I, \theta_l^I}, \quad \text{for } j, l = y, m, w. \end{aligned} \tag{2.12}$$

Also, the function $f\left(x_{i1}, ..., x_{iT}\right)$ is potentially a function of all exogenous variables in all period. The matrix Σ_i^I is indexed by i, since we also allow for σ_{ji} to be heteroscedastic, i.e., to depend on x_{yit}, x_{mit}, and x_{wit}, respectively. That is,

$$\sigma_{ji}^2 = \exp\left(h_j\left(x_{i1}, ..., x_{iT}\right)\right), \quad \text{for } j = y, m, w, \tag{2.13}$$

where the $h_j(\cdot)$'s are some real valued functions. The ultimate goal in doing so is to control for the possible existence of heterogeneity in a parsimonious way. Hence, we base our estimation on only the sample averages of the regressors' vector, i.e. $\overline{x}_{ji} = (\sum_{i=1}^{T} x_{jit})/T$ for each individual. We then use the first three principle components of $\bar{x}_{ji}$, as well as a constant term to approximate $h_j\left(x_{i1}, ..., x_{iT}\right)$ by[5]

$$\widehat{h}_j(\gamma_j, x_{ji1}, ..., x_{jiT}) = pc_i'\gamma_j, \tag{2.14}$$

where pc_i is the vector containing the principal components. This significantly reduce the computation burden. This is because the posterior distribution for $\gamma = (\gamma_y', \gamma_m', \gamma_w')'$ is difficult to obtain and require the use of a Metropolis-Hastings step.

In addition, we assume that the individual specific effects are stochastically independent of the idiosyncratic shocks, that is $\theta_i^I \perp (v_{it}, u_{it}, \epsilon_{it})$.

Finally, for the idiosyncratic error terms we assume

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

This assumption of i.i.d. income innovations is used for convenience and for an easier implementation. This is a simplistic assumption: several papers point out the need for modeling the income innovations as the sum of a permanent and a stochastic components (see Bonhomme and Robin (2008), Meghir and Pistaferri (2004), Guvenen (2007)). In these papers, the stochastic component presents persistence over time (first-order Markov or MA process...) unlike the assumption made above.[6]

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 the corresponding random effects. To see this, consider an individual with seniority level $s_{it} = s$. Note that s_{it} can be written as:

[5]The γ_j terms are estimated separately in a factor analysis of individual data. The variables that enter this analysis are the sex, the 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. The first three principle components account for over 90% of the total variance of $\overline{x}_{ji}$, so that there is almost no loss of information by doing so.

[6]This assumption must have no influence on the consistency of the estimation but rather on its efficiency. This is based on a reasoning on the only wage equation: the residual mean, conditional on the unobserved heterogeneity, equal to zero is a sufficient condition to ensure convergence.

$$s_{it} = (s_{it-1} + 1)1\left(m_{i,t-1} = 0, y_{it} = 1\right).$$

This equation can be expanded by recursion to the individual's entry year into 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 $\theta_i^{W,I}$. This, in turn, is correlated with $\theta_i^{M,I}$ and $\theta_i^{Y,I}$, the person-specific effects in the mobility and participation equations, respectively. Similarly, experience and the J^W function are also correlated with $\theta_i^{W,I}$. 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 $\theta_i^{M,I}$ and $\theta_i^{Y,I}$, respectively.

This reasoning also applies to the idiosyncratic error terms. Therefore, the individual specific effect and the idiosyncratic error term in the wage equation are both correlated with the experience and seniority variables through the correlation of the individual effects and idiosyncratic error terms across our system of equations. Putting it differently the system of equations specified here allows for correlated random effects.

3. Estimation

As in Buchinsky, Fougère, Kramarz, and Tchernis (2006), we adopt a Bayesian method. The estimates provided are given by the mean of the posterior distribution of the various parameters. We construct the posterior distribution via the use of a Markov Chain Monte Carlo (MCMC) procedure, where in each iteration we draw from the posterior distribution of these parameters conditional on the data. We do so, because the computation of the analytical form for posterior distribution is intractable. Specifically, we use a combination of the Gibbs Sampling algorithm, augmented by Metropolis-Hastings whenever needed, (for example when drawing the correlation coefficients), to obtain draws from this posterior distribution. Below we briefly explain the implementation of the MCMC for our problem. For a more detailed description see Appendix A.

3.1. Principles of the Gibbs Sampler

Given a parameter set and the 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 need to specify a prior density for each parameter. Recall that, when prior independence is assumed between φ and $\mathcal{P}_{(\varphi)}$, the conditional posterior distribution for a subset of parameter vector φ satisfies:

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

where $\mathcal{P}$ denotes the vector containing all parameters of the model, $\mathcal{P}_{(\varphi)}$ denotes all other parameters, except for φ, and $\pi(\varphi)$ is the prior density of φ.

The Gibbs Sampler allows for an easy treatment of the latent variables through the so-called data augmentation procedure (Tanner and Wong (1987), Albert and Chib (1993)). Therefore, completion of censored observations becomes possible. In particular, we can never observe the latent variables m^*_{it} and y^*_{it}, and the wage w_{it} is observed only if the ith individual works at time t. Censored or unobserved data are simply "augmented ", that is, we compute m^*_{it} and y^*_{it} based on (2.5)+(2.6), conditional on all the parameters and on the observed data.

Finally, the Gibbs Sampler procedure does not involve optimization algorithms. Sequential simulations of the conditional densities are the only computations required. There is somewhat of a complication in this procedure when the densities have no natural conjugate (i.e., when the prior and the posterior do not belong to the same family). In these cases we use the standard Metropolis-Hastings algorithm. Specifically, in this case we cannot directly draw from the true conditional distribution. Hence, we draw the parameters using another distribution (the proposal distribution) and we use a rejection method in order to decide whether or not to keep that draw. In our estimation, we need to resort to the Metropolis-Hastings step when drawing elements for the variance-covariance matrix.

3.2. Application to our Problem

In order to use Bayes' rule, we first need to specify the full conditional likelihood, that is, the density of all variables, observed and augmented, namely y, w, m, m^* and y^*, given all parameters (the parameters of interest as well as the set of augmented parameters). We thus have to properly define the parameter set and to properly “augment ”our data.

The full parameter set is given by

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

so that for $\mathcal{P}$ we have

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

where $\bar{\gamma} = (\gamma_1', \ldots, \gamma_5')'$ and $\eta = (\eta_1, \ldots, \eta_{10})'$.

When specifying the relevant set of variables corresponding to each period, special care needs to be given for the (censored) mobility variable. There are four cases depending on the values of the couple (y_{it-1}, y_{it}). For a given individual i we define X_t, the completed set of endogenous variables 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

$$\begin{aligned} X_t^{11} &= \left(y_t^*, y_t, w_t, m_{t-1}^*, m_{t-1}\right), \\ X_t^{10} &= \left(y_t^*, y_t, m_{t-1}^*\right), \\ X_t^{01} &= (y_t^*, y_t, w_t), \quad \text{and} \\ X_t^{00} &= (y_t^*, y_t). \end{aligned}$$

For the initial year we similarly define

$$\begin{aligned} X_1 &= y_1 X_1^1 + (1 - y_1) X_1^0, \\ X_1^1 &= (y_1^*, y_1, w_1), \quad \text{and} \\ X_1^0 &= (y_1^*, y_1). \end{aligned}$$

The contribution of the ith individual to the conditional likelihood function is given then by[7]

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

where $\underline{X}_{i,t} = (X_{i1},...,X_{it})$, $\mathcal{F}_{i,t-1} = \underline{X}_{i,t-1}$, and

$$\begin{aligned} l(X_{it}|\mathcal{P},\mathcal{F}_{i,t-1}) \;=\; & l(X_{it}^{11}|\mathcal{P},\mathcal{F}_{i,t-1})^{y_{i,t-1}y_{it}}\, l(X_{it}^{10}|\mathcal{P},\mathcal{F}_{i,t-1})^{y_{i,t-1}(1-y_{it})} \\ & l(X_{it}^{01}|\mathcal{P},\mathcal{F}_{i,t-1})^{(1-y_{i,t-1})y_{it}}\, l(X_{it}^{00}|\mathcal{P},\mathcal{F}_{i,t-1})^{(1-y_{i,t-1})(1-y_{it})}. \end{aligned}$$

Thus, the full conditional likelihood is given by

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

where, because of the normal residuals, we have

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

[7]Even though our notations do not make this explicit, all our computations allow for an individual-specific entry and exit date in the panel, that is, an unbalanced panel.

and the residuals' correlations are parameterized by:

$$\begin{aligned} \theta &= (\theta_{yw}, \theta_{ym}, \theta_{wm})', \quad \rho_{yw} = \cos(\theta_{yw}), \quad \rho_{ym} = \cos(\theta_{ym}), \quad \text{and} \\ \rho_{wm} &= \cos(\theta_{yw})\cos(\theta_{ym}) - \sin(\theta_{yw})\sin(\theta_{ym})\cos(\theta_{wm}). \end{aligned}$$

Finally, prior distributions are needed, we define them as follows:

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

Based on these prior distributions and the full conditional likelihood, all posterior densities can be evaluated (for a more detailed description see Appendix A). The prior distributions are key elements for computing the posterior distribution. We adopt here conjugate, generally zero-mean, but very diffuse priors, reflecting our lack of knowledge about the possible values of the parameters.

4. The 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 data set is longitudinal and covers the period 1976-1995 for all workers employed in the private and semi-public sector who were 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 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.[8] 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 system[9]. 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. Each observation in this initial DADS file includes an identifier that corresponds to the employee (called ID below), an identifier that corresponds to the establishment (SIRET), and an identifier that corresponds to the parent enterprize of the establishment (SIREN). For each individual, 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 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

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

[9] The SIRENE system is a directory identifying all French firms and their corresponding establishments.

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 living in France (1/4 or 1/5 of the population, 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.[10]

For every individual, education, measured as the highest degree, and the age at the end of school are collected. Since the categories differ in the three censuses, we first created eight education groups (identical to those used in Abowd, Kramarz, and Margolis (1999), namely: (1) No terminal degree; (2) Elementary School; (3) Junior High School; (4) High School; (5) Vocational-Technical School (basic); (6) Vocational Technical School (advanced); (7) Technical College and Undergraduate University; and (8) Graduate School and Other Post-Secondary Education. Other variables that are regularly collected are: nationality (including possible naturalization to French citizenship), country of birth, year of arrival in France, marital status, number of children, 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 département).[11] In some of the censuses, data on parents' education and social status were collected as well.

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. This information includes any birth, death, wedding, and divorce involving an individual of the EDP. For each of the above events, additional information on the dates, as well as the occupation of the persons concerned, are collected. Finally, both censuses and civil status information contain the person identifier (ID) of the individual, so the two sources of data can be merged.

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 that month. Notice that

[10]It is important to note that no earnings or income variables have ever been asked in the French censuses.

[11]A French "département" corresponds roughly to a county in the U.S. Several départements form a region which is an administrative division.

we do not have wages of the civil-servants (even though the census information allows us to determine whether a person is a civil-servant), or the income of self-employed individuals. The individual-level information also 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.

Some descriptive statistics

To be completed

5. The Empirical Results

Below we present the estimation results, which are organized as follows. Table 3 presents the estimation results for the wage equation for each of the four education groups. Table 5 presents the estimation results for the participation equation, by education groups, while Table 6 does the same for the inter-firm mobility equation. Table 8 presents the estimates of the variance-covariance matrices for the individual-specific effects (across the five equations) and for the idiosyncratic terms (across the three main equations).[12]

Tables 9 through 11 in the next section provide a detailed comparison between the results obtained for the U.S. and those obtained for France. Since we have essentially estimated 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 9 presents estimates for the college graduates in the U.S. and France. Table 10 presents similar estimates for high school dropouts. Table 11 compares the marginal and cumulative returns to experience and seniority at various points of the life cycle for these two groups. Finally, Table 12 presents estimates using two other methods that have been previously used in the literature—a simple OLS and IV method—of the returns to seniority and of the cumulative returns to seniority, for the two groups and in the two countries.

5.1. A brief summary of main results

Wage equation: Whatever the degree, returns to seniority are small, even non-significant for high-school graduates. College graduates stand in sharp contrast since their returns to seniority

[12]Descriptive Statistics are presented in Appendix B, table 1

are large, equal to 2.64%. Even though, returns to experience are the biggest whatever the subgroup: from 5.04% for high school dropouts to 7.64% for high school graduates. Moreover the timing of mobility in one's career matters for every degree, but the estimates for the J^W function differ between subgroups.

The gender wage gap is higher than usually estimated. This may be due to different reasons: first, mobility and participation processes are supposed to be identical for both men and women (except for a gender dummy). The gender dummy in the wage equation hence may capture gender differences in career paths (Le Minez and Roux (2002)) and it may overestimate the gender wage gap. Furthermore, occupation is not controlled for, since this variable is not available in the data. But the structure of men and women occupations and job qualifications differ even when degree is controlled for (Meurs and Ponthieux (2006)). Finally, papers usually study the gender wage gap by the means of cross-sectional data, and they do not take into account the endogeneity of tenure and experience and the presence of unobserved heterogeneity. These may be the reasons why the gender dummy is higher than what is usually obtained using cross sectional data. Worth to be pointed out are the higher gender wage gaps that are also estimated using the method proposed by Altonji (greater than 30%). Another way to proceed in order to circumvent this issue would be to estimate the model separately for men and women.

As far as the cohort effects are concerned, in the private sector, the mean real wage increased by more than 4% a year from the beginning of the fifties to the end of the seventies (Bayet and Demailly (1996)). Since it dropped down to 0.5% a year. This may explain the estimation of cohort effects[13] in the wage equation.

Participation-employment equation: the family variables are in line with the economic theory: the presence of young children, as well as to be married, lower the probability to participate. But due to a stronger attachment to the labor force, children have marginally no effect on participation for college graduates. Furthermore, whatever the degree, lagged participation and mobility favor participation, and young cohorts are more likely to be employed than older ones.

Mobility equation: for college graduates and high-school dropouts, the level of experience is largely irrelevant. In contrast, the effect of seniority is strong and negative for all education groups. More senior workers tend to move less. But for vocational and high-school degrees, the effect of experience on mobility, as well as the effect of tenure, is large and negative.

[13]The youngest cohort (born after 1970) is the reference.

Individual specific effects: the correlations between the various person-specific components are highly significant and large. Since higher participation rates imply faster accumulation of labor market experience, the estimates of $\rho_{y,w}$ imply that, all other things equal, high-wage workers tend to be more experienced workers. High-mobility workers also tend to be low-wage workers and low-participation workers (ρ_{α_y,α_m} and ρ_{α_m,α_w} are large and negative). High-wage workers have higher seniority than low-wage workers, they tend to be more immobile.

5.2. Certificat d'Etudes Primaires Holders (High School Dropouts)

In France, apart from those quitting the education system without any degree, the Certificat d'Etudes Primaires (CEP, hereafter) holders are those leaving the system with the lowest possible level of education.[14] They are essentially comparable to High School dropouts in the United States.

Wage Equation:

The results for this group are presented in the first four columns of Table 3. In line 4 of the table we clearly see that the return to seniority is small, only less than 0.3% per year in the first few years (when the linear term is the dominating term). In contrast, the return to experience is almost twenty times larger than the return to tenure.

However, the results of Table 3 also show that the timing of mobility in one's career matters. First, time spent in a firm makes a significant difference as this is indicated from the coefficient estimates in lines 33–36. Moves after relatively short spells are rewarded. There is a 5% increase for change that takes place in less than one year on a job and 10% if the job last between two to five years. However, the part induced by the level of seniority (lines 37–39) is negative. In particular, a move after a two-year spell on a job is better compensated than moves after a five-year spell. The overall jump after 5 years is essentially zero. In comparison, a job spell of between 6 to 10 years of seniority carries neither a penalty nor a reward. For jobs that last more than ten years, workers lose almost 2% per year of seniority (line 39). Finally, there is also the component of wage jump due to experience (lines 40–43). Moves early in one's work life have a small negative impact on wage gains. In contrast, moves that occur later in one's career, e.g. after 10 years of experience, add 0.6% for every year of experience, for a total of more than

[14]There is a possibility of some confusion, although relatively small, between not having education and missing response to the question about education in the various censuses.

6% for experience above 10 years. Overall, the loss of earning can be substantial, especially for people who spend long spells in one firm. For example, displaced workers who spent their entire career, of say 20 years, in a single firm face on average a wage loss of about 15% in their new firm (i.e., from lines 36, 39, and 43 we have $100\,[1-\exp\{.054-.0167\cdot 20+.006\cdot 20\}] = 85.2\%$). It is important to note though, that mobility is very low in France, as Table 1 clearly indicates: an average CEP worker moves only once over the entire period. However, mobility across firms is not evenly distributed over the population. Hence, benefits of voluntary mobility, as well as difficulties that stem from involuntary moves, are confined to a relatively very small fraction of the workers' population.

Table 3 provides additional facts worthy of notice. Confirming results by Abowd, Kramarz, Lengerman, and Roux (2005), inter-industry wage differences for CEP workers are compressed relatively to the groups with higher levels of education. This is clearly one of the consequences of minimum wage policies in France, because many workers in this group are at the very bottom of the overall wage distribution.

Participation and Mobility Equations:

The first four columns of Tables 5 and 6 present the estimates for the participation and mobility equations, respectively, for the CEP workers. Most of the results are not surprising and are on the order of magnitude that one might expect. For example, having young children lowers the probability of participation significantly, as well as the probability of a move. Also, experience and seniority have an enormous effect on the mobility decision. Individuals with higher experience and tenure are a lot less likely to move.

Also of major interest are the coefficients on the lagged mobility and lagged participation. In contrast with most previous analyses (Altonji and Shakotko (1987), Altonji and Williams (1992), Altonji and Williams (1997) and Topel (1991)), we are able to distinguish between state-dependence and unobserved heterogeneity. Not surprisingly, past participation and past mobility favors participation. However, lagged mobility has virtually no impact on the mobility decision. The results in BFKT for the mobility decision imply that a move is optimal only every few years. Hence, a move in the previous period is associated with lower mobility in the period immediately after (see also the France-U.S. comparison of Table 10). This lack of state-dependence in the current results is obviously a reflection of the French labor market institutions where some workers often go from one short-term contract to another, especially for the CEP group. Unfortunately, as already mentioned above, our data sources provide no information on the nature of the contract, so we cannot examine this point any further.

Stochastic Components:

The first four columns of Table 8 present estimates of variance-covariance components for the CEP group. The individual specific effects for the five-equation model are presented in the first panel, while the results for the residual terms of the three main equations are provided in the second panel. The results clearly show that in terms of the individual specific effects, those who participate more also tend to be high-wage workers. Non-participation (non-employment) and mobility are negatively correlated in terms of individual effects but the corresponding idiosyncratic components are positively correlated. Consequently, we find that high mobility workers tend to be low-employment workers. However, temporary positive shock on mobility (as measured by large draw of the idiosyncratic term) "enhances" participation. Finally, both the idiosyncratic terms and the individual specific effects in the mobility and wage equations are negatively correlated. This implies that high-wage workers tend to be relatively immobile.

It is important to note that most parameters in Table 8 are quite large in absolute terms and are highly significant. This exemplifies the need for the joint estimation adopted here. Joint estimation of these equations clearly has a strong effect on the estimated returns to seniority and experience. Neglecting to control for the joint simultaneous effects would therefore lead to severe bias in the estimated returns to seniority and experience.

5.3. CAP-BEP Holders (Vocational Technical School, basic)

One element that distinguishes the education systems in Continental Europe from that in the U.S., and especially in France and Germany, is the existence of a well-developed apprenticeship training. Indeed, this feature is well-known for Germany but it is also quite important in France. Students who qualify for the Certificat d'Aptitude Professionnelle (CAP) or the Brevet d'Enseignement Professionnel (BEP) have to spend part of their education in firms, and the rest within schools where they are taught both general and vocational subjects. There is no real analog to this system in the U.S.

Wage Equation:

The returns to seniority coefficient, presented in Table 3 (columns 5-8), for workers with vocational/technical education are slightly negative and barely significant. The estimates for the parameters that correspond to the J^W function (lines 33-43) are somewhat different from those obtained for the high school dropouts. Focusing on the two components related to seniority, in lines 33-36, we see that a move after one year in a job brings with it an average increase in wages of about 3%. Between 2 and 5 years this increase amounts to almost 20%, while moves after 6 to 10 years on a job correspond to an average increase of over 16%. However, the coefficients on the seniority level are all negative (lines 37-39), so the overall jump is much smaller. For example, an individual with 8 years of seniority has an increase of $20\% - 8 \cdot .2\% = 4\%$. Furthermore, for those who have long tenure on the job, say 15 years, there is a significant loss associated with moving from one firm to another, which amounts to approximately $-6\% - 15 \cdot 1.8\% = -33\%$. However, this severe decline is compensated somewhat because of an increase that stems from having more experience. Therefore, for an individual who also has 15 years of experience the overall change in wage is $-6\% - 15 \cdot 1.8\% + 15 \cdot 0.9\% = -19.5\%$. Clearly, relative to the changes observed for the high school dropouts, the losses incurred by the CAP-BEP workers are larger and more significant.

In terms of the return to experience, the experience profile for the CAP-BEP workers is steeper than that observed for the CEP workers, as is apparent from the results reported in lines 2-3 of the table. That is, the CAP-BEP workers tend to accumulate human capital on the job, which is more general and transferable across firms, while the CEP workers gain more firm-specific human capital. Nevertheless, for both groups general human capital is far more important than firm-specific human capital as is demonstrated by the magnitude of the coefficient that relates to experience and seniority.

Participation and Mobility Equations:

As one might expect, the estimated coefficients for the participation and the mobility equations are quite similar to those obtained for the CEP group. In particular, lagged mobility has no significant effect on current mobility. While for the CAP-BEP group longer experience has a more significant effect on the participation decision (see lines 2-3), and lagged participation has a smaller effect. That is, state-dependence is stronger for the less skilled group. The effect of seniority on mobility is virtually the same for the two groups. That is, longer seniority on the job significantly reduces the likelihood of a move.

Stochastic Components:

As Table 8 indicates, the results for main effects for the CAP-BEP group are again quite similar to those obtained for the high school dropout group. In particular, as for the previous group, high-wage workers tend to participate more and they are also a lot less likely to move.

5.4. Baccalauréat Holders (High-School Graduates)

In order to qualify for a high school degree in France a student has to pass a national exam, called the Baccalauréat. It is a “passport” to higher education, even though not all holders of the Baccalauréat choose to pursue post-secondary education. There are some individuals who choose to attend a university, but never complete the requirement toward a specific degree. We include all these individual in the Baccalauréat Holders group, that is, this group includes all workers who received their Baccalauréat and, in addition, may have had some college education. The results for this group are presented in columns 9-12 of Tables 3 through 8.

Wage Equation:

The results for this group, presented again in Table 3, display some substantial differences relative to the other two groups discussed above. First, the return to experience is much larger, and, in fact, it is the largest of all groups. However, the return to seniority is, essentially, zero. The estimates for the parameters embedded in the J^W function are quite similar to those previously observed, especially for workers in the the CAP-BEP group. While moves after short spells seems to induce wage increase (see line 33), they also carry some losses of 3.4% per year of seniority (line 37). The overall average change for a worker with 3 years of seniority is hence $12.8\% - 3 \cdot 3.4\% = 2.4\%$. Moves after relatively long employment spells in firms entail large wage losses. For example moves that lasted more than 5 years carry with them a loss of about 1.5% per year of seniority. It can also be seen that the level of experience has very little effect on the initial jump when moving to a new firm, and the effect is usually negative (lines 40-43).

Participation and Mobility Equations:

The results obtained for this group (presented in Tables 5 and 6 are largely consistent with those obtained for the lower education groups discussed above. Nevertheless, the dependence of mobility on lagged mobility becomes marginally negative. This result is consistent with results previously obtained for the U.S., which are discussed below. Also, workers are less mobile the larger their experience and seniority levels, and more pronouncedly so for the high school graduate than for the two lower education groups. Moreover, longer experience has a more significant effect on the participation decision (see lines 2-3) than for the two lower education groups, while lagged participation has a smaller effect. That is, more highly educated workers have a stronger attachment to the labor force. However, state-dependence is a much less significant factor than for the less educated workers.

Stochastic Components:

As was previously observed for the lower education groups, we see that high-wage workers also tend to be high-participation workers. Nevertheless, in contrast to the other two groups, high-wage workers are only marginally low-mobility workers. Indeed, Table 1 in Appendix B shows that mobility for Baccalauréat holders is the highest among all four education groups, whereas the levels of tenure and experience are the lowest. Part of the reason for these results is that this group contains a disproportionately large number of relatively young individuals. In contrast, the CEP group, for example, includes a relatively large fraction of mature individuals who have, on average, significantly lower levels of education.

5.5. University and Grandes Ecoles Graduates

An important feature that distinguishes the French education system from other European education systems, as well as from the American system, is the existence of a very selective set of educational institutions, known as Grandes Ecoles, that work in parallel with Universities. The system intends to provide master degrees, mostly in engineering and in business. Unlike the regular university system, the Grandes Ecoles system is very selective and only a relatively small fraction of the relevant population is admitted to the various programs. We include in this group all graduates from both regular universities, as well as graduate from the Grandes Ecoles system, and, for simplicity, we refer to this group as the college graduate group. The results for this education group are provided in the last four columns of Tables 3 through 8.

Wage Equation:

Interestingly, the results for the group of graduates stand in sharp contrast with those obtained for all other education groups. The returns to experience are quite large as for the other groups. However, there is a striking difference in the return to seniority, which is large and significant for the college graduate group. The return to seniority is about 2.6% per year of tenure, with very little curvature. Nevertheless, the return to seniority is small relative to the return experience, namely only one half that of the return to experience.

Lines 33–43 also indicate that the J^W function for the college graduates is quite different from that for the other groups. In general, moves are associated with some loss that is attributed to general experience (see lines 40-43), but it is compensated by a large positive contribution of seniority. For example, a move after a very short employment spell in a firm (up to one year) is associated with an average increase in wages at the new firm of over 18% (line 33). A job change after a spell of 2 to 5 years carries with it an average increase of 5.3%, with an additional increase of over 3% per year of seniority at the time of the move. For a spell lasting between 6 and 10 years the wage increase is even larger and amounts to 17.3%, with an additional increase of close to 1% per year of seniority. A sizeable increase is also evident for larger spells of over 10 years. Clearly, for this highly educated group, seniority is well compensated for.

There are some other additional results worth noting for this group. First, working part-time entails much bigger losses for individuals in this group than for individuals in all other groups. Furthermore, there are sizeable and significant inter-industry wage differences (see lines 30-40). These results are largely consistent with those obtained by Abowd, Kramarz, Lengerman, and Roux (2005). In France minimum wages compress the bottom part of the wage distribution, and wage inequality is confined mostly to the upper part of the distribution, relevant indeed for this college-educated group. Finally, in contrast to all other education groups, it seems that foreign born are being discriminated against relative to their French counterparts (see line 12). While it might be true, in general, that having a higher education allows one to find a job more easily, the wages paid to college graduates who are foreign born is on average 7.5% lower than that paid to French born individuals.

Participation and Mobility Equations:

Similar to the results for the other education groups, lagged mobility seems to have no effect on current mobility. Moreover, experience has virtually no effect on the likelihood of a move. Less experienced workers are no more likely to move than their more experienced counterparts. One possible explanation for this is that while the individuals in this group are not compensated for their level of experience (see the results for the J^W function) they are well compensated for their seniority , which, in turn, has a significant, yet very small, negative effect on mobility. These results seem to indicate that career paths for engineers and other professionals entail job changes at all ages. Furthermore, in contrast to all other groups, participation choices are only marginally affected by having young children. This might simply indicate that individuals in this group have a stronger attachment to the labor force and hence they choose to acquire much higher levels of education for which they are well compensated.

Stochastic Components:

Similar to what has already been found above for the other educational groups, we find that high-participation individuals are also high-wage individuals. In addition, for the most highly educated workers, we also find that high-wage workers are also low-mobility workers. Also, individuals that are faced with a positive idiosyncratic wage shock tend to be faced with a negative mobility shock. These correlation are similar to those obtained for the other groups. However, this is the only group for which a move entails a jump in wages, compensating them for their seniority.

6. A Comparison with the United States

In this section, we compare our results with those obtained previously by BFKT for the U.S. using very similar model specification. The model was estimated for three education groups: High school dropouts, high school graduates, and college graduates, using an extract from the Panel Study of Income Dynamics (PSID) for the years 1976-1992. Some variables included in BFKT were not available in the panel that we use here (e.g. race, family unearned income, number of years of education, residence in a SMSA)[15], but for the most part very similar definitions were used, especially for the main variables of interest, namely seniority and experience.[16]

6.1. Comparison of Selected Parameters

We present here a comparison of the estimates for a subset of the parameters that are most important. Estimates for the college graduate group are presented in Table 9, while estimates for high school dropouts are presented in Table 10. In each table, the first four columns provide the results for the U.S., while the last four columns report the results for France.

The first and most significant difference between the two studies is in the estimated returns to seniority. They are large and significant in the U.S.: The linear component is around

[15] Hence the specification of the three equations differ by race, family unearned income, number of years of education, and residence in a SMSA.

[16] Unfortunately, we cannot use administrative data sources for the United States even though they exist (LEHD program) since their access is restricted. And, on the French side, there is no equivalent of the PSID, i.e. a survey that follows individuals within households for a sufficient period of time. At this stage, it is impossible to assess the implications of these constraints.

5% per year for both low and high-education groups. In contrast, these returns are insignificant for all the lower educational groups in France. For the college graduates they are around 2.6%, a lot smaller than for their American counterparts. We also see that the returns to experience are larger in France than they are in the U.S. for the high school dropouts. For the the college-educated workers the return to experience are very similar in both countries. Overall, the combined returns to experiences and seniority are much larger in the U.S. than in France for both groups.

To meaningfully compare wage changes that are associated with a firm-to-firm move we concentrate our discussion on the estimated components of the J^W functions. Some major differences stand out. First, the coefficient on the number of job to job switches appears to indicate that for both education groups, job changes are better compensated in the U.S. than they are in France. For example, for the college-educated workers, who move to a new job from jobs that lasted more than 10 years receive a 60% ($(\exp\{.4717\} - 1) * 100$) increase in wages in their next job. In comparison, the equivalent premium in France is only 6%. This phenomenon is even more pronounced for the high school dropouts: while French workers lose a substantial fraction of their wage after a long tenure in a firm, their American counterparts gain a substantial amount.

Other results on wages are worth noting as well. Inter-industry wage differentials are very small in France for the less educated individuals, but are somewhat more spread for the college graduates. In contrast, the U.S. inter-industry wage differentials are quite large for all education groups (see Table 3 for France, and Table 5 of BFKT for the United States).

There are also significant differences in the mobility processes for the two countries. The mobility process in the U.S. exhibits negative lagged dependence. That is, a worker who just moved is less likely to move in the next period. For France, lagged mobility has virtually no effect at all on current mobility. However, in the U.S., as well as in France, workers tend to move early in a job, as is demonstrated by the negative coefficient on seniority in the mobility equation.

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), which is largely based on administrative data. More precisely, since individuals are directly interviewed in the PSID, much better data on personal characteristics 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 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 France. Also, imputations of seniority have to be performed in year 1976 for the French data.[17] Consequently, the correlations between the random terms of the initial condition equations and the other equations are generally weaker for France.

Second, concentrating on the correlation between individual specific effects in the three main equations, several facts stand out. In both countries high-wage workers also tend to be high-participation workers. Moreover, high-mobility individuals tend also to be low-wage workers in both countries, but with a much stronger effect in the U.S. (especially for the college graduate workers). This signifies the different roles played by mobility in the two countries as far as wage growth is concerned. France is a country with very low mobility, while mobility across firms is quite common in the U.S. Finally, high-participation workers also tend to be low-mobility, and here again the effect is much stronger in the United States.

6.2. The Returns to Experience and Seniority

To summarize the overall impact of the results presented above, Table 11 presents the estimated cumulative and marginal returns to experience, as well as the cumulative and marginal returns to seniority in the U.S. and France at various points in the life cycle.[18] The cumulative returns to experience are large for both countries, with larger returns in France for both education groups. In complete contrast, the cumulative returns to tenure are much larger in the U.S. For high school dropouts we see that there is absolutely no return to seniority in France. This is somewhat different for the college graduates, even though the cumulative returns to seniority in

[17] In practice, the conditional expectation of seniority is obtained using the “structure des salaires” survey, see Abowd, Kramarz, and Margolis (1999) for more details.

[18] In all panels, the specifications include a quadratic function of experience and seniority in the wage equation. For the U.S., BFKT compares the estimates with those obtained based on a quartic specification of experience and education. Estimates of the cumulative returns to experience and seniority are very similar. Hence, we resort here to a comparison based on the quadratic version only.

France are less than half what they are in the U.S.

Note that for the high school dropouts the cumulative return to seniority at 5 years of seniority is almost 27% in the U.S., while in France it is statistically not different from zero. At 15 years of seniority the cumulative return in the U.S. rises to 39%, while in France it remains unchanged. That is, the marginal returns to seniority, at all levels of seniority, are virtually zero in France and hence the cumulative returns remain zeros.

The situation for the college graduate is less pronounced, but as indicated above, the cumulative returns in the U.S. are more than twice as large as those in France. For example, at 5 years of experience the return in the U.S. is almost 24%, while in France it is barely 12%. Similarly, at 15 years of seniority the return in the U.S. is 64%, while in France it is a mere 31%. These differences are mitigated somewhat when one takes into account the return to experiences, but the overall growth of wages in the U.S. that stems from both experience and seniority is still much larger in the U.S. than it is in France.

6.3. Robustness and Specification Checks

We tested various specifications to assess the robustness of the results obtained here. In particular, we examined whether the differences between the U.S. and France stem from inherent differences in the data extracts used for the two countries.

Particular attention was given to investigating to what extent the results obtained here are induced by the specific method employed in this paper. Specifically we examine how the results changed relative to those previously obtained in the literature. To do that we use the methods used by Altonji and Williams (1992). We first estimated a wage regression using a simple OLS regression. Then, we estimated the exact same equation using Altonji and Williams's methodology (specifically the method they label as IV1). The estimation was carried out for both data sets—the PSID for the U.S. and the DADS-EDP for France. The results are reported in Table 12. The top panel of the table presents the IV estimates, while the bottom panel presents the OLS estimates.

First, the OLS estimates of the returns to seniority in France are somewhat smaller than those obtained from our model for the college graduate group. For the high school dropouts they are essentially the same as those obtained by our model, namely zero. For France, the IV method yields point estimates of the returns to seniority that are lower and insignificant. That is, all estimation methods indicate that the returns to seniority in France are quite small, and in most cases are not significantly different from zero. The result for the returns to seniority in the U.S. are strikingly different. The returns to seniority are larger in all specifications than those obtained for France. For both levels of education, the IV method yields the lowest returns to seniority (see the linear tenure effect, but most importantly, the cumulative returns). The OLS estimates for the linear term are slightly larger than those estimated by the IV method. The cumulative returns to seniority have a clear order: The IV method yields the lowest returns. Our estimation method, based on a system of equations, yields the largest, while the OLS estimates are exactly in between, for both groups and both countries.[19]

To summarize, all tests show that the returns to seniority and experience are biased when endogeneity is not accounted for. Irrespective of the method used to correct for this endogeneity, the returns to seniority are much larger in the U.S. than in France, and more so for the least educated individuals, who are also most likely to face higher unemployment rates.

6.4. Are the Returns to Seniority an "Incentive Device"?

A natural question arising from the above comparison of the U.S. and France can be formulated as follows: Are the different features that seem to prevail in the two countries related? Do these features lead to lower returns to seniority in France than in the U.S.?

The results presented above indicate that there is relatively low job-to-job mobility in France[20], while there is relatively high job-to-job mobility in the U.S. In addition the risk of unemployment in France is significantly higher than that faced by the American workers. Can these institutional differences lead to the observed differences in the returns to seniority in the two countries?

In this section, we show that these features are indeed part of a global system and are, hence, tightly connected. We use an equilibrium search model with wage-tenure contracts to examine this question. The properties of the wage profiles implied by the model at the stationary equilibrium are contracted using the respective differential characteristics of the two labor markets, namely the U.S. and France.

[19] BFKT also presents estimates of the returns to experience and seniority without introducing the J^W function. Cumulative returns most often decrease when J^W is excluded. Similar estimates for France for high school dropouts and college graduates (not included here for brevity) show a similar pattern: The linear component of the return to seniority is roughly equal to zero for the former group and equal to about 1% for the latter group.

[20] Mobility increases with education and is much larger for the more recent cohorts.

It turns out that the labor market characteristics that have significant explanatory power are (1) the unemployment rate and (2) the job arrival rate. The unemployment rate in France has always been larger than that in the U.S. For example, OECD data indicate that the unemployment rates in March of 2004 were 9.4% and 5.7%, for France and the U.S., respectively. It is also been estimated in the literature that the job offer arrival rate in the U.S. is larger that that in most European countries. For example, Jolivet, Postel-Vinay, and Robin (2004) use a job search model to provide such estimates. Using the PSID for the U.S. they estimate the job arrival rate to be 1.71 per annum. Similar estimates for several European countries (using the ECHP, for 1994-2001) provide an estimate of 0.56 per annum.

The job search model we employ here has been introduced recently by Burdett and Coles (2003). The most important feature for us in this model is the fact that it generates a unique equilibrium wage-tenure contract. We show below that this wage-tenure contract is such that the slope of tenure in the wage function is an increasing function of the job offer arrival rate. That is, the return to seniority increases when the mobility rate of workers in the economy increases.

We start by summarizing the important aspects of the model. The model is a continuous time model in which individuals are risk adverse. 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 from the labor market. Let p denote the instantaneous revenue received by firms for each worker employed and let b be the instantaneous benefit received by each unemployed worker ($p > b > 0$). Let $u(\cdot)$ denote the instantaneous utility, which is assumed to be strictly increasing and concave. Also, there is no recall of workers.

Burdett and Coles show that under certain assumptions the implied equilibrium is unique. Also, the optimal wage-tenure contract selected by the firm offering the lower starting wage satisfies

$$\frac{d\,w}{d\,t} = \frac{\delta}{\sqrt{p - w_2}} \, \frac{p - w}{u'(w)} \int_{w}^{w_2} \frac{u'(s)}{\sqrt{p - s}} \, d\,s, \tag{6.15}$$

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

$$\left(\frac{\delta}{\lambda + \delta} \right)^2 = \frac{p - w_2}{p - w_1}, \tag{6.16}$$

$$u(w_1) = u(b) - \frac{\sqrt{p - w_1}}{2} \int_{w_1}^{w_2} \frac{u'(s)}{\sqrt{p - s}} \, d\,s, \tag{6.17}$$

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

Assume now that the utility function is constant relative risk aversion (CRRA) of the form $u(w) = w^{1-\sigma}/(1-\sigma)$, where $\sigma > 0$. Burdett and Coles (2003) show that the optimal wage-tenure contract, namely the baseline salary contract, is such that there exists a tenure level such that from that level onward the baseline salary contract is identical to the contract offered by a high-wage firm with a higher entry wage. That is,

$$\frac{d^2 w}{d t^2} = \left(\frac{d w}{d t}\right)^2 \frac{1}{p-w}\left[\frac{\sigma p}{w} - (\sigma+1)\right] - \delta \frac{\sqrt{p-w}}{\sqrt{p-w_2}}\frac{d w}{d t}, \tag{6.18}$$

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

$$\frac{d\,w(0)}{d t} = \frac{\delta}{\sqrt{p-w_2}}\,\frac{p-w_1}{u'(w_1)} \int_{w_1}^{w_2} \frac{u'(s)}{\sqrt{p-s}}\, d s. \tag{6.19}$$

The differential equation (6.18) is highly non-linear and has to be solved numerically. This can be done by assigning some values for the parameter vector $(\lambda, \delta, \sigma, p)$, and solving the model numerically (e.g. using the procedure NDSolve of Mathematica).

In order to study the shape of the wage-tenure contract curve and its sensitivity with respect to the values of the job offers arrival rate, we used the same parameter values as Burdett and Coles (see section 5.2 in their paper). We, set $p = 5$, $\delta = 5.5.10^{-5}$ and $b = 4.6$. For each value of the relative risk aversion coefficient ($\sigma = 0.2, 0.4, 0.8, 1.4$), we solve the system of equations (6.18)–(6.19) numerically for a set a values of the job offer arrival rates. The results are depicted in Figure 1 for $\sigma = 0.2$, in Figure 3 for $\sigma = 0.4$, in Figure 5 for $\sigma = 0.8$, and in Figure 7 for $\sigma = 1.4$ for a range of λ. The figures present the wage contract profiles for the first 10 years of seniority. For all values of the relative risk aversion coefficient, we note that the wage profiles are steeper, especially in the first year, when the job offers arrival rates is larger.

The values of the job offer arrival rates (per year) estimated by Jolivet, Postel-Vinay, and Robin (2004) correspond to the values $\lambda = 0.005$ for the U.S., and $\lambda = 0.001$ for France (job offer arrival rate per day). Regardless of the particular value of the relative risk aversion parameter, the equilibrium wage-tenure contract curves are such that there are larger returns to seniority for the high-mobility country, namely the U.S., than the low mobility country, namely France.

Two points are worth noting. First, we take—as firms appear to be doing—institutions that affect mobility as given. For example, the housing market in the U.S. is a lot more developed than in France (because of strong regulations and transaction costs in the latter country). Also, subsidies and government interventions preventing firms from going bankrupt seem to be more prevalent in France, dampening the forces of "creative destruction" in this country. Consequently, 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 (2003) argues, it is more 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, these firms should rely on general human capital.

Does this mean that the return to seniority should be larger in France than in the U.S.? Or, putting it differently: Should French firms pay for something they get "by construction" due to strong institutional forces? It seems that there is somewhat of a misconception that has plagued some of the research in this area in recent years. The model discussed here provides a useful tool for the empirical results we obtained in this paper. That is, the optimal return to tenure when individuals are mobile should be larger than when there are not.

7. Conclusion

A central tenet of many theories in labor economics states that compensation should rise with seniority. Nevertheless, there has been much disagreement about the empirical support for this general claim, especially in papers that use data from the U.S. Part of the reason that the empirical research has not lead to a conclusive answer is because of the vast disagreement about the proper method for assessing these theories (see, among others, Altonji and Shakotko (1987), and Topel (1991) for the United States and Abowd, Kramarz, and Margolis (1999) for France).

In this paper we reinvestigate the relations between wages, participation, and firm-to-firm mobility in France. We contrast the result with those obtained in the BFKT analysis that reexamined the return to seniority in the U.S., using the same data source as that used by Topel (1991), Altonji and Shakotko (1987), and Altonji and Williams (1992).

We start with a structural model and estimate the return to seniority in a model in which participation, mobility and wages are jointly determined. We include both state-dependence parameters, as well as unobserved correlated individual specific effects in all the model's equations. To estimate this complex structure, we use a state of the art Bayesian MCMC technique.

The model is estimated using French longitudinal data sources for the period 1976-1995 for four separate education groups.

The results indicate that the returns to seniority are virtually zero, and potentially negative for the low education groups. In contrast, the return for the college graduates group is positive and significant, i.e., 2.5% per year of seniority.

We provide a detailed comparison with results previously obtained for the U.S. in BFKT, using the exact same specification used here, and an identical estimation method. The comparison shows that while the returns to seniority are much lower in France than in the U.S., the returns to experience are very close. Furthermore, we find that in both countries there is a significant impact on the estimated returns to seniority when one controls for wage changes when switching from one firm to another (as is summarized by the J^W function introduced here). Hence, we conclude that there is strong evidence that controlling for the individual's career path and past mobility are essential for proper estimation of the return to seniority.

Additional results show that OLS estimates of the cumulative returns to seniority are lower than those obtained from the system of equations. Furthermore, the same results demonstrate that instrumental variables estimation, following Altonji and Williams (1992), give the smallest cumulative returns to seniority among all methods used. This is true for both the U.S. and for France. Finally, a comparison between the two countries shows that regardless of the technique used the 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 is that the returns to seniority are directly related to patterns of mobility. We discuss this aspect using a theoretical framework borrowed from Burdett and Coles (2003). The model clearly indicates that rewarding seniority is likely to play the role of an incentive device designed to counter excessive mobility.

Consequently, the modeling approach adopted here, of jointly estimating the participation, mobility decision along with the wage outcome has non-trivial consequences that may vary across countries. In particular, labor market institutions, state regulations, and other state factors affecting the local economy are likely to have far-reaching effects on the participation, and most importantly the mobility process. This, in turn, is very likely to affect the estimated return to seniority.

A. Appendix A

A.1. Mobility equation

Parameter γ : The parameter γ enters $m_{m_{it^*}}$ for $t = 2, ..., T-1$

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

With Ω_i^I is a row vector $(1 \times N)$ equal to $(0..01000...0)$ where the unique 1 is located at the ith position. The term in the full conditional likelihood that contains this parameter is given by

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

where

$$\begin{aligned}
M_{it}^m &= m_{m_{it}^*} + \underbrace{\frac{\rho_{y,m} - \rho_{w,m}\rho_{y,w}}{1-\rho_{y,w}^2}}_{a}(y_{it}^* - m_{y_{it}^*}) + \underbrace{\frac{\rho_{w,m} - \rho_{y,m}\rho_{y,w}}{\sigma(1-\rho_{y,w}^2)}}_{b}(w_{it} - m_{w_{it}}), \\
\widetilde{\underline{m}_i^*}^{2,T-1} &= \left(y_{i2}m_{i2}^*, ...y_{iT-1}m_{iT-1}^*\right)', \\
\widetilde{\underline{M}_i^m}^{2,T-1} &= \left(y_{i2}M_{i2}^m, ..., y_{iT-1}M_{iT-1}^m\right)', \quad \text{and} \\
A_{it} &= m_{it}^* - M_{it}^m + \gamma m_{it-1} \\
&= m_{it}^* - X_{it}^M\delta^M - \Omega_i^I\theta^{I,M} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - m_{w_{it}}).
\end{aligned}$$

Collecting the squared and crossed terms gives

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

Parameter δ^M : We proceed in the same way as for the parameter γ discussed above, to get

$$V_{\delta^M}^{post,-1} = V_{\delta^M}^{prior,-1} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\underline{\widetilde{X_i^M}}^{2,T-1}\right)'\underline{\widetilde{X_i^M}}^{2,T-1}, \quad \text{and}$$

$$V_{\delta^M}^{post,-1}M_{\delta^M}^{post} = V_{\delta^M}^{prior,-1}M_{\delta^M}^{prior} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\underline{\widetilde{X_i^M}}^{2,T-1}\right)'\underline{\widetilde{A_i}}^{2,T-1},$$

where

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

A.2. Wage equation

Parameter δ^W : Note that we have to take into account that the parameter δ^W enters both $m_{w_{it}}$, for $t = 1...T$, as well as M_{it}^m , for $t = 1...T-1$. The corresponding terms in the full conditional likelihood are given by

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

where

$$\begin{aligned} w_{it} - M_{it}^w &= A_{it} - X_{it}^W\delta^W, \quad \text{and} \\ m_{it}^* - M_{it}^m &= B_{it} + bX_{it}^W\delta^W, \end{aligned}$$

which is equivalent to

$$\begin{aligned} A_{it} &= w_{it} - \Omega_i^I\theta^{I,W} - \rho_{y,w}\sigma(y_{it}^* - m_{y_{it}^*})), \quad \text{and} \\ B_{it} &= m_{it}^* - m_{m_{it}^*} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - \Omega_i^I\theta^{I,W}). \end{aligned}$$

Using analogous notation to the ones used above we have

$$V_{\delta^W}^{post,-1} = V_{\delta^W}^{prior,-1} + \frac{1}{V^w}\sum_{i=1}^{N}\left(\underline{\widetilde{X_i^W}}^{1,T}\right)'\underline{\widetilde{X_i^W}}^{1,T} + \frac{b^2}{V^m}\sum_{i=1}^{N}\left(\underline{\widetilde{X_i^W}}^{1,T-1}\right)'\underline{\widetilde{X_i^W}}^{1,T-1}, \quad \text{and}$$

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

A.3. Participation equation

Parameter γ^Y : We have to take into account that γ^Y enters both $m_{y^*_{it}}$ for $t = 2...T$, M^w_{it} for $t = 2...T$ and M^m_{it} for $t = 2...T-1$. The corresponding terms in the full conditional likelihood are

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

where

$$\begin{aligned}
y^*_{it} - m_{y^*_{it}} &= A_{it} - \gamma^Y Ly_{it}, \\
w_{it} - M^w_{it} &= B_{it} + \rho_{y,w}\sigma\gamma^Y Ly_{it}, \quad \text{and} \\
m^*_{it} - M^m_{it} &= C_{it} + a\gamma^Y Ly_{it},
\end{aligned}$$

which is equivalent to

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

Using analogous notation to the notations used above, we have

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

Parameter γ^M : We proceed in a similar fashion with the parameter γ^M , to get

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

where

$$\begin{aligned}
A_{it} &= y_{it}^* - \gamma^Y L y_{it} - X_{it}^Y \delta^Y - \Omega_i^I \theta^{I,Y}, \\
B_{it} &= w_{it} - m_{w_{it}} - \rho_{y,w}\sigma\left(A_{it}\right), \quad \text{and} \\
C_{it} &= m_{it}^* - m_{m_{it}^*} - b(w_{it} - m_{w_{it}}) - a\left(A_{it}\right).
\end{aligned}$$

Parameter δ^Y : We proceed the same way and we get

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

where

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

A.4. Initial equations

Parameter δ_0^M : Similarly, for the parameter δ_0^M , which enters only m_{i1}^* we have

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

where

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

Parameter δ_0^Y : We proceed the same way for δ_0^Y and get

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

where

$$\begin{aligned} A_i &= y_{i1}^* - \Omega_i^E\alpha^{I,Y}, \\ B_i &= w_{i1} - m_{w_{i1}} - \rho_{y,w}\sigma A_i, \quad \text{and} \\ C_i &= m_{i1}^* - m_{m_{i1}^*} - b(w_{i1} - m_{w_{i1}}) - aA_i. \end{aligned}$$

A.5. Latent variables

Latent participation y_{it}^* : several cases are possible here for y_{it}^* , depending on whether $y_{it} = 1$ or $y_{it} = 0$.

1. For $t = 1...T-1$ we have the following:

   (a.) If $y_{it} = 1$, then

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

(b.) If $y_{it} = 0$, then

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

2. For $t = T$ we have the following:

(a.) If $y_{iT} = 1$, then

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

(b.) If $y_{iT} = 0$, then

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

Latent mobility m^*_{it} : Two conditions must be checked: First, $t = 1...T-1$, and second, it must be that $y_{it} = 1$. When these two conditions are met, we distinguish between several different cases:

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

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

2. If $y_{it+1} = 1$, then: (a.) If $m_{it} = 1$, then

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

(b.) If $m_{it} = 0$, then

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

A.6. Variance-Covariance Matrix of Residuals

Because the prior distribution is not conjugate (i.e., the posterior distribution does not belong to the same family of distributions as the prior), we have to resort to the Metropolis-Hastings algorithm.

Variance-Covariance Matrices of Individual Effects $\Sigma^I_i|(...); z; y, w$:

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

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

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

A.7. Individual effects

The likelihood terms that include θ^I are given by

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

where

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

The following notations are useful:

1. In the first term:

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

2. In the second term:

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

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

3. In the 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. In the fourth term:

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

5. In the fifth term:

   For $t > 1$:

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

   For $t = 1$:

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

The posterior distribution satisfies then:

$$l(\theta^E|...) \propto \exp\left(-\frac{1}{2}\theta^{I\prime}D^{I,-1}\theta^I\right)$$
$$\times \exp\left(-\frac{1}{2}\sum_{i=1}^{n}(A_{i1} - \Omega_i^I\alpha^{Y,I})^2 - \frac{1}{2V^w}\sum_i\left(\widetilde{B}_{i1} - \widetilde{\Omega}_{i1}^I(\theta^{W,I} - \rho_{v,\varepsilon}\sigma\alpha^{Y,I})\right)^2\right)$$

$$\times \exp\left(-\frac{1}{2}\sum_i\sum_{t=2}^{T}(C_{it}-\Omega_i^I\theta^{Y,I})^2-\frac{1}{2V^w}\sum_i\sum_{t=2}^{T}\left(\widetilde{D}_{it}-\widetilde{\Omega}_{it}^I(\theta^{W,I}-\rho_{v,\varepsilon}\sigma\theta^{Y,I})\right)^2\right)$$
$$\times \exp\left(-\frac{1}{2V^m}\sum_i(\widetilde{G}_{i1}+\widetilde{\Omega}_{i1}^I(-\alpha^{M,I}+a\alpha^{Y,I}+b\theta^{W,I}))^2\right)$$
$$\times \exp\left(-\frac{1}{2V^m}\sum_i\sum_{t=2}^{T-1}\left(\widetilde{F}_{it}+\widetilde{\Omega}_{it}^I(-\theta^{M,I}+a\theta^{Y,I}+b\theta^{W,I})\right)^2\right).$$

We define several projection operators. Let $P_1=(I_J,0_J,0_J,0_J,0_J)$, so that $P_1\theta^I=\alpha^{I,Y}$, and similarly, define $P_2,...,P_5$, so that $P_2\theta^I=\alpha^{I,M}$, $P_3\theta^I=\theta^{I,Y}$, $P_4\theta^I=\theta^{I,W}$, and $P_5\theta^I=\theta^{I,M}$. We also denote:

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

Now we can write for the variance-covariance matrix:

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

for the posterior mean we have

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

B. Results

Table 1: Descriptive Statistics

No.	Variable	HS Dropouts (CEP)		Vocational HS (CAP-BEP)		HS Grad. (Baccalauréat)		College Graduates	
		Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
1.	Participation	0.5045	0.5000	0.5860	0.4926	0.4604	0.4984	0.4700	0.4991
2.	Log wage	4.0874	0.8093	4.1991	0.7463	4.1573	0.9801	4.7006	1.1599
3.	Mobility	0.0752	0.2637	0.0938	0.2916	0.1232	0.3287	0.0952	0.2935
4.	Tenure	7.6476	7.8048	5.9895	6.9210	4.1165	6.1718	6.2467	7.7694
5.	Experience	24.7733	11.4711	17.4464	10.7499	11.7819	9.9945	15.7837	9.6285
6.	Lives in couple	0.0648	0.2461	0.0613	0.2399	0.0661	0.2484	0.0551	0.2281
7.	Married	0.6347	0.4815	0.5650	0.4958	0.3540	0.4782	0.5706	0.4950
8.	Children between 0 and 3	0.0863	0.2809	0.1317	0.3381	0.1019	0.3025	0.1225	0.3279
9.	Children between 3 and 6	0.0898	0.2859	0.1142	0.3180	0.0749	0.2633	0.1096	0.3125
10,	Number of Children	1.3196	1.3771	1.0712	1.2158	0.5873	0.9889	0.9830	1.4218
11.	Live in Ile de France	0.1196	0.3245	0.1124	0.3160	0.1531	0.3600	0.2088	0.4064
12.	Live in Paris	0.1182	0.3228	0.1120	0.3153	0.1532	0.3602	0.2707	0.4443
13.	Live in a town	0.2033	0.4024	0.2167	0.4120	0.2417	0.4281	0.2251	0.4176
14.	Live in rural area	0.6785	0.4670	0.6714	0.4697	0.6051	0.4888	0.5043	0.5000
15.	Part-time	0.1846	0.3880	0.1528	0.3598	0.2394	0.4267	0.2137	0.4100
16.	Local unemp. rate	8.1940	3.6354	8.3736	3.4322	8.2858	3.5824	8.9162	2.7771

Table 2: Descriptive Statistics (Continued)

No.	Variable	HS Dropouts (CEP)		Vocational HS (CAP-BEP)		HS Grad. (Baccalauréat)		College Graduates	
		Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
17.	Agriculture	0.0424	0.2016	0.0379	0.1909	0.0216	0.1454	0.0130	0.1133
18.	Energy	0.0095	0.0969	0.0164	0.1272	0.0117	0.1076	0.0219	0.1463
19.	Intermediate goods	0.1007	0.3009	0.0960	0.2946	0.0489	0.2157	0.0634	0.2436
20.	Equipment goods	0.1122	0.3157	0.1305	0.3368	0.0691	0.2536	0.1277	0.3337
21.	Consumption goods	0.1127	0.3162	0.0741	0.2620	0.0551	0.2281	0.0555	0.2289
22.	Construction	0.0884	0.2840	0.1159	0.3201	0.0387	0.1930	0.0357	0.1856
23.	Retail and wholesale	0.1611	0.3676	0.1436	0.3507	0.1554	0.3623	0.0939	0.2917
24.	Transport	0.0606	0.2385	0.0629	0.2428	0.0699	0.2550	0.0531	0.2242
25.	Market services	0.2083	0.4061	0.2222	0.4158	0.3082	0.4617	0.3383	0.4731
26.	Insurance	0.0079	0.0886	0.0080	0.0893	0.0197	0.1390	0.0156	0.1238
27.	Banking and Finance	0.0155	0.1234	0.0213	0.1445	0.0558	0.2296	0.0452	0.2077
28.	Non-market services	0.0748	0.2630	0.0661	0.2484	0.1396	0.3466	0.1306	0.3370
29.	Born before 1929	0.2380	0.4258	0.0540	0.2261	0.0452	0.2078	0.0956	0.2941
30.	Born between 1930 and 1939	0.2132	0.4096	0.1215	0.3268	0.0480	0.2137	0.1314	0.3378
31.	Born between 1940 and 1949	0.2290	0.4202	0.2013	0.4010	0.1048	0.3063	0.2867	0.4522
32.	Born between 1950 and 1959	0.2329	0.4227	0.3084	0.4618	0.2123	0.4089	0.3266	0.4690
33.	Born between 1960 and 1969	0.0646	0.2459	0.2758	0.4469	0.4476	0.4973	0.1580	0.3648
34.	Born after 1970	0.0222	0.1475	0.0390	0.1935	0.1421	0.3492	0.0017	0.0417
	Number of Observations	32,596		12,405		34,071		7,579	

Notes: Source is the DADS-EDP from 1976 through 1996.

Table 3: Wage equation

No.	Variable	High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Job characteristics:																	
1.	Constant	2.3537	0.057	2.150	2.634	2.5619	0.052	2.352	2.738	2.7754	0.050	2.594	2.949	2.5562	0.061	2.324	2.782
2.	Experience	0.0504	0.004	0.037	0.066	0.0590	0.003	0.046	0.070	0.0764	0.005	0.059	0.096	0.0537	0.004	0.041	0.067
3.	Exper. sq.	-0.0005	0.000	-0.001	-0.000	-0.0006	0.000	-0.001	-0.000	-0.0009	0.000	-0.001	-0.001	-0.0008	0.000	-0.001	-0.001
4.	Seniority	0.0027	0.003	-0.009	0.014	-0.0046	0.003	-0.015	0.006	-0.0062	0.005	-0.024	0.010	0.0264	0.003	0.016	0.038
5.	Sen. sq.	-0.0002	0.000	-0.001	0.000	-0.0002	0.000	-0.001	0.000	-0.0001	0.000	-0.001	0.000	-0.0004	0.000	-0.001	-0.000
6.	Part-time	-0.5199	0.012	-0.563	-0.472	-0.4432	0.011	-0.481	-0.404	-0.6559	0.013	-0.706	-0.600	-0.8207	0.015	-0.882	-0.768
Individual and family characteristics:																	
7.	Male	0.5242	0.035	0.382	0.643	0.4111	0.034	0.268	0.304	0.3811	0.038	0.258	0.518	0.5480	0.040	0.404	0.713
8.	Married	-0.0059	0.014	-0.057	0.046	0.0216	0.012	-0.023	0.000	-0.0070	0.018	-0.070	0.060	0.1960	0.022	0.112	0.288
9.	Couple	0.0101	0.019	-0.060	0.094	-0.0078	0.017	-0.073	0.071	-0.0106	0.025	-0.121	0.090	0.0178	0.023	-0.062	0.102
10,	Ile de France	0.0787	0.023	-0.005	0.169	0.0668	0.021	-0.018	0.066	0.1022	0.024	0.020	0.190	0.1358	0.020	0.067	0.207
11.	Unemp. rate	0.0055	0.095	-0.357	0.361	0.1361	0.094	-0.255	0.487	0.1902	0.096	-0.147	0.552	0.1523	0.095	-0.232	0.521
Non-French nationality:																	
12.	Own	0.0764	0.040	-0.057	0.207	0.0550	0.045	-0.088	0.214	0.0240	0.045	-0.140	0.187	-0.0752	0.034	-0.185	0.069
13.	Father	0.1064	0.083	-0.184	0.500	0.0460	0.071	-0.195	0.375	0.0856	0.069	-0.167	0.329	-0.0183	0.069	-0.344	0.237
14.	Mother	0.1250	0.079	-0.174	0.483	0.0176	0.072	-0.229	0.306	-0.0010	0.061	-0.240	0.230	0.0551	0.064	-0.217	0.282
Cohort effects (born between):																	
15.	<1929	0.0873	0.067	-0.173	0.405	0.0047	0.075	-0.256	0.281	-0.0284	0.084	-0.364	0.289	0.3720	0.068	0.118	0.635
16.	1930–1939	0.2579	0.057	0.054	0.484	0.2006	0.062	-0.051	0.432	-0.0411	0.075	-0.330	0.224	0.4487	0.060	0.205	0.686
17.	1940–1949	0.5079	0.054	0.2975	0.7440	0.3587	0.053	0.1463	0.5545	0.1396	0.059	-0.063	0.356	0.5208	0.052	0.326	0.725
18.	1950–1959	0.6393	0.053	0.4305	0.8285	0.5828	0.048	0.4076	0.7567	0.3839	0.052	0.216	0.591	0.6085	0.052	0.416	0.821
19.	1960–1969	0.4583	0.068	0.1732	0.7463	0.6027	0.051	0.4159	0.7751	0.4775	0.045	0.297	0.721	0.5722	0.061	0.332	0.819

Notes: Data sources are DADS-EDP from 1976 to 1996. The number of observations for the four education groups are 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 4: Wage Equation (Continued)

No.	Variable	High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Industry:																	
20.	Energy	0.1153	0.065	-0.152	0.356	0.0099	0.058	-0.187	0.225	0.1294	0.068	-0.110	0.374	0.2386	0.054	0.029	0.453
21.	Intermediate	0.1317	0.031	0.020	0.256	0.1856	0.027	0.092	0.279	0.2055	0.040	0.026	0.366	0.1364	0.035	-0.028	0.282
22.	Equipment	0.1827	0.031	0.072	0.323	0.1455	0.027	0.049	0.255	0.2490	0.037	0.113	0.394	0.2274	0.033	0.110	0.363
23.	Consumption	0.1411	0.030	0.028	0.251	0.1452	0.028	0.027	0.264	0.1865	0.038	0.015	0.335	0.1349	0.035	0.004	0.253
24.	Construction	0.0647	0.032	-0.057	0.198	0.1537	0.027	0.051	0.240	0.2773	0.044	0.124	0.434	0.1341	0.042	-0.033	0.277
25	Retail/Whole	0.0954	0.026	-0.020	0.182	0.0608	0.024	-0.039	0.151	0.1758	0.031	0.065	0.308	0.1664	0.031	0.047	0.283
26.	Transport	0.1018	0.035	-0.037	0.239	0.0697	0.032	-0.054	0.193	0.1812	0.040	0.013	0.333	0.1363	0.038	-0.017	0.273
27.	Services	0.0171	0.025	-0.086	0.103	0.0114	0.023	-0.084	0.107	0.1637	0.028	0.052	0.272	0.0777	0.027	-0.028	0.191
28.	Insurance	0.1034	0.074	-0.182	0.374	-0.0232	0.062	-0.242	0.196	0.2501	0.051	0.056	0.439	0.1614	0.056	-0.043	0.354
29.	Financial	0.2026	0.061	-0.074	0.425	0.1510	0.054	-0.045	0.364	0.2712	0.043	0.112	0.441	0.2214	0.043	0.061	0.392
30.	Oth. serv.	-0.0573	0.030	-0.184	0.061	-0.0902	0.028	-0.191	0.025	-0.1539	0.033	-0.281	-0.022	-0.3711	0.032	-0.489	-0.221
Job switch in first year:																	
31.	1st year	0.1077	0.065	-0.119	0.364	0.0154	0.065	-0.238	0.231	0.0401	0.069	-0.198	0.301	0.1441	0.074	-0.201	0.386
32.	Exp at $t-1$	-0.0049	0.003	-0.018	0.007	-0.0083	0.005	-0.026	0.008	-0.0059	0.007	-0.031	0.019	-0.0030	0.008	-0.035	0.027
Constant of job switch that lasted:																	
33.	Up to 1 year	0.0529	0.015	-0.005	0.107	0.0301	0.010	-0.007	0.065	0.0451	0.013	-0.011	0.095	0.1829	0.015	0.120	0.238
34.	2 to 5 years	0.0985	0.030	-0.025	0.201	0.1967	0.024	0.107	0.294	0.1283	0.033	0.002	0.248	0.0529	0.030	-0.070	0.179
35.	6 to 10 years	-0.0164	0.067	-0.255	0.228	0.1635	0.059	-0.060	0.399	-0.0217	0.081	-0.304	0.270	0.1731	0.071	-0.109	0.424
36.	10+ years	0.0585	0.051	-0.141	0.249	-0.0619	0.048	-0.242	0.135	0.0851	0.072	-0.183	0.399	0.0582	0.053	-0.164	0.280
Coefficient on lagged seniority for job that lasted:																	
37.	2 to 5 years	-0.0242	0.009	-0.060	0.015	-0.0316	0.008	-0.063	-0.003	-0.0344	0.012	-0.075	0.012	0.0308	0.010	-0.008	0.068
38.	6 to 10 years	-0.0025	0.009	-0.036	0.033	-0.0199	0.008	-0.054	0.014	-0.0156	0.013	-0.064	0.034	0.0079	0.010	-0.029	0.046
39.	10+ years	-0.0167	0.004	-0.034	-0.002	-0.0180	0.005	-0.037	-0.001	-0.0145	0.008	-0.051	0.014	0.0189	0.004	0.000	0.036
Coefficient on lagged experience for job that lasted:																	
40.	Up to 1 year	-0.0055	0.001	-0.008	-0.002	-0.0029	0.001	-0.006	-0.001	-0.0059	0.001	-0.011	-0.001	-0.0095	0.001	-0.014	-0.005
41.	2 to 5 years	-0.0031	0.001	-0.007	0.001	-0.0070	0.001	-0.011	-0.003	-0.0036	0.002	-0.012	0.004	-0.0039	0.001	-0.009	0.002
42.	6 to 10 years	0.0016	0.002	-0.005	0.009	-0.0106	0.002	-0.018	-0.003	0.0003	0.004	-0.014	0.014	-0.0096	0.002	-0.018	-0.001
43.	10+ years	0.0060	0.002	-0.002	0.014	0.0094	0.002	0.001	0.019	-0.0011	0.004	-0.020	0.015	-0.0082	0.003	-0.020	0.002

Notes: See Table 3 for details.

Table 5: Participation Equation

		High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
No.	Variable	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Job characteristics:																	
1.	Constant	-1.2059	0.226	-2.046	-0.308	-1.1824	0.227	-2.150	-0.376	-0.8397	0.224	-1.685	0.024	-0.8050	0.230	-1.685	0.101
2.	Experience	0.2211	0.005	0.203	0.239	0.3273	0.005	0.309	0.348	0.4304	0.006	0.409	0.452	0.1777	0.005	0.158	0.196
3.	Exp. squared	-0.0040	0.000	-0.004	-0.004	-0.0061	0.000	-0.007	-0.006	-0.0088	0.000	-0.009	-0.008	-0.0040	0.000	-0.004	-0.004
4.	Unemp. rate	7.4407	0.286	6.337	8.561	8.6314	0.340	7.359	9.950	6.4389	0.280	5.466	7.410	6.4504	0.511	4.397	8.307
Lagged dependent variables:																	
5.	Mobility	0.2041	0.025	0.101	0.295	0.2081	0.024	0.125	0.293	0.2450	0.023	0.132	0.334	0.2665	0.026	0.176	0.350
6.	Participation	0.5192	0.009	0.485	0.556	0.3961	0.009	0.360	0.430	0.2600	0.009	0.224	0.292	0.3414	0.010	0.307	0.375
Individual and family characteristics																	
7.	Male	0.3000	0.040	0.168	0.441	0.2096	0.041	0.061	-0.073	-0.0796	0.000	-0.222	0.043	0.3530	0.045	0.199	0.518
8.	Children 0–3	-0.3319	0.031	-0.443	-0.222	-0.1685	0.027	-0.277	-0.185	-0.2517	0.031	-0.374	-0.125	0.1060	0.032	-0.031	0.217
9.	Children 4–6	-0.3387	0.029	-0.439	-0.234	-0.2828	0.027	-0.403	0.134	-0.4096	0.035	-0.534	-0.266	-0.0304	0.031	-0.153	0.084
10.	Couple	-0.0546	0.036	-0.187	0.085	-0.0060	0.041	-0.172	-0.127	-0.2256	0.042	-0.432	-0.031	0.0499	0.046	-0.138	0.206
11.	Married	-0.1070	0.025	-0.195	-0.013	-0.2155	0.027	-0.314	-0.336	-0.2101	0.030	-0.320	-0.110	0.1099	0.037	-0.015	0.228
12.	Ile de France	0.0659	0.033	-0.054	0.188	0.1177	0.037	0.000	0.251	0.0109	0.025	-0.085	0.102	6.0465	0.186	5.409	6.547
Non-French nationality:																	
13.	Own	-0.3225	0.045	-0.502	-0.157	-0.5103	0.055	-0.721	-0.336	-0.2459	0.052	-0.421	-0.040	-0.2613	0.043	-0.407	-0.121
14.	Father	0.2813	0.173	-0.276	0.915	0.2403	0.115	-0.132	0.689	0.0532	0.098	-0.323	0.381	0.1492	0.130	-0.273	0.572
15.	Mother	-0.0161	0.144	-0.588	0.472	0.0175	0.123	-0.381	0.463	-0.1245	0.081	-0.392	0.204	-0.1337	0.120	-0.560	0.249
Cohort effects:																	
16.	$<$1929	-2.4810	0.059	-2.750	-2.229	-3.3449	0.113	-3.758	-2.962	-3.0419	0.117	-3.464	-2.637	-2.5581	0.093	-2.918	-2.215
17.	1930–1939	-2.2575	0.068	-2.508	-2.023	-3.1446	0.084	-3.455	-2.866	-3.9734	0.111	-4.394	-3.621	-2.5230	0.086	-2.883	-2.167
18.	1940–1949	-1.9738	0.072	-2.228	-1.723	-2.9346	0.078	-3.226	-2.681	-3.7966	0.083	-4.104	-3.513	-2.3254	0.070	-2.608	-2.082
19.	1950–1959	-1.3127	0.065	-1.568	-1.041	-1.7896	0.059	-1.996	-1.579	-1.9638	0.055	-2.190	-1.785	-1.9746	0.062	-2.205	-1.762
20.	1960–1969	-0.4090	0.090	-0.730	-0.048	-0.6373	0.050	-0.812	-0.466	-0.8580	0.037	-0.995	-0.730	-1.4472	0.071	-1.719	-1.184

Notes: See Table 3 for details.

Table 6: Mobility Equation

No.	Variable	High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Job characteristics:																	
1.	Constant	-0.9936	0.319	-2.061	0.144	-1.0834	0.277	-2.107	-0.113	-0.5756	0.271	-1.557	0.449	-1.0982	0.425	-2.596	0.495
2.	Experience	-0.0119	0.012	-0.058	0.034	-0.0344	0.011	-0.083	0.003	-0.0557	0.014	-0.098	-0.010	-0.0072	0.009	-0.037	0.024
3.	Exp. squared	0.0001	0.000	-0.001	0.001	0.0006	0.000	0.000	0.001	0.0013	0.000	0.000	0.002	0.0003	0.000	-0.001	0.001
4.	Seniority	-0.0315	0.009	-0.060	0.002	-0.0315	0.008	-0.060	0.001	-0.0335	0.012	-0.078	0.021	-0.0197	0.008	-0.046	0.005
5.	Sen. squared	0.0018	0.000	0.000	0.003	0.0017	0.000	0.001	0.003	0.0017	0.001	-0.001	0.004	0.0010	0.000	0.000	0.002
6.	Unemp. rate	0.4218	0.741	-2.102	3.242	0.3087	0.684	-2.264	2.868	-0.1282	0.684	-2.794	2.409	0.0516	0.697	-2.874	2.900
7.	Part-time	0.4738	0.045	0.291	0.648	0.6054	0.039	0.443	0.755	0.4737	0.039	0.318	0.645	0.4497	0.041	0.308	0.600
Lagged dependent variables:																	
8.	Mobility	0.0150	0.051	-0.175	0.223	0.0477	0.040	-0.102	0.190	-0.0638	0.046	-0.241	0.098	-0.0161	0.043	-0.194	0.141
Individual and family characteristics																	
9.	Male	0.2164	0.058	0.010	0.448	0.1942	0.057	-0.005	0.392	0.1455	0.056	-0.033	0.309	0.0932	0.061	-0.162	0.310
10.	Children 0–3	-0.3319	0.031	-0.443	0.207	-0.0116	0.044	-0.158	0.143	-0.0512	0.059	-0.249	0.222	0.0042	0.049	-0.166	0.177
11.	Children 4–6	-0.3387	0.029	-0.439	0.155	-0.0724	0.045	-0.267	0.089	-0.1150	0.069	-0.383	0.114	-0.0832	0.047	-0.274	0.097
12.	Married	-0.1400	0.051	-0.313	0.088	-0.0989	0.070	-0.348	0.128	-0.2122	0.077	-0.492	0.053	-0.1520	0.056	-0.343	0.062
13.	Couple	-0.0055	0.076	-0.315	0.283	-0.1666	0.045	-0.321	0.006	-0.2443	0.055	-0.437	-0.057	0.0116	0.078	-0.286	0.315
14.	Ile de France	0.1744	0.069	-0.074	0.407	0.0931	0.062	-0.107	0.325	0.1122	0.061	-0.134	0.362	0.2268	0.050	0.023	0.426
Non-French Nationality:																	
15.	Own	0.1540	0.067	-0.066	0.391	0.0313	0.080	-0.212	0.311	0.0035	0.077	-0.254	0.251	-0.0358	0.058	-0.235	0.180
16.	Father	0.0417	0.220	-0.824	0.887	0.0291	0.132	-0.438	0.509	-0.0410	0.132	-0.507	0.420	0.0162	0.157	-0.554	0.581
17.	Mother	0.2582	0.208	-0.432	1.070	-0.1501	0.145	-0.683	0.335	0.1056	0.105	-0.256	0.495	0.0848	0.147	-0.421	0.706
Cohort effects:																	
18.	<1929	-1.2194	0.327	-2.518	-0.026	-0.9357	0.302	-1.997	0.099	-1.9495	0.372	-3.292	-0.631	-0.9637	0.387	-2.364	0.503
19.	1930–1939	-1.1365	0.286	-2.168	0.122	-0.7139	0.233	-1.608	0.097	-1.1395	0.264	-2.004	-0.230	-0.6508	0.373	-1.896	0.810
20.	1940–1949	-0.7240	0.247	-1.570	0.359	-0.4582	0.187	-1.263	0.208	-0.9366	0.182	-1.530	-0.349	-0.3260	0.365	-1.613	0.916
21.	1950–1959	-0.6070	0.217	-1.411	0.252	-0.2721	0.150	-1.004	0.239	-0.5250	0.123	-0.959	-0.083	0.0686	0.363	-1.149	1.304
22.	1960–1969	-0.4095	0.218	-1.199	0.393	-0.2520	0.132	-0.734	0.253	-0.2829	0.086	-0.617	0.032	0.4750	0.368	-0.688	1.730

Table 7: Mobility Equation (Continued)

No.	Variable	High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Industry:																	
23.	Energy	-0.0565	0.737	-3.066	2.255	-1.2534	0.247	-2.250	-0.447	-1.1784	0.297	-2.186	-0.098	-0.7395	0.192	-1.453	-0.074
24.	Intermediate	-0.3374	0.319	-1.640	0.955	-0.1361	0.099	-0.491	0.201	-0.0747	0.143	-0.589	0.515	-0.3868	0.126	-0.854	0.072
25.	Equipment	0.3442	0.313	-0.764	1.538	-0.2215	0.098	-0.573	0.125	-0.0281	0.135	-0.536	0.480	-0.4903	0.123	-1.000	-0.067
26.	Consumption	0.5253	0.295	-0.517	1.738	0.0385	0.102	-0.327	0.386	-0.0535	0.136	-0.590	0.520	-0.4103	0.133	-0.989	0.100
27.	Construction	0.0887	0.297	-1.230	1.227	0.2799	0.092	-0.051	0.648	0.2324	0.147	-0.436	0.725	-0.1671	0.144	-0.664	0.374
28.	Retail/Whole	0.3397	0.274	-0.727	1.302	0.0454	0.089	-0.286	0.372	0.1300	0.121	-0.272	0.576	-0.4348	0.123	-1.071	0.011
29.	Transport	0.4488	0.380	-1.129	1.949	-0.2613	0.107	-0.655	0.112	-0.3924	0.143	-0.924	0.171	-0.7423	0.143	-1.307	-0.220
30.	Services	0.5872	0.275	-0.525	1.617	0.1569	0.086	-0.123	0.501	0.1053	0.114	-0.348	0.529	-0.4290	0.113	-0.989	-0.006
31.	Insurance	0.6985	0.576	-1.345	3.295	-0.0065	0.230	-0.825	0.830	-0.0588	0.174	-0.892	0.583	-0.3698	0.200	-1.073	0.500
32.	Financial	-0.7652	0.821	-4.565	2.069	-0.5870	0.186	-1.271	0.087	-0.2091	0.141	-0.744	0.349	-0.6057	0.147	-1.136	-0.108
33.	Oth. serv.	0.0160	0.470	-2.190	1.745	-0.3484	0.109	-0.723	0.112	-0.2473	0.125	-0.719	0.182	-0.5744	0.124	-1.170	-0.098

Notes: See Table 3 for details.

Table 8: Elements of Variance Covariance Matrices

No.	Variable	High School Dropouts (CEP)				Vocational HS (CAP-BEP)				HS Grad. (Baccalauréat)				College Graduates			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Individual specific effects:																	
1.	$\rho_{y_0 m_0}$	0.0254	0.025	-0.047	0.077	-0.0143	0.023	-0.068	0.040	0.0397	0.024	-0.008	0.098	0.0214	0.014	-0.017	0.067
2.	$\rho_{y_0 y}$	0.1458	0.029	0.074	0.200	0.1238	0.023	0.073	0.182	0.1199	0.033	0.050	0.195	0.1364	0.019	0.085	0.183
3.	$\rho_{y_0 w}$	0.0596	0.036	-0.007	0.149	-0.0120	0.021	-0.057	0.036	0.0576	0.033	0.002	0.128	0.0525	0.019	0.009	0.103
4.	$\rho_{y_0 m}$	0.0206	0.019	-0.041	0.063	-0.0261	0.016	-0.059	0.026	0.0422	0.037	-0.021	0.129	-0.0311	0.018	-0.066	0.010
5.	$\rho_{m_0 y}$	0.0087	0.023	-0.065	0.055	-0.0025	0.034	-0.069	0.054	0.0245	0.023	-0.030	0.072	-0.0033	0.035	-0.078	0.060
6.	$\rho_{m_0 w}$	0.0407	0.030	-0.008	0.138	0.0202	0.029	-0.043	0.088	-0.0168	0.036	-0.120	0.041	0.0045	0.011	-0.028	0.035
7.	$\rho_{m_0 m}$	-0.0312	0.024	-0.087	0.028	0.0155	0.020	-0.035	0.060	-0.0154	0.016	-0.054	0.023	-0.0091	0.017	-0.049	0.029
8.	ρ_{yw}	0.2538	0.037	0.174	0.327	0.1260	0.021	0.077	0.174	0.2068	0.022	0.149	0.250	0.1773	0.020	0.124	0.219
9.	ρ_{ym}	-0.0677	0.019	-0.129	-0.024	-0.1013	0.017	-0.160	-0.060	-0.0643	0.020	-0.111	-0.009	-0.0287	0.020	-0.071	0.023
10.	ρ_{wm}	-0.1578	0.028	-0.219	-0.103	-0.1897	0.037	-0.244	-0.088	-0.0275	0.018	-0.081	0.012	-0.0629	0.021	-0.110	-0.009
Idiosyncratic terms:																	
11.	σ^2	0.2669	0.002	0.259	0.277	0.2653	0.002	0.257	0.274	0.3964	0.004	0.383	0.413	0.3728	0.004	0.364	0.387
12.	ρ_{wm}	-0.0595	0.013	-0.109	0.000	-0.0574	0.011	-0.103	0.000	-0.0553	0.014	-0.117	0.000	-0.0835	0.013	-0.135	0.000
13.	ρ_{ym}	0.1455	0.057	-0.030	0.359	0.1097	0.054	-0.092	0.254	0.0383	0.050	-0.119	0.201	0.2026	0.050	-0.043	0.343
14.	ρ_{yw}	0.0171	0.016	-0.044	0.068	-0.0099	0.016	-0.071	0.054	0.0161	0.020	-0.051	0.079	0.0373	0.022	-0.057	0.114

Notes: See Table 3 for details.

Table 9: Comparison of the United States and France, College Graduates

No.	Variable	College Graduates, U.S.				College Graduates, France			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
	Wage equation								
Main characteristics:									
1.	Experience	0.0580	0.0032	0.0518	0.0643	0.0537	0.0035	0.0410	0.0667
2.	Exp. squared	-0.0013	0.0001	-0.0015	-0.0012	-0.0008	0.0001	-0.0010	-0.0005
3.	Seniority	0.0518	0.0029	0.0460	0.0576	0.0264	0.0027	0.0157	0.0375
4.	Sen. squared	-0.0005	0.0001	-0.0007	-0.0004	-0.0004	0.0001	-0.0007	-0.0001
Constant of job switch that lasted:									
5.	Up to 1 year	0.2240	0.0172	0.1905	0.2572	0.1829	0.0150	0.1198	0.2384
6.	2 to 5 years	0.1648	0.0189	0.1274	0.2018	0.0529	0.0300	-0.0704	0.1786
7.	6 to 10 years	0.3231	0.0683	0.1861	0.4572	0.1731	0.0708	-0.1087	0.4239
8.	10+ years	0.4717	0.0869	0.3031	0.6425	0.0582	0.0530	-0.1644	0.2796
Coefficient on lagged seniority for job that lasted:									
9.	2 to 5 years	0.0567	0.0070	0.0432	0.0709	0.0308	0.0102	-0.0080	0.0678
10.	6 to 10 years	0.0111	0.0097	-0.0079	0.0303	0.0079	0.0101	-0.0290	0.0457
11.	10+ years	0.0062	0.0055	-0.0050	0.0166	0.0189	0.0042	0.0004	0.0357
Coefficient on lagged experience for job that lasted:									
12.	Up to 1 year	-0.0071	0.0016	-0.0102	-0.0040	-0.0095	0.0012	-0.0135	-0.0045
13.	2 to 5 years	-0.0058	0.0016	-0.0090	-0.0027	-0.0039	0.0014	-0.0094	0.0015
14.	6 to 10 years	-0.0025	0.0025	-0.0073	0.0024	-0.0096	0.0024	-0.0181	-0.0013
15.	10+ years	-0.0026	0.0033	-0.0090	0.0036	-0.0082	0.0027	-0.0196	0.0018
	Participation equation								
16.	Lagged mobility	0.3336	0.1646	0.0111	0.6274	0.2665	0.0255	0.1764	0.3501
17.	Lagged participation	2.0046	0.0944	1.8178	2.1978	0.3414	0.0095	0.3067	0.3748
	Mobility equation								
18.	Seniority	-0.0878	0.0074	-0.1024	-0.0734	-0.0197	0.0080	-0.0462	0.0049
19.	Sen. squared	0.0020	0.0003	0.0015	0.0026	0.0010	0.0003	0.0000	0.0022
20.	Lagged mobility	-0.9019	0.0552	-1.0133	-0.7953	-0.0161	0.0432	-0.1940	0.1412
	Variance-covariance elements								
Individual effects:									
21.	$\rho_{y_0 m_0}$	0.8040	0.0556	0.7024	0.9005	0.0214	0.0136	-0.0165	0.0674
22.	$\rho_{y_0 y}$	0.5716	0.0286	0.5190	0.6224	0.1364	0.0187	0.0852	0.1834
23.	$\rho_{y_0 w}$	0.1335	0.0757	0.0169	0.2714	0.0525	0.0194	0.0087	0.1025
24.	$\rho_{y_0 m}$	-0.6044	0.0773	-0.7595	-0.4892	-0.0311	0.0179	-0.0659	0.0101
25.	$\rho_{m_0 y}$	0.2896	0.0429	0.2268	0.3845	-0.0033	0.0353	-0.0775	0.0595
26.	$\rho_{m_0 w}$	-0.1450	0.0884	-0.2586	0.0403	0.0045	0.0110	-0.0278	0.0346
27.	$\rho_{m_0 m}$	-0.4234	0.0789	-0.5691	-0.2668	-0.0091	0.0173	-0.0491	0.0292
28.	ρ_{yw}	0.2174	0.0553	0.1066	0.3017	0.1773	0.0200	0.1243	0.2185
29.	ρ_{ym}	-0.5061	0.0656	-0.6172	-0.3874	-0.0287	0.0200	-0.0707	0.0231
30.	ρ_{wm}	-0.5352	0.0590	-0.6371	-0.4131	-0.0629	0.0214	-0.1099	-0.0089
Idiosyncratic terms:									
31.	σ^2	0.2062	0.0023	0.2016	0.2104	0.3728	0.0035	0.3640	0.3869
32.	ρ_{yw}	0.0013	-0.0111	0.0075	0.0161	-0.0835	0.0134	-0.1350	0.0000
33.	ρ_{ym}	-0.0005	0.0113	-0.0217	0.0188	0.2026	0.0499	-0.0427	0.3431
34.	ρ_{wm}	-0.0496	0.0124	-0.0672	-0.0205	0.0373	0.0222	-0.0571	0.1140

Table 10: Comparison of the United States and France, High School Dropouts

No.	Variable	High School Dropouts, U.S.				High School Dropouts, France			
		Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
	Wage equation								
Main characteristics:									
1.	Experience	0.0283	0.0027	0.0229	0.0334	0.0504	0.0035	0.0372	0.0658
2.	Exp. squared	-0.0007	0.0000	-0.0007	-0.0006	-0.0005	0.0001	-0.0007	-0.0003
3.	Seniority	0.0517	0.0034	0.0455	0.0580	0.0027	0.0030	-0.0091	0.0143
4.	Sen. squared	-0.0005	0.0001	-0.0008	-0.0003	-0.0002	0.0001	-0.0006	0.0000
Constant of job switch that lasted:									
5.	Up to 1 year	0.0923	0.0144	0.0635	0.1203	0.0529	0.0146	-0.0051	0.1067
6.	2 to 5 years	0.0958	0.0219	0.0526	0.1386	0.0985	0.0298	-0.0245	0.2012
7.	6 to 10 years	0.1229	0.1027	-0.0569	0.3076	-0.0164	0.0667	-0.2545	0.2278
8.	10+ years	0.2457	0.1078	0.0474	0.4606	0.0585	0.0509	-0.1409	0.2493
Coefficient on lagged seniority for job that lasted:									
9.	2 to 5 years	0.0293	0.0084	0.0127	0.0456	-0.0242	0.0093	-0.0603	0.0147
10.	6 to 10 years	0.0213	0.0109	0.0003	0.0422	-0.0025	0.0090	-0.0357	0.0327
11.	10+ years	0.0350	0.0053	0.0238	0.0444	-0.0167	0.0043	-0.0341	-0.0015
Coefficient on lagged experience for job that lasted:									
12.	Up to 1 year	0.0009	0.0012	-0.0015	0.0033	-0.0055	0.0008	-0.0082	-0.0023
13.	2 to 5 years	-0.0007	0.0016	-0.0038	0.0024	-0.0031	0.0010	-0.0071	0.0005
14.	6 to 10 years	0.0007	0.0030	-0.0049	0.0060	0.0016	0.0018	-0.0053	0.0085
15.	10+ years	-0.0090	0.0029	-0.0150	-0.0035	0.0060	0.0021	-0.0017	0.0139
	Participation equation								
16.	Lagged mobility	0.5295	0.1258	0.3043	0.7836	0.2041	0.0249	0.1008	0.2945
17.	Lagged participation	1.7349	0.0660	1.5999	1.8530	0.5192	0.0090	0.4845	0.5557
	Mobility equation								
18.	Seniority	-0.0812	0.0115	-0.1007	-0.0605	-0.0315	0.0089	-0.0603	0.0018
19.	Sen. squared	0.0018	0.0003	0.0011	0.0024	0.0018	0.0004	0.0003	0.0032
20.	Lagged mobility	-0.7190	0.0738	-0.8544	-0.5807	0.0150	0.0509	-0.1753	0.2228
	Variance-covariance elements								
Individual effects:									
21.	$\rho_{y_0 m_0}$	-0.1020	0.1146	-0.2589	0.1067	0.0254	0.0245	-0.0472	0.0771
22.	$\rho_{y_0 y}$	0.7548	0.0566	0.6525	0.8747	0.1458	0.0285	0.0742	0.2000
23.	$\rho_{y_0 w}$	0.3447	0.0351	0.2732	0.4142	0.0596	0.0357	-0.0066	0.1485
24.	$\rho_{y_0 m}$	0.0278	0.2007	-0.2908	0.2281	0.0206	0.0193	-0.0414	0.0632
25.	$\rho_{m_0 y}$	0.1972	0.0746	0.0260	0.2971	0.0087	0.0229	-0.0653	0.0545
26.	$\rho_{m_0 w}$	0.0646	0.0505	-0.0061	0.1794	0.0407	0.0301	-0.0079	0.1382
27.	$\rho_{m_0 m}$	-0.0573	0.1666	-0.2619	0.2194	-0.0312	0.0236	-0.0865	0.0281
28.	ρ_{yw}	0.2958	0.0282	0.2292	0.3560	0.2538	0.0369	0.1737	0.3272
29.	ρ_{ym}	-0.2100	0.1053	-0.3832	-0.0429	-0.0677	0.0185	-0.1291	-0.0241
30.	ρ_{wm}	-0.2744	0.0799	-0.4083	-0.1348	-0.1578	0.0282	-0.2188	-0.1027
Idiosyncratic terms:									
31.	σ^2	0.2448	0.0064	0.2331	0.2539	0.2669	0.0024	0.2591	0.2765
32.	ρ_{yw}	-0.0055	0.0074	-0.0185	0.0072	-0.0595	0.0133	-0.1085	0.0000
33.	ρ_{ym}	0.0029	0.0077	-0.0117	0.0160	0.1455	0.0573	-0.0299	0.3588
34.	ρ_{wm}	-0.0346	0.0072	-0.0497	-0.0183	0.0171	0.0160	-0.0436	0.0677

Table 11: Cumulative and Marginal Returns to Experience and Seniority for the United States and France

Country and Group		Cumulative			Marginal		
		Years			Years		
		5	10	15	5	10	15
Panel A: Return to Experience							
United States:							
1.	High school dropouts	0.101	0.246	0.472	2.661	1.959	1.256
		(0.005)	(0.012)	(0.022)	(0.286)	(0.248)	(0.215)
2.	College graduates	0.256	0.446	0.567	4.455	3.109	1.763
		(0.015)	(0.029)	(0.040)	(0.285)	(0.253)	(0.231)
France:							
3.	High school dropouts	0.240	0.458	0.652	4.575	4.112	3.648
		(0.017)	(0.031)	(0.045)	(0.314)	(0.285)	(0.265)
4.	College graduates	0.249	0.459	0.630	4.587	3.808	3.030
		(0.016)	(0.030)	(0.042)	(0.303)	(0.263)	(0.241)
Panel B: Return to Seniority							
United States:							
5.	High school dropouts	0.266	0.347	0.392	4.721	4.314	3.906
		(0.029)	(0.040)	(0.050)	(0.216)	(0.169)	(0.156)
6.	College graduates	0.236	0.449	0.637	4.485	4.001	3.517
		(0.014)	(0.025)	(0.034)	(0.247)	(0.209)	(0.205)
France:							
7.	High school dropouts	0.006	-0.002	-0.025	-0.021	-0.307	-0.594
		(0.014)	(0.027)	(0.039)	(0.269)	(0.257)	(0.267)
8.	College graduates	0.122	0.225	0.307	2.245	1.849	1.453
		(0.012)	(0.023)	(0.031)	(0.225)	(0.199)	(0.207)

Table 12: Comparison of Alternative Estimates of the Return to Seniority

	United States		France	
	High school dropouts	College graduates	High school dropouts	College graduates
Instrumental variable (Altonji-Williams):				
Linear tenure	0.046	0.037	-0.004	-0.001
	(0.006)	(0.006)	(0.003)	(0.003)
Linear experience	0.055	0.058	0.036	0.051
	(0.011)	(0.014)	(0.004)	(0.004)
Cumulative returns to tenure:				
2 years	0.062	0.043	-0.008	-0.002
	(0.010)	(0.008)	(0.005)	(0.007)
5 years	0.112	0.078	-0.020	-0.005
	(0.017)	(0.014)	(0.014)	(0.017)
10 years	0.131	0.092	-0.042	-0.013
	(0.019)	(0.015)	(0.029)	(0.035)
15 years	0.131	0.090	-0.064	-0.022
	(0.018)	(0.016)	(0.046)	(0.056)
20 years	0.146	0.099	-0.088	-0.034
	(0.019)	(0.020)	(0.066)	(0.080)
Ordinary least-squares:				
Linear tenure	0.058	0.040	0.001	0.021
	(0.006)	(0.005)	(0.002)	(0.002)
Linear experience	0.059	0.059	0.037	0.039
	(0.010)	(0.008)	(0.003)	(0.004)
Cumulative returns to tenure:				
2 years	0.099	0.068	0.003	0.041
	(0.009)	(0.007)	(0.004)	(0.005)
5 years	0.197	0.136	0.013	0.096
	(0.015)	(0.012)	(0.009)	(0.012)
10 years	0.273	0.189	0.042	0.171
	(0.016)	(0.013)	(0.020)	(0.026)
15 years	0.300	0.208	0.087	0.226
	(0.017)	(0.015)	(0.032)	(0.041)
20 years	0.328	0.223	0.147	0.260
	(0.017)	(0.018)	(0.046)	(0.059)
Our model:				
Linear tenure	0.052	0.052	0.003	0.026
	(0.003)	(0.003)	(0.003)	(0.003)
Linear experience	0.028	0.058	0.050	0.054
	(0.003)	(0.003)	(0.004)	(0.004)

C. Simulations

Figure 1. Wage Profile as a function of Tenure (in days) and $\sigma = 0.2$

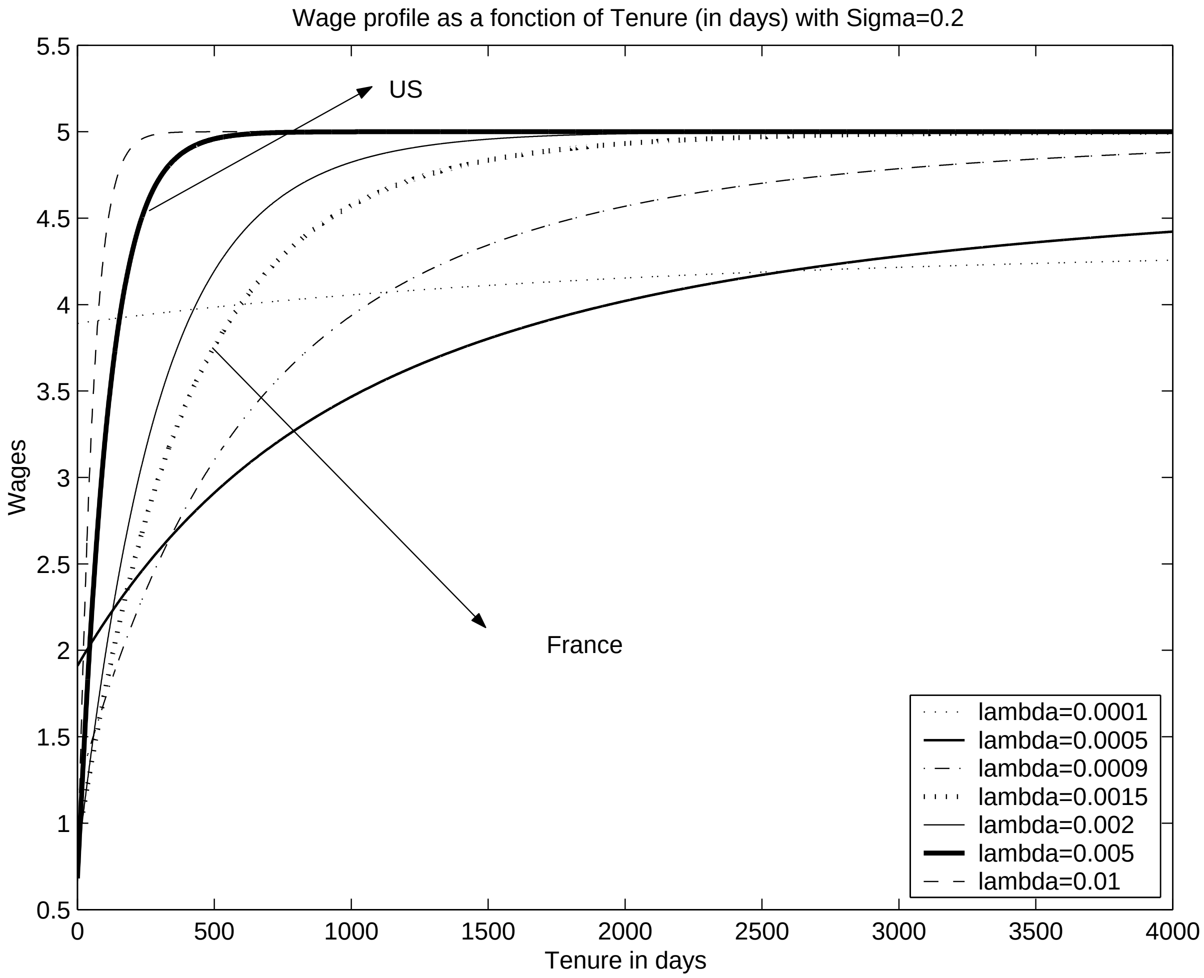


Figure 2. Log of Wage Profile as a function of Tenure (in days) and $\sigma = 0.2$

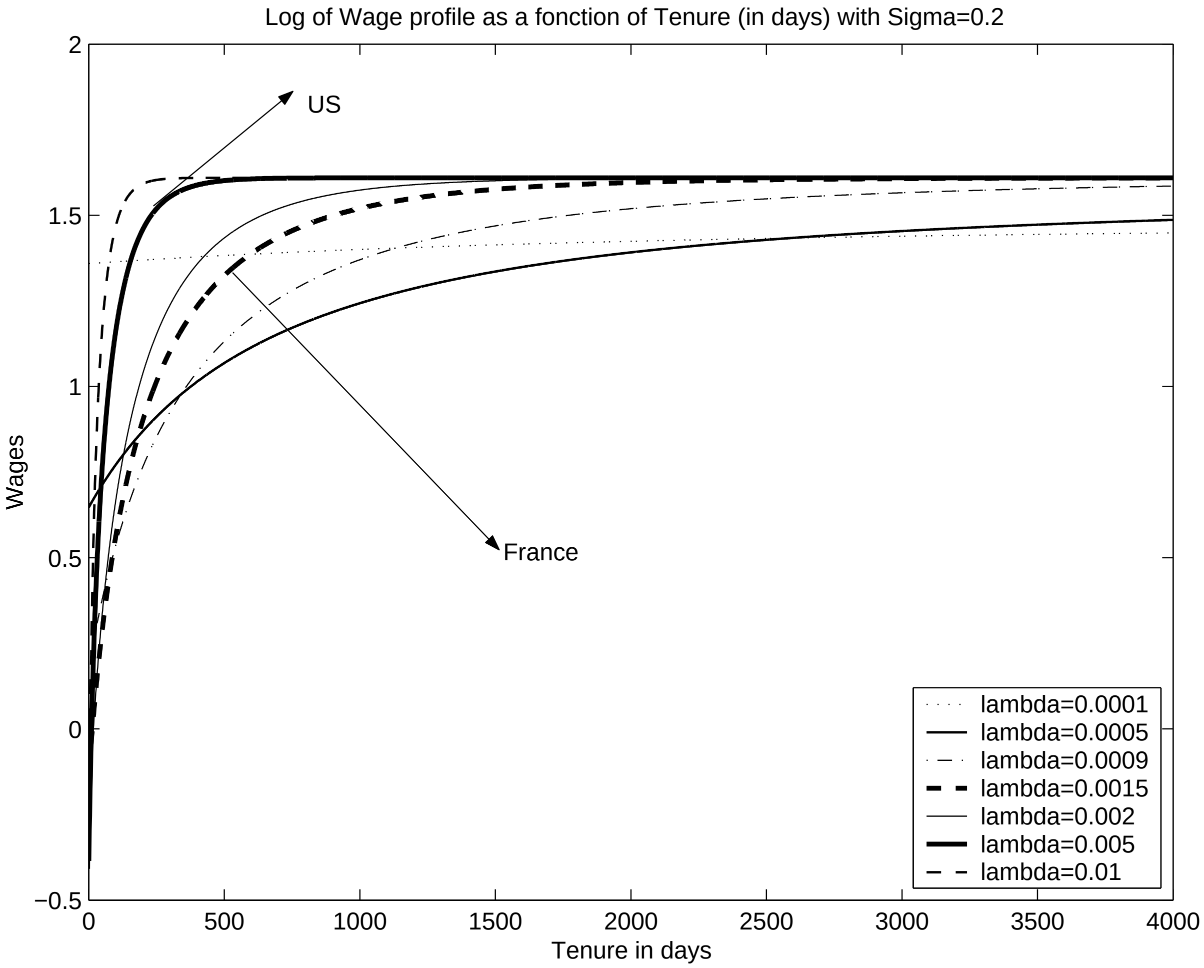


Figure 3. Wage Profile as a function of Tenure (in days) and $\sigma = 0.4$

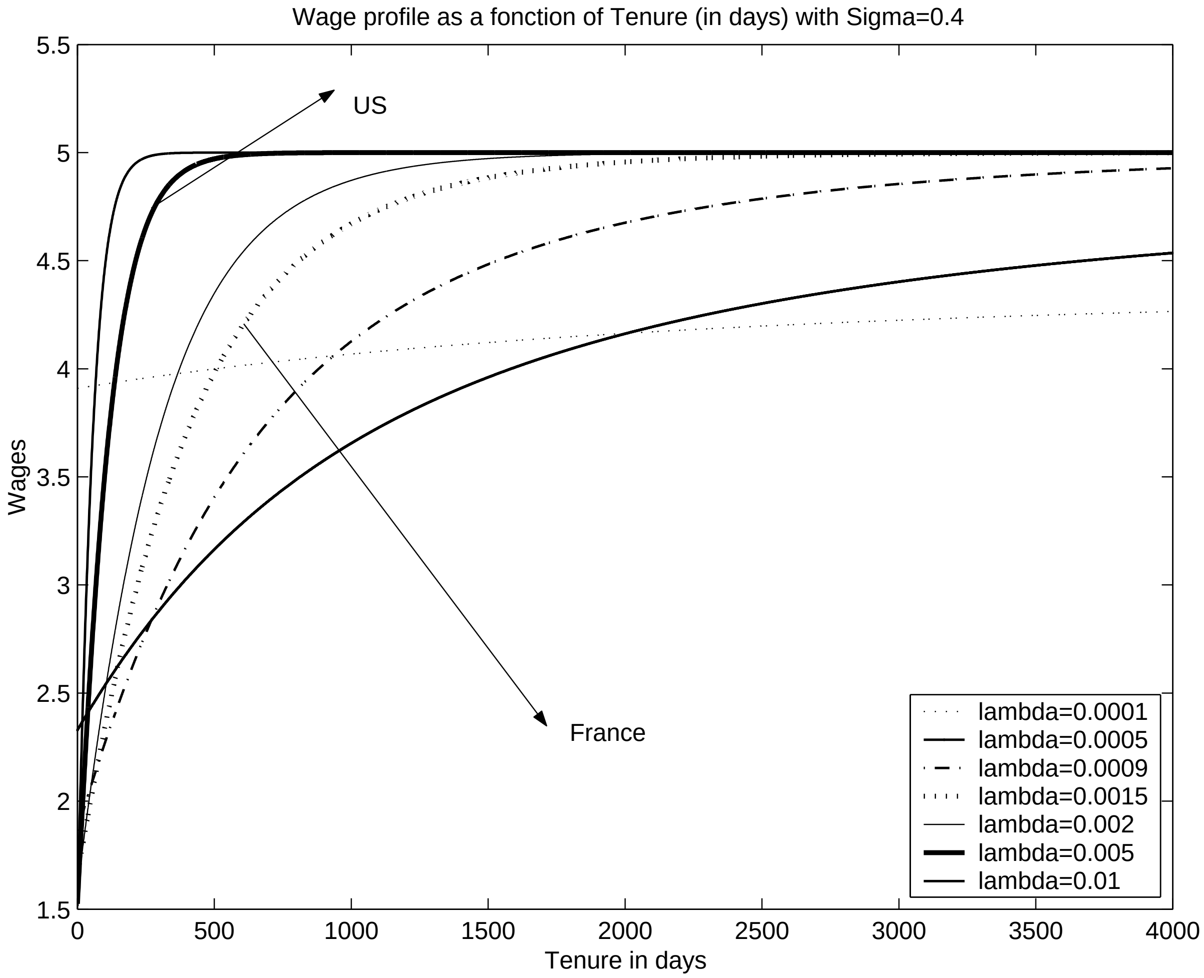


Figure 4. Log of Wage Profile as a function of Tenure (in days) and $\sigma = 0.4$

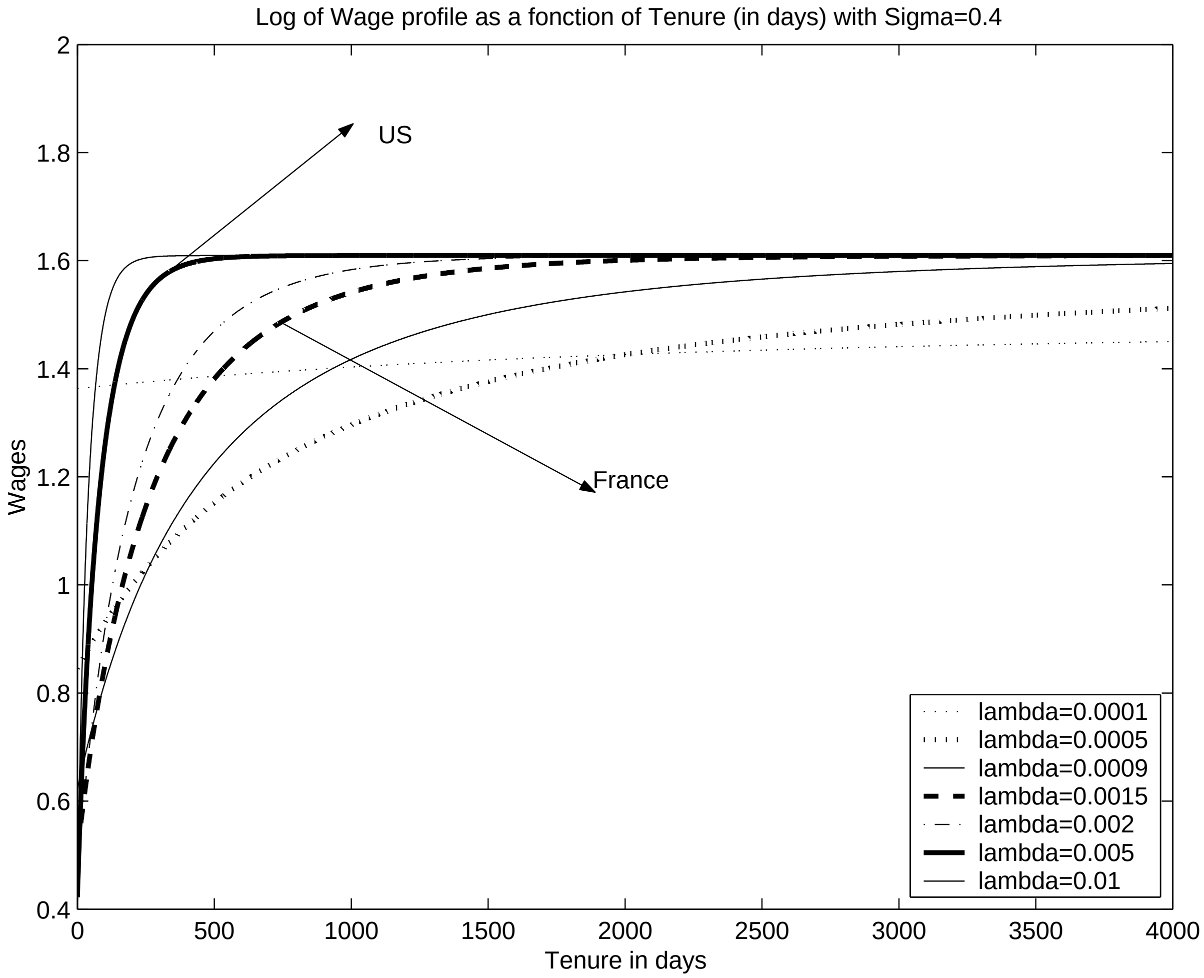


Figure 5. Wage Profile as a function of Tenure (in days) and $\sigma = 0.8$

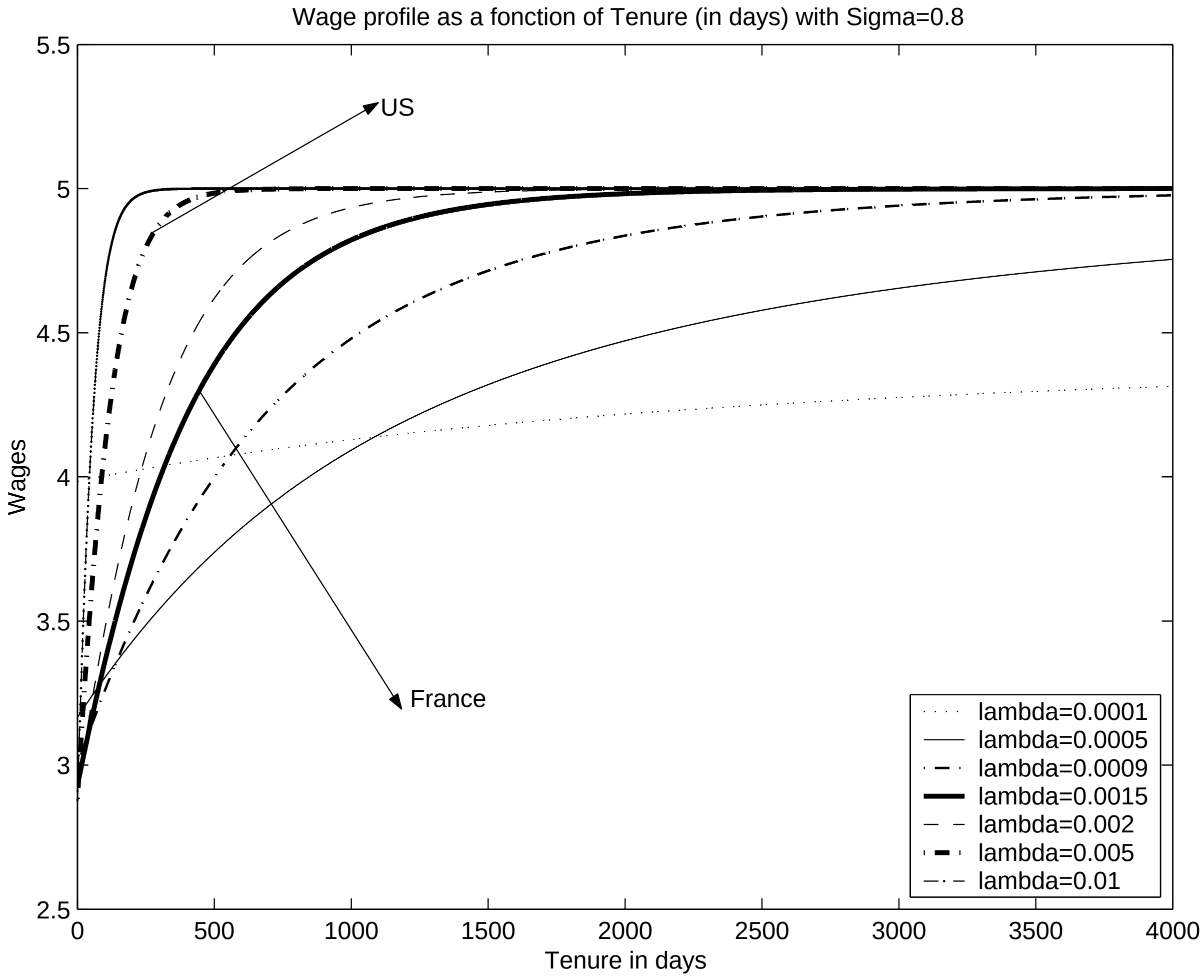


Figure 6. Log of Wage Profile as a function of Tenure (in days) and $\sigma = 0.8$

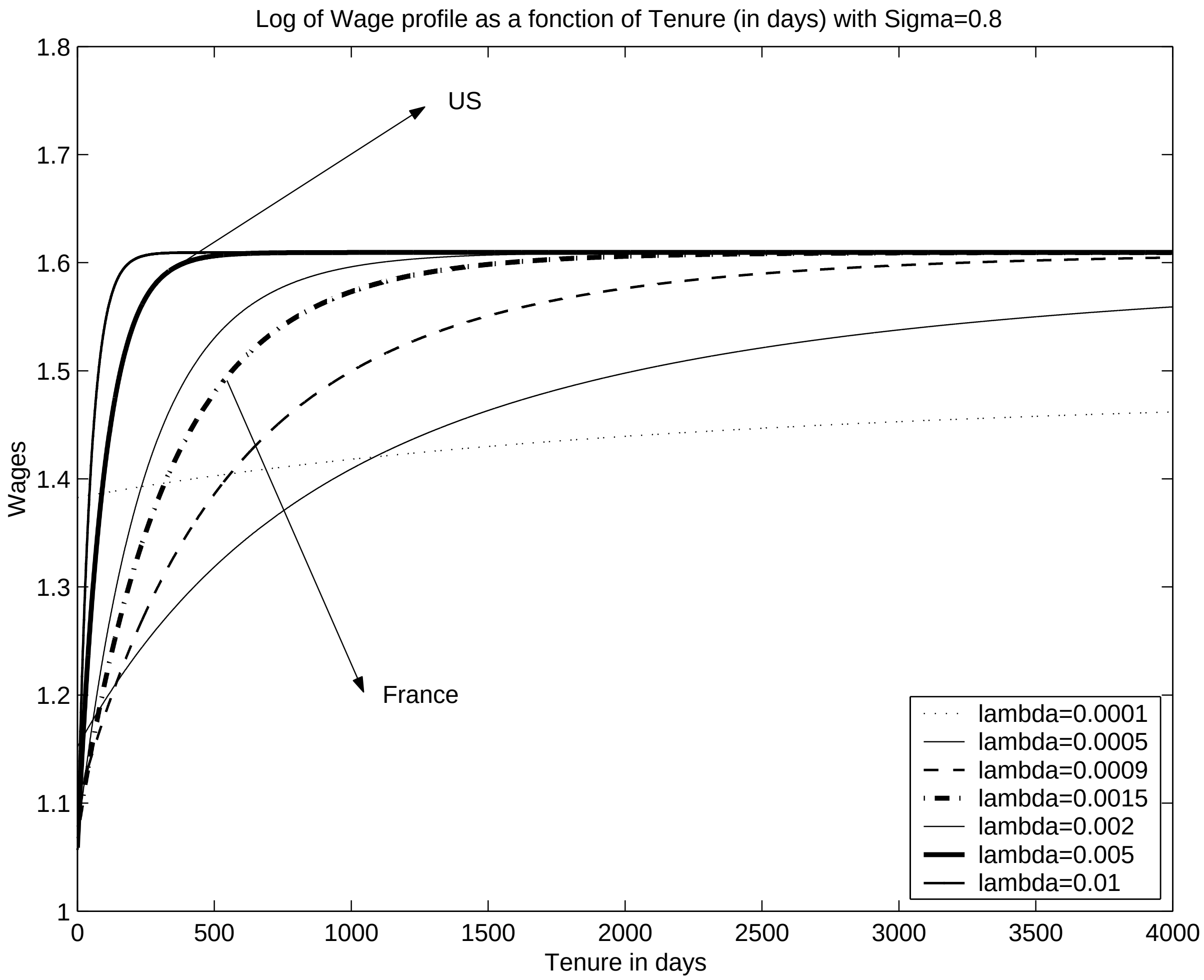


Figure 7. Wage Profile as a function of Tenure (in days) and $\sigma = 1.4$

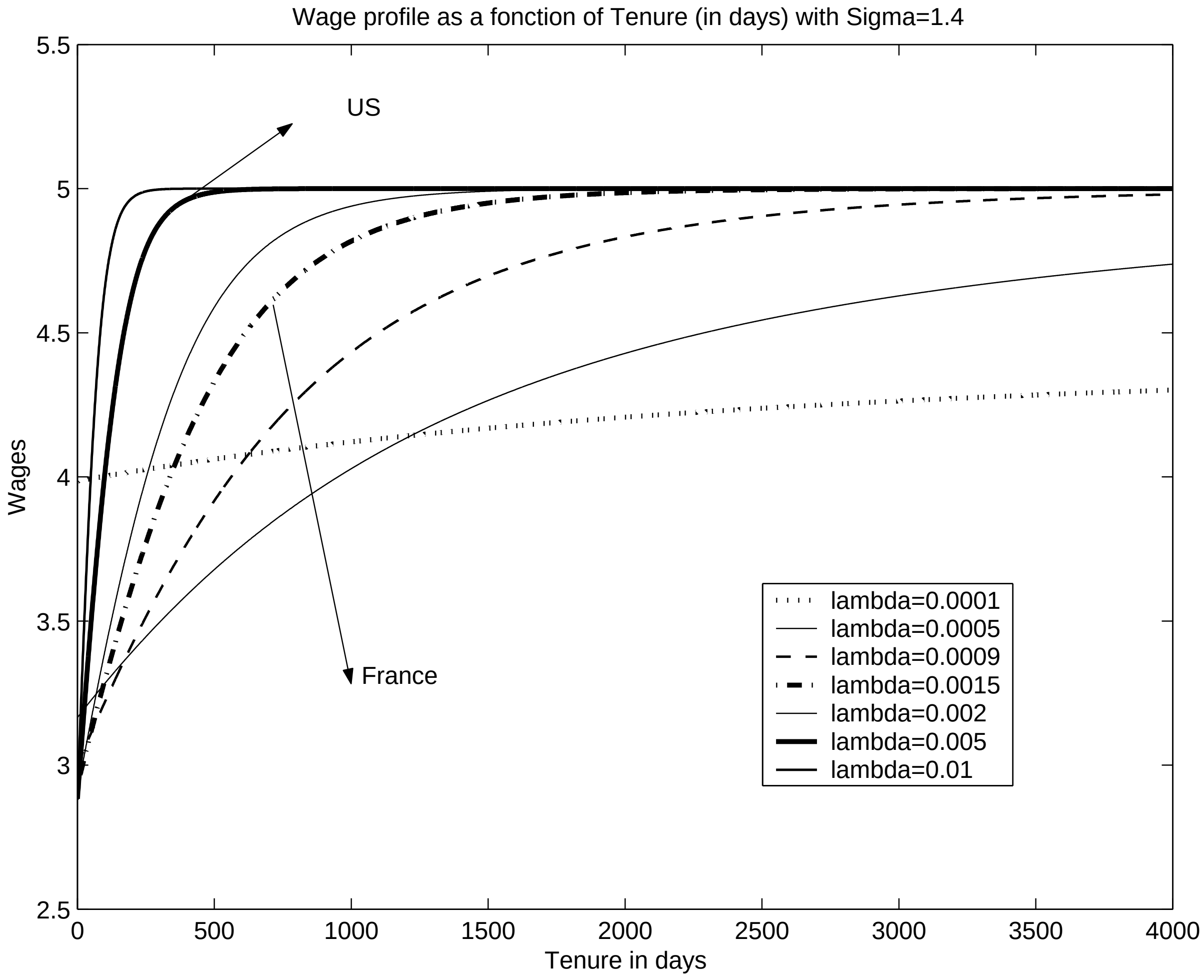
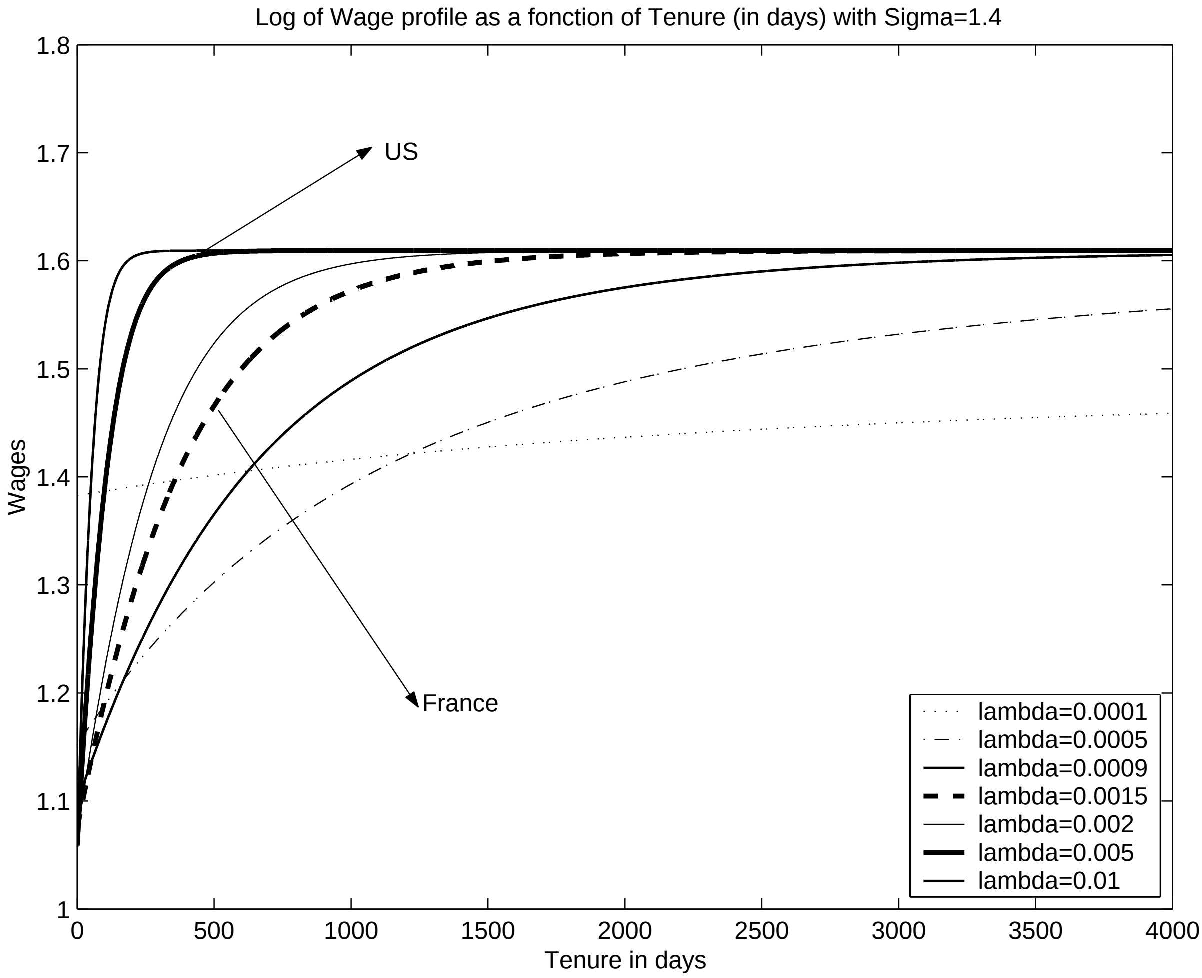


Figure 8. Log of Wage Profile as a function of Tenure (in days) and $\sigma = 1.4$



Chapitre 2

Job Mobility and Wages with Worker and Firm Heterogeneity

1. Introduction

The relation existing between wage growth, experience and job seniority has been the subject of multiple studies. Some find that seniority matters (most notably Topel (1991)). Others tend to show that experience is more important (most notably Altonji, in Altonji and Shakotko (1987), Altonji and Williams (1992) and Altonji and Williams (1997)). However, all such analysis have shown the extreme importance of the quality of the data used to characterize this relation, the definition of the variables, the identification hypotheses, and the estimation methods that are used.

The nature and magnitude of the effects of experience and job tenure are directly related to the role of general - transferable - and specific - non transferable - human capital (see Mincer (1974) and Mincer and Jovanovic (1979)). Unfortunately, the empirical measurement of the various components of wage growth is extremely difficult. Identification problems abound. In particular, experience, job seniority and time increase simultaneously except when workers move between firms or do not participate. If one focuses only on workers constantly present on the labor market, more so if one restricts attention to those with at least two observations for a given job, non-parametric identification is impossible. Hence, all observations should be used. But then, mobility and participation become even more central determinants of wages. Workers choose to stay in a firm or move. Workers choose to participate or not. As a consequence of this selectivity, seniority and experience have to be modeled. Topel and Ward (1992) is such an attempt for young workers. More recently, Buchinsky, Fougère, Kramarz, and Tchernis (2006) explicitly model these variables together with wage. These authors (BFKT, hereafter) concur with Topel (1991) in finding that, indeed, returns to seniority are large, at least in the United States.

Decisions presiding to movements of workers between firms are driven by myriads of reasons. Some are firm-based; others are person-based. For instance, it is often noted that job mobility decreases with job seniority. Explanations for this behavior are multiple. Economists and econometricians have summarized these reasons by invoking the so-called unobserved heterogeneity. For instance, matching theories assume that there exists an idiosyncratic (ex-ante unobserved) component in a worker-firm pair productivity (Jovanovic (1979b) and Miller (1984)). This may explain why some workers move quickly between occupations whereas others stay for long periods of time in the same job (see Blumen, Kogan, and MacCarthy (1955)). Others see job tenure as the reflection of accumulation of job-specific human capital. These stories can be viewed as complementary (see Mincer and Jovanovic (1979)). A common feature of these theories is the central role of both workers and firm's contributions to productivity. On the empirical side, only a few studies have considered this mixed source of heterogeneity (see Flinn (1986), Abowd, Kramarz, and Margolis (1999) and Kramarz, 2003). Unfortunately, the first two papers do not treat seniority or experience as endogenous variables whereas the last one considers that seniority is endogenous but not experience. An interesting attempt, though, is BFKT who jointly estimate a wage, a seniority, and a participation equation with duration-dependence and unobserved worker-heterogeneity (following a line initiated by Lillard and Willis (1978)). As mentioned above, these authors find that, in the United-States, returns to seniority are large whereas returns to experience tend to be smaller than what other authors have found (albeit these papers did not consider experience as endogenous). Results for France stand in sharp contrast with those found for the United-States. More precisely, both authors that have used matched employer-employee data sources Abowd, Kramarz, and Margolis (1999) and Kramarz (2003) find that returns to seniority are small (less than 1% per year). In addition, the former provide evidence of heterogeneous returns across firms some being even negative. This last result is confirmed by the latter where instrumented returns to seniority are zero and often negative in the manufacturing industries.

Because we believe that both firm and workers decisions matter, our estimating model incorporates both firm and worker heterogeneity components. Following BFKT, these unobserved effects are treated as random. We consider, in each equation of the model, an unobserved heterogeneity term specific to the firm and an unobserved component specific to the worker. These terms are correlated across equations, allowing, for instance, low-wage workers to be highly mobile. Hence, in our approach both person and firm effects are potentially correlated to experience and seniority; they are correlated random effects. The model is estimated, following again Buchinsky, Fougère, Kramarz, and Tchernis (2006) or Geweke and Keane (2000), by MCMC techniques. We use the Gibbs sampler with Metropolis-Hastings steps and data augmentation (see Robert and Casella (1999), and Chibb (1996)). In presence of firm and worker heterogeneity, data augmentation is useful because the likelihood function is not separable any more (in contrast to Buchinsky, Fougère, Kramarz, and Tchernis (2006) or Geweke and Keane (2000)) because workers move from firm to firm and each firm potentially employs multiple workers in the sample.

One of our data sources, the DADS (see Abowd, Kramarz, and Margolis (1999)), matches longitudinal information on workers and on their employing firms. The DADS spans years 1976 to 1995 and covers all workers employed in France in the private and semi-public sectors and born in October of an even year. Because this administrative data set does not provide us with person-level information, we match it with the EDP(*échantillon démographique permanent*) that contains variables from the Censuses and the Civil Status registers for all workers born in the first four days of October. Our analysis data set contains approximately 1.5 million observations.

The paper is structured as follows. The model is presented in section 2. Section 3 includes a description of the estimation procedure. Section 4 contains a detailed description of the data set we use. Section 5 presents the results. Section 6 concludes.

2. Statistical model

2.1. Some definitions

This model extends BFKT to incorporate the firm dimension. In addition to an unobserved person heterogeneity, we include unobserved firm heterogeneity as well as a match (associating a worker and a firm) equation.

Therefore, our statistical model consists of four equations (plus two initial conditions): a simple random matching equation, a participation equation, a wage equation and finally, an inter-firm mobility equation.

Even though our data are quite extensive and precise, they have some limitations that bear consequences on our modeling strategy. First, we only have wage information for those who are employed in a private or semi-public firm. Hence, no wage data are available for those employed in the public sector or the self-employed. Therefore, we define a participant as someone for whom wage data are available. This also implies that unemployed workers are considered non-participants. Indeed, participation here means employment in the private and semi-public sector.

Defining mobility is apparently simpler. When an individual participates in two consecutive periods, mobility is easily defined as not working in the same firm at those two dates. However, when an individual participates at t but not at $t+1$, mobility is censored: we do not observe if the individual was laid off or if he quit his firm. No information allows to distinguish these cases.

Finally, since we do not observe job offers issued by firms, our matching equation takes a very simple form where offers are generated randomly. Given the simplistic nature of this equation, it is legitimate to wonder why we included it altogether. We need this equation since our participation equation includes a current firm effect. Therefore, we need to generate firm offers for the non-participants since we do not observe the exact job offer they received.

2.2. Specification of the General Model

Following Buchinsky, Fougère, Kramarz, and Tchernis (2006), and the structural interpretation they develop, our participation equation and our inter-firm mobility equation include state-dependence and unobserved heterogeneity. But, as mentioned above, a firm-specific unobserved heterogeneity component is added to the person-specific term. The wage equation follows Abowd, Kramarz, and Margolis (1999) by including a person and a firm-specific effect.

Inter-firm mobility at date t depends on the realized mobility at date $t-1$, and similarly for participation that depends on past participation and mobility. Hence, we include initial conditions, modeled following Heckman (1981).

This yields the following system of equations:

Initial Conditions

$$z_{i1} \sim \mathcal{U}_{1,\dots,J} \tag{2.1}$$

$$y_{i1} = \mathbb{I}\left(X_{i1}^{Y}\delta_0^{Y} + \alpha_{z_{i1}}^{Y,E} + v_{i1} > 0\right) \tag{2.2}$$

$$w_{i1} = y_{i1}\left(X_{i1}^{W}\delta^{W} + \theta_{z_{i1}}^{W,E} + \theta_i^{W,I} + \epsilon_{i1}\right) \tag{2.3}$$

$$m_{i1} = y_{i1}\mathbb{I}\left(X_{i1}^{M}\delta_0^{M} + \alpha_{z_{i1}}^{M,E} + u_{i1} > 0\right) \tag{2.4}$$

Main Equations

$$\forall t > 1, \quad z_{it} = y_{it-1}\left((1-m_{it-1})z_{it-1} + m_{it-1}\widetilde{\eta}_{it}\right) + (1-y_{it-1})\eta \tag{2.5}$$

$$\eta \sim \mathcal{U}_{1,\dots,J} \quad \widetilde{\eta}_{it} \sim \mathcal{U}_{(1,\dots,J)-(z_{it-1})} \tag{2.6}$$

$$\forall t > 1, \quad y_{it} = \mathbb{I}\left(\underbrace{\gamma^M m_{it-1} + \gamma^Y y_{it-1} + X_{it}^Y \delta^Y + \theta_{z_{it}}^{Y,E} + \theta_i^{Y,I} + v_{it}}_{y_{it}^*} > 0\right) \tag{2.7}$$

$$\forall t > 1, \quad w_{it} = y_{it}\left(X_{it}^W \delta^W + \theta_{z_{it}}^{W,E} + \theta_i^{W,I} + \epsilon_{it}\right) \tag{2.8}$$

$$\forall t > 1, \quad m_{it} = y_{it}.\mathbb{I}\left(\underbrace{\gamma m_{it-1} + X_{it}^M \delta^M + \theta_{z_{it}}^{M,E} + \theta_i^{M,I} + u_{it}}_{m_{it}^*} > 0\right) \tag{2.9}$$

The variable z_{it} denotes the latent identifier of the firm and $J(i,t)$ denotes the realized identifier of the firm at which worker i is employed at date t. Therefore, $J(i,t) = z_{it}$ if individual i participates at date t.

y_{it} and m_{it} denote, respectively, participation and mobility, as previously defined. y_{it} is an indicator function, which is equal to 1 if the individual i participates at date t and 0 otherwise. Because m_{it}^* measures worker's i propensity to move between t and $t+1$, the quantity m_{it} is a dummy variable equal to 1 if the individual is mobile between time t and time $t+1$ and it is equal to 0 otherwise. The observed mobility m_{it} is equal to 0 when the individual does not participate at time t or at time $t+1$. When the worker changes firm from time t to time $t+1$, the mobility is set to 1.

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

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

2.3. Stochastic Assumptions

In order to specify our stochastic assumptions for the person and firm-effects, let us first rewrite our system of equations as:

$$\forall t > 1, \quad z_{it} = y_{it-1}\left((1 - m_{it-1}) z_{it-1} + m_{it-1} \widetilde{\eta}_{it}\right) + (1 - y_{it-1})\eta$$

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

Ω_{it}^E is a design matrix (firm effects) for the couple (i, t). Hence, it is a $1 \times J$ matrix composed of $J - 1$ zeros and of a 1 at column $z_{i,t}$. Similarly, Ω_{it}^I is a $1 \times N$ matrix composed of $N - 1$ zeros and of a 1 at column i.

Our model includes two dimensions of heterogeneity. This double dimension crucially affects the statistical structure of the likelihood function. The presence of these firm effects makes the likelihood non-separable (person by person). Indeed, two individuals employed at the same firm, not necessarily at the same date, are not independent any more.

The next equations present our stochastic assumptions for the person and firm effects:

$$
\begin{aligned}
\theta^E &= \left(\alpha^{Y,E}, \alpha^{M,E}, \theta^{Y,E}, \theta^{W,E}, \theta^{M,E}\right) \quad \text{of dimension} \quad [5J, 1] \\
\theta^I &= \left(\theta^{Y,I}, \theta^{W,I}, \theta^{M,I}\right) \quad \text{of dimension} \quad [3N, 1]
\end{aligned}
$$

Moreover,

$$\theta^E | \Sigma^E \sim \mathcal{N}(0, D_0^E) \tag{2.10}$$

$$\theta^I | \Sigma^I \sim \mathcal{N}(0, D_0^I) \tag{2.11}$$

$$D_0^E = \Sigma^E \otimes I_J \tag{2.12}$$

$$D_0^I = \Sigma^I \otimes I_N \tag{2.13}$$

Σ^E (resp. Σ^I) is a symmetric positive definite matrix $[5, 5]$ (resp. $[3, 3]$) with mean zero. Notice that these assumptions imply that correlations between the wage, the mobility, and the participation equations come from both person and firm heterogeneity (in addition to that coming from the idiosyncratic error terms). Furthermore, our assumptions exclude explicit correlation between different firms (for instance, we could have considered a non-zero correlation of the firm effects within an industry, a non-tractable assumption). Notice though that we could have included in the wage equation, for instance, the lagged firm effects of those firms at which a worker was employed in her career. This is difficult, but feasible in our framework.

Finally, we assume that the idiosyncratic error terms follow:

$$\begin{pmatrix} v_{it} \\ \epsilon_{it} \\ u_{it} \end{pmatrix} \sim_{iid} \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{yw}\sigma & \rho_{ym} \\ \rho_{yw}\sigma & \sigma^2 & \rho_{wm}\sigma \\ \rho_{ym} & \sigma\rho_{wm} & 1 \end{pmatrix}\right) \tag{2.14}$$

3. Estimation

Several difficulties have to be overcome to estimate our model. As explained above, firm effects make the likelihood highly non-separable : two individuals working in the same firm at different dates are correlated, so are two couples (i, t_1) and (i, t_2) such that $J(i, t_1) = J(i, t_2)$. Given the size of our problem, maximum likelihood, simulated or not, is not feasible in this case.

However, notice that, conditional on firm effects, the likelihood becomes separable, individual by individual. Hence, the Gibbs Sampler is a natural way to estimate our model. Indeed, given a sample and unknown parameters, this technique is based on the evaluation of the conditional densities. And, conditional on all unknown parameters (including the random effects), the full conditional likelihood is easily written, with all integrals disappearing.

3.1. Principles of the Gibbs Sampler

Given a parameter set and data, the Gibbs sampler relies on the recursive and repeated computation of the conditional distribution of each parameter, conditional on all others and conditional on the data. We thus need to specify a prior density for each parameter. Then, the conditional distribution satisfies:

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

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

In addition to increased separability, the Gibbs Sampler allows an easy treatment of latent variables through the so-called data augmentation procedure. Therefore, completion of the censored observations becomes possible. In particular, in our model, we do not observe job offers for the non-participants. Similarly, we do not observe latent variables m_{it}^*, y_{it}^*. Censored or unobserved data are simply "augmented".

Finally, the Gibbs Sampler procedure does not involve optimization algorithms. Simulation of conditional densities is the only computation required. Notice however that when the densities have no conjugate, we use the standard Hasting-Metropolis algorithm.

3.2. Application

In order to use Bayes' rule, we first write the full conditional likelihood. Once the parameter set has been properly defined, we are left with variables that must be "augmented".

The parameter set is the following:

$$\left(\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \Sigma^E; \Sigma^I\right) \tag{3.15}$$

and $\mathcal{P}$ denotes:

$$\mathcal{P} = \left(\delta_0^Y, \delta_0^M; \delta^Y, \gamma^M, \gamma^Y; \delta^M, \gamma; \delta^W; \sigma^2, \rho_{yw}, \rho_{ym}, \rho_{wm}; \Sigma^E; \Sigma^I; \theta^E; \theta^I\right) \tag{3.16}$$

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 must be different conditional on these values. For a given individual i and conditional on both parameters and random effects, we have:

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

$$
\begin{aligned}
X_t^{00} &= (y_t^*, y_t, z_t) \\
X_1 &= y_1 X_1^1 + (1 - y_1) X_1^0 \\
X_1^1 &= (y_1^*, y_1, w_1, z_1) \\
X_1^0 &= (y_1^*, y_1, z_1)
\end{aligned}
$$

Notice also that we do not need to complete the mobility equation at date T[1]. For a given individual i,

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

with:

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

Thus, the full conditional likelihood writes as:

$$
L(\underline{X}_T|\mathcal{P}) = \left(\frac{1}{V^w}\right)^{\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}}{2}} \left(\frac{1}{V^m}\right)^{\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1} y_{it}}{2}}
$$
$$
\prod_{i=1}^{N} l_{P_1}(z_{i1}) (\mathbb{I}_{y_{i1}^*>0})^{y_{i1}} (\mathbb{I}_{y_{i1}^*\leq 0})^{1-y_{i1}} \exp\left(-\frac{1}{2}(y_{i1}^* - m_{y_{i1}^*})^2\right) \exp\left(-\frac{y_{i1}}{2V^w}(w_{i1} - M_{i1}^w)^2\right)
$$
$$
\prod_{t=2}^{T} \left(\delta_{z_{it-1}}^{1-m_{it-1}} l_{\eta_{it}}^{m_{it-1}}(z_{it})\right)^{y_{it-1}} l_\eta(z_{it})^{1-y_{it-1}} (\mathbb{I}_{y_{it}^*\leq 0})^{1-y_{it}} (\mathbb{I}_{y_{it}^*>0})^{y_{it}} \exp\left(-\frac{1}{2}(y_{it}^* - m_{y_{it}^*})^2\right)
$$
$$
\exp\left(-\frac{y_{it}}{2V^w}(w_{it}^* - M_{it}^w)^2\right) \left((\mathbb{I}_{m_{it-1}^*\leq 0})^{1-m_{it-1}} (\mathbb{I}_{m_{it-1}^*>0})^{m_{it-1}}\right)^{y_{it-1}y_{it}} \exp\left(-\frac{y_{it-1}}{2V^m}(m_{it-1}^* - M_{it-1}^m)^2\right)
$$

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

with:

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

and the following spherical coordinates:

$$
\theta = \begin{pmatrix} \theta_{yw} \\ \theta_{ym} \\ \theta_{wm} \end{pmatrix} \tag{3.17}
$$

$$
\begin{pmatrix} \rho_{yw} \\ \rho_{ym} \\ \rho_{wm} \end{pmatrix} = \begin{pmatrix} \cos(\theta_{yw}) \\ \cos(\theta_{ym}) \\ \cos(\theta_{yw})\cos(\theta_{ym}) - \sin(\theta_{yw})\sin(\theta_{ym})\cos(\theta_{wm}) \end{pmatrix} \tag{3.18}
$$

Finally, we define the various prior distributions as follows:

$$
\begin{aligned}
&\delta_0^Y \sim \mathcal{N}(m_{\delta_0^Y}, v_{\delta_0^Y}) && \delta_0^M \sim \mathcal{N}(m_{\delta_0^M}, v_{\delta_0^M})\\
&\delta^Y \sim \mathcal{N}(m_{\delta^Y}, v_{\delta^Y}) && \gamma^Y \sim \mathcal{N}(m_{\gamma^Y}, v_{\gamma^Y})\\
&\gamma^M \sim \mathcal{N}(m_{\gamma^M}, v_{\gamma^M}) && \delta^W \sim \mathcal{N}(m_{\delta^W}, v_{\delta^W})\\
&\delta^M \sim \mathcal{N}(m_{\delta^M}, v_{\delta^M}) && \gamma \sim \mathcal{N}(m_{\gamma}, v_{\gamma})\\
&\sigma^2 \sim \mathcal{IG}(\frac{v}{2}, \frac{d}{2}) && \theta \sim_{iid} \mathcal{U}[0,\pi]\\
&\Sigma^E \sim \mathcal{IW}(\rho_E, R_E) && \Sigma^I \sim \mathcal{IW}(\rho_I, R_I)
\end{aligned}
$$

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

4. Data

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

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

The Division des revenus prepares an extract of the DADS for scientific analysis, covering all individuals employed in French enterprises who were born in October of even-numbered years, with civil servants excluded.[2] Our extract runs from 1976 through 1995, with 1981, 1983, and 1990 excluded because the underlying administrative data were not sampled in those years. Starting in 1976, the division revenus kept information on the employing firm using the newly created SIREN number from the SIRENE system. However, before this date, there was no available identifier of the employing firm. Each observation of the initial dataset 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

[2] Meron (1988) shows that individuals employed in the civil service move almost exclusively to other positions within the civil service. Thus the exclusion of civil servants should not affect our estimation of a worker's market wage equation.

the parent enterprise of the establishment (SIREN). For each observation, we have information on the number of days during the calendar year the individual worked in the establishment and the full-time/part-time status of the employee. For each observation, in addition to the variables mentioned above, we have information on the individual's sex, date and place of birth, occupation, total net nominal earnings during the year and annualized net nominal earnings during the year for the individual, as well as the location and industry of the employing establishment. The resulting data set has 13,770,082 observations.

The Echantillon Démographique Permanent: The division of Etudes Démographiques at INSEE maintains a large longitudinal dataset containing information on many sociodemographic variables of all French individual. All individuals born in the first four days of the month of October of an even year are included in this sample. All questionaires for these individuals from the 1968, 1975, 1982, and 1990 Censuses are gathered into the EDP. Since the exhaustive long-forms of the various Censuses were entered under electronic form only for a fraction of the population leaving in France (1/4 or 1/5 depending on the date), the division des Etudes Démographiques had to find all the Censuses questionaires for these individuals. The INSEE regional agencies were in charge of this task. But, not all information from these forms were entered. The most important sociodemographic variables are however available.[3]

For every individual, education measured as the highest diploma and the age at the end of school are collected. Since the categories differ in the three Censuses, we first created eight education groups (identical to those used in Abowd, Kramarz, and Margolis (1999)) that can be aggregated in three education groups, labeled low-, medium-, and high-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 department). At some of the Censuses, data on the parents education or social status are collected.

In addition to the Census information, all French town-halls in charge of Civil Status registers and ceremonies transmit information to INSEE for the same individuals. Indeed, any birth, death, wedding, and divorce involving an individual of the EDP is recorded. For each of

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

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 as well as knowing employees' co-workers at any date. This final data set has approximately 1.5 million observations.

5. Results

5.1. Women with a Vocational-Technical Degree (Basic, CAP - BEP)

The results are presented in tables 1 to 7. The table 1 contains the results for the participation equation. Table 2 provide results for the mobility equation. Table 3 provides the results for the wage equation. Tables 4 and 5 contain the results for the initial participation and mobility equations respectively. Table 6 is dedicated to the presentations of the estimation results for variance-covariance matrices elements. In addition figure 1 depicts the marginal posterior distribution for the return to experience and job seniority and the marginal posterior distributions of experience, seniority, experience squared and seniority squared in the mobility and in the participation equations for this group.

From tables 1, 2 and 3, time effect is not statistically significant for participation and mobility decisions but this is a relevant variable for the wage equation (for individuals born between 1940 and 1969). The cohort effect dummy variables have negative effect on participation. When we control for other individual characteristics and firm unobserved heterogeneity, wages are higher for the youngest cohorts (individuals born between 1950 and 1970). Moreover, participation is decreasing with age (for individuals born before 1970).

Lagged value of experience has a significant and positive impact on participation and wages but, for this group, the effect of experience is not significant for the mobility decision. Lagged value of job tenure, as expected, has a positive effect on wage but is not relevant for mobility. This result is rather surprising because it is often noted that mobility decreases with job tenure. It is an important result. This indicates that the accumulation of job-specific human capital has no significant impact on the decisions to move between firms. This result shows that the mobility decisions are mainly governed by the impact of the observed and unobserved components of the individual contribution to the productivity in the line of matching theories (Jovanovic (1979b) and Miller (1984)). In other words, unobserved productivity components induce a spurious duration dependence.

The results indicate that the presence of young children have an impact on the participation decision but has no significant impact on mobility decisions and wage. This result for the participation decision may reflect in part women preferences and may be the consequence of the costs associated to daycare of young children. As expected the marriage has no significant effect on the distribution of wages. The marriage is not a relevant variable for the participation decision for this group of individuals. However, marriage has a positive effect on the mobility decision. Couples of workers may encounter difficulties to find jobs located in the same place. This explain why they are more mobiles.

Being French has a positive and significant effect on the participation probability, but there is no impact of the nationality on the mobility decision and the conditional distribution of wage. The individuals who live in the region around Paris and in Paris, have a greater probability to participate and more important wages. This can be explained by the importance of the wage offer arrival rate in this region of France. Consequently, workers should have greater reservation wages in the corresponding region. In addition, the effect of part time work on the mobility decision is negative and significant. This result indicates that women who choose part time work have a weaker search intensity. The impact of the unemployment rate is positive on the participation decision. This indicates that the individuals who are participating in a period of high unemployment rate are more likely to stay employee rather than, for instance, try to become self-employed. This is compatible with the existence of weaker exit rate from unemployment.

The lagged mobility has a positive and significant impact on the participation decision and on mobility. Moreover, the lagged value of participation has a positive effect on participation.

We can then conclude that participation and mobility decisions are characterized by significant state dependence. This result allows us to extend to mobility the conclusions obtained by Hyslop (1999) for the participation decisions of married women. Moreover, the women with a vocational-technical school who moved the past year have a greater probability to leave the jobs they currently occupy.

Table 4 provides the results for the wage equation. Given the observed and unobserved characteristics of the workers, given the unobserved component specific to the firm, the impact of experience is relatively important on the distribution of wage. This result is similar with the findings of Altonji and Williams (1992) and Altonji and Williams (1997) but not consistent with the results of Topel (1991) and Buchinsky, Fougère, Kramarz, and Tchernis (2006). We can show using the estimation results that 10 years of experience for a women with a vocational-technical school (CAP, BEP) increases her earnings by 40.78%[4]. On the other side, 10 years of job tenure for a women belonging to the same group, increases her wages by 16.30%[5]. These results are slightly different from the ones obtained by Bushinsky et al. for the United States who report, for instance for high school dropout, that 10 years of job seniority increases wages by 59.5%. Altonji and Williams (1997) find a 10 years return to seniority approximately equal to 11% whereas Topel (1991) finds a 10 years return to job seniority approximately equal to 24.45%. Consequently, our results are in line of those of Altonji and Williams (1997).

Figure 1 shows that the return to experience are more important than the return to job seniority for a similar level of experience and seniority.

Table 6 reports the posterior mean of the elements of variance covariance matrices in our model. The correlation between the residual term relative to wage and mobility is positive and significantly different from zero. Consequently, high wage workers are more likely to be highly mobile. The correlation between participation and wage is positive and significant. The correlation between mobility and participation is not significant. However, the correlation between the corresponding individual effects is negative. Consequently, the individuals who are more likely to participate are also the ones who are less likely to be mobile.

[4]More precisely, we have (exp(0.4020-0.0600)-1)*100 = (exp(0.342)-1)*100 = 40.78%.
[5]In this case, we obtain for job seniority that (exp(0.1810-0.0300)-1)*100 = (exp(0.151)-1)*100 = 16.30%.

5.2. Men with a Vocational Technical degree

Table 12 provides the results for the wage equation. Once again, given the observed and unobserved characteristics of the workers and firms, the impact of experience is relatively important on the distribution of wage. Using the posterior moment estimation we find that 10 years of experience for a men with a vocational technical (CAP, BEP) increases his earnings by 32.45%[6]. On the other side, 10 years of job tenure for a women belonging to the same group, increases her wages by 7.79%[7]. Our results, for this group of men, are in line of those of Altonji and Williams (1997).

5.3. Women with Technical College and Undergraduate University (BTS, DEUG)

The results for the group of women are presented in tables 15 to 21. The table 15 contains the results for the participation equation. Table 16 provides results for the mobility equation. Table 17 includes the corresponding results for the wage equation. Tables 18 and 19 contain the results for the initial participation and mobility equations respectively. Table 20 is dedicated to the presentations of the estimation results for variance-covariance matrices elements. Figure 2 depicts the marginal posterior distribution for the return to experience and job seniority and the marginal posterior distributions of experience, seniority, experience squared and seniority squared in the mobility equation for this group.

Time effect is generally not statistically significant for participation decisions and mobility equations. The parameters associated to some time effects are significantly different from zero and positive. The cohort effect dummy variables have negative effect on participation. Participation is more important for the most recent cohorts (for individuals born before 1970). Cohort effect is generally non significant on the mobility decision but has a positive and significant impact on wage for the youngest cohorts (individuals born form 1940 to 1969).

Lagged value of experience has positive impact on participation and wages. Lagged value of experience is not significant for the mobility decision. Lagged value of job tenure, as expected, has a positive effect on wages. Moreover, the lagged value of job seniority is not relevant for the mobility decision. This results is similar to the one obtained for other age groups (see section

[6] More precisely, we have (exp(0.341-0.06)-1)*100 = (exp(0.281)-1)*100 = 32.45%.

[7] In this case, we obtain for job seniority that (exp(0.075-0)-1)*100 = (exp(0.075)-1)*100 = 7.79%.

relative to woman with a vocational-technical school).

The presence of a young children (0 to 2 years old) has, as expected, a negative impact on the participation decision but has no significant impact on mobility decision and wages. The presence of older children has, however, no effect on participation decision. Marriage has a positive effect on participation, mobility and wage. This result for the wage equation is rather surprising. This can be explained by the following argument: the individuals who are married are likely to have a higher non labor income, higher reservation wage and higher accepted wage. This effect is particularly important for the corresponding group of women.

Being French has no significant effect on the three equations. The individuals who live in the region around Paris and in Paris, have a greater probability to participate and more important wages. This result can be interpreted relatively to job offer opportunities (see section relative to woman with a vocational-technical school). The effect of part time work on the mobility decision is negative and significant. This result indicates, once again, that women who choose part time work have a weaker search intensity.

The lagged mobility has a positive and significant impact on the participation decision and on mobility. The lagged value of participation has a positive effect on participation attesting the presence of a state dependence associated to the corresponding equation. Moreover, lagged mobility has not significant effect on the mobility decision.

Table 17 provides the results for the wage equation. Once again, given the observed and unobserved characteristics of the workers and firms, the impact of experience is relatively important on the distribution of wage. Using the posterior moment estimation we find that 10 years of experience for a women with a Technical college or Undergraduate University (BTS, DEUG) increases her earnings by 59.84%[8]. On the other side, 10 years of job tenure for a women belonging to the same group, increases her wages by 23.86%[9]. Our results, for this group of women, are in line of those of Altonji and Williams (1997).

Figure 2 shows that the return to experience is more important than the return to job seniority for a similar level of experience and seniority.

Table 20 reports the posterior mean of the elements of variance covariance matrices in our model. The correlation between the residual term relative to wage and mobility is positive and significantly different from zero. So, high wage workers are highly mobiles. The correlation

[8]More precisely, we have (exp(0.529-0.06)-1)*100 = (exp(0.469)-1)*100 = 59.84%.

[9]In this case, we obtain for job seniority that (exp(0.244-0.03)-1)*100 = (exp(0.214)-1)*100 = 23.86%.

between participation and wage is positive and significant. The correlation between mobility and participation is negative but not significant. The correlation between the individual effects relative to participation and wage is positive. The correlation between the individual effects relative to participation and mobility is negative but not statistically significant.

5.4. Men with a Technical College or a Undergraduate University degree (BTS, DEUG)

Table 24 provides the results for the wage equation. Once again, given the observed and unobserved characteristics of the workers and firms, the impact of experience is relatively important on the distribution of wage. Using the posterior moment estimation we find that 10 years of experience for a men with a vocational technical (CAP, BEP) increases her earnings by 44.77%[10]. On the other side, 10 years of job tenure for a women belonging to the same group, increases her wages by 11.52%[11]. Our results, for this group of men, are in line of those of Altonji and Williams (1997).

6. Conclusion

In this paper we model jointly participation, wages and the mobility decision in order to compare returns of wage to seniority and to experience. The model incorporates both worker and firm heterogeneity components. These unobserved firm-specific and worker-specific unobserved heterogeneity terms are treated as random effects and they are correlated across the equations of the model. The initial conditions are modeled. Correlations are permitted between residuals terms across the equations. There is no analytic expression for the likelihood function of the model under our assumptions because each individual can move between firms and a given firm can hire several workers. Consequently, we have chosen to use a Monte Carlo Markov Chain technique (MCMC) in order to estimate the model. We use data augmentation in order to obtain a conditional expression of the likelihood function with respect to the generated values of the firm-specific and worker-specific heterogeneity components at each step of the algorithm. Posterior estimates of the parameters are obtained using a Gibbs Sampling algorithm with Hastings-Metropolis steps (see, for instance, Robert and Casella (1999)). The Gibbs

[10] More precisely, we have (exp(0.430-0.06)-1)*100 = (exp(0.370)-1)*100 = 44.77%.
[11] In this case, we obtain for job seniority that (exp(0.129-0.02)-1)*100 = (exp(0.1090)-1)*100 = 11.52%.

Sampler, as we applied it, is a very practical estimation method. Our data sources match very complete longitudinal informations on workers and their employing firms in France. Our results are similar to Altonji and Williams's conclusions. Indeed, in France, for the period 1976 to 1995, returns to experience are greater than returns to seniority. For instance, for men, with an undergraduate university degree, returns of wage to 10 years of experience are estimated equal to 52.81% whereas returns of wage to 10 years of seniority are estimated equal to 11.52%. It is important to underline that our model is very complete and takes into account the presence of individual and firm specific unobserved heterogeneity terms. Further research could consist to consider other expression for the distribution of the workers across the firms. Moreover, adding other effects should be straightforward. For instance, match effects (Jovanovic (1979b) and Flinn (1986)), autoregressive effects (Lillard and Willis (1978)), or even more complex effects such as firm-specific (random) returns to seniority.

A. Appendix A

A.1. Mobility equation

- *Parameter* γ

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

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

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

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

with:

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

$$= \quad m_{it}^* - X_{it}^M \delta^M - \Omega_{z_{it}}^E \theta^{E,M} - \Omega_i^I \theta^{I,M} - a(y_{it}^* - m_{y_{it}^*}) - b(w_{it} - m_{w_{it}})$$

By gathering squared and crossed terms, we get:

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

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

- *Parameter* δ^M

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

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

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

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

A.2. Wage equation

- *Parameter* δ^W

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

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

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

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:

- $A_{it} = w_{it} - \Omega^E_{z_{it}}\theta^{E,W} - \Omega^I_i\theta^{I,W} - \rho_{y,w}\sigma(y^*_{it} - m_{y^*_{it}}))$
- $B_{it} = m^*_{it} - m_{m^*_{it}} - a(y^*_{it} - m_{y^*_{it}}) - b(w_{it} - \Omega^E_{z_{it}}\theta^{E,W} - \Omega^I_i\theta^{I,W})$

If we use analogous notations as before, we get:

$$\begin{aligned} V^{post,-1}_{\delta^W} &= V^{prior,-1}_{\delta^W} + \frac{1}{V^w}\sum_{i=1}^N \left(\widetilde{\underline{X^W_i}}^{1,T}\right)' \widetilde{\underline{X^W_i}}^{1,T} + \frac{b^2}{V^m}\sum_{i=1}^N \left(\widetilde{\underline{X^W_i}}^{1,T-1}\right)' \widetilde{\underline{X^W_i}}^{1,T-1} \\ V^{post,-1}_{\delta^W} M^{post}_{\delta^W} &= V^{prior,-1}_{\delta^W} M^{prior}_{\delta^W} + \frac{1}{V^w}\sum_{i=1}^N \left(\widetilde{\underline{X^W_i}}^{1,T}\right)' \widetilde{\underline{A_i}}^{1,T} - \frac{b}{V^m}\sum_{i=1}^N \left(\widetilde{\underline{X^W_i}}^{1,T-1}\right)' \widetilde{\underline{B_i}}^{1,T-1} \end{aligned}$$

A.3. Participation equation

- *Parameter* γ^Y

We have to take into account that γ^Y enters both $m_{y^*_{it}}$ for $t = 2...T$, M^w_{it} for $t = 2...T$ and M^m_{it} for $t = 2...T-1$

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

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

with:

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

which is equivalent to:

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

If we use analogous notations as before, we get:

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

- *Parameter* γ^M

We proceed the same way and we get:

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

with:

- $A_{it} = y^*_{it} - \gamma^Y Ly_{it} - X^Y_{it}\delta^Y - \Omega^E_{z_{it}}\theta^{E,Y} - \Omega^I_i\theta^{I,Y}$

- $B_{it} = w_{it} - m_{w_{it}} - \rho_{y,w}\sigma\left(A_{it}\right)$
- $C_{it} = m^*_{it} - m_{m^*_{it}} - b(w_{it} - m_{w_{it}}) - a\left(A_{it}\right)$

- *Parameter* δ^Y

  We proceed the same way and we get:

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

  with:

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

A.4. Initial equations

- *Parameter* δ^M_0

  δ^M_0 only enters m^*_{i1}. We thus get:

$$V^{post,-1}_{\delta^M_0} = V^{prior,-1}_{\delta^M_0} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{X^M_{i1}}\right)' \widetilde{X^M_{i1}}$$

$$V^{post,-1}_{\delta^M_0} M^{post}_{\delta^M_0} = V^{prior,-1}_{\delta^M_0} M^{prior}_{\delta^M_0} + \frac{1}{V^m}\sum_{i=1}^{N}\left(\widetilde{X^M_{i1}}\right)' \widetilde{A}_{i1}$$

with:

- $A_{i1} = m^*_{i1} - \Omega^E_{z_{i1}}\alpha^{E,M} - a(y^*_{i1} - m_{y^*_{i1}}) - b(w_{i1} - m_{w_{i1}})$

- *Parameter* δ^Y_0

  We proceed the same way and we get:

$$V^{post,-1}_{\delta^Y_0} = V^{prior,-1}_{\delta^Y_0} + \sum_{i=1}^{N} X^{Y\prime}_{i1} X^Y_{i1} + \left(\frac{\rho^2_{y,w}\sigma^2}{V^w} + \frac{a^2}{V^m}\right)\sum_{i=1}^{N} \widetilde{X^Y_{i1}}' \widetilde{X^Y_{i1}}$$
$$V^{post,-1}_{\delta^Y_0} M^{post}_{\delta^Y_0} = V^{prior,-1}_{\delta^Y_0} M^{prior}_{\delta^Y_0} + \sum_{i=1}^{N} X^{Y\prime}_{i1} A_i - \sum_{i=1}^{N} \widetilde{X^Y_{i1}}' \left(\frac{\rho_{y,w}\sigma}{V^w}\widetilde{B}_i + \frac{a}{V^m}\widetilde{C}_i\right)$$

with:

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

A.5. Latent variables

A.5.1. Latent participation

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

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

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

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

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

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

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

2. For $t = T$

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

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

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

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

A.5.2. Latent mobility

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

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

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

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

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

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

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

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

A.5.3. Latent location

1. First case: $y_{it} = 1$

   We know where the individual works.

$$\mathbb{P}(z_{it} = j | y_{it} = 1, ...) = \delta_{J(i,t)}(j)$$

2. Second case: $y_{it} = 0$

   - First case: $y_{it-1} = 0$

     Let us note: $\mathcal{F}_{it-1} = (y_{it-1} = 0, z_{it-1}, ...)$

$$\mathbb{P}(z_{it} = j | y_{it} = 0, y^*_{it}, \mathcal{F}_{it-1}) = \frac{\exp\left(-\frac{1}{2}(y^*_{it} - m^j_{y^*_{it}})^2\right) p_j}{\sum_{j=1}^{J} \exp\left(-\frac{1}{2}(y^*_{it} - m^j_{y^*_{it}})^2\right) p_j}$$

   - Second case: $y_{it-1} = 1, m_{it-1} = 0$

     Let us note: $\mathcal{F}_{it-1} = (y_{it-1} = 1, z_{it-1} = J(i, t-1), m_{it-1} = 0, ...)$

     $m_{it-1} = 0$ therefore the individual a priori does not want to move.

$$\mathbb{P}(z_{it} = j | y_{it} = 0, y_{it}^*, \mathcal{F}_{it-1}) = \delta_{J(i,t-1)}(j)$$

- Third case: $y_{it-1} = 1, m_{it-1} = 1$

  Let us note: $\mathcal{F}_{it-1} = (y_{it-1} = 1, z_{it-1} = J(i,t-1), m_{it-1} = 1, ...)$

  For $j \neq J(i,t-1)$,

$$\mathbb{P}(z_{it} = j | y_{it} = 0, y_{it}^*, \mathcal{F}_{it-1}) = \frac{\exp\left(-\frac{1}{2}(y_{it}^* - m_{y_{it}^*}^j)^2\right) p_j}{\sum_{j=1, j\neq J(i,t-1)}^{J} \exp\left(-\frac{1}{2}(y_{it}^* - m_{y_{it}^*}^j)^2\right) p_j}$$

A.6. Variance-Covariance Matrix of Residuals

We use Hasting Metropolis algorithm because we do not get conjugate priors.

A.7. Variance-Covariance Matrices of Effects

- For Individual Effects $\Sigma^{I,-1} | (...); z; y, w$

  Σ^I only enters the parameter distribution but it does not enter the full conditional likelihood. Moreover, in the parameter distribution, the interesting terms are:

$$L(\theta^I | \Sigma^{I,-1}).L(\Sigma^{I,-1})$$

  We get:

$$\begin{aligned} & L(\theta^I | \Sigma^{I,-1}).L(\Sigma^{I,-1}) \\ \propto \quad & \frac{1}{(\det(\Sigma^I))^{\frac{N}{2}}} \exp\left(-\frac{1}{2}\theta^{I'}(D_0^I)^{-1}\theta^I\right).(\det(\Sigma^{I,-1}))^{\frac{\rho_I - 3 - 1}{2}} \exp(-\frac{1}{2}tr(R_I^{-1}\Sigma^{I,-1})) \end{aligned}$$

  We need to simplify $\theta^{I'}(D_0^I)^{-1}\theta^I$.

$$\theta^{I'}(D_0^I)^{-1}\theta^I = \theta^{I'}\left(\Sigma^{I,-1} \otimes I_N\right)\theta^I$$

$$
\begin{aligned}
&= tr\left(\theta^{I'}\left(\Sigma^{I,-1}\otimes I_N\right)\theta^{I}\right)\\
&= tr\left(\theta^{I}\theta^{I'}\left(\Sigma^{I,-1}\otimes I_N\right)\right)
\end{aligned}
$$

Let us rewrite the matrix $\theta^I\theta^{I'}$ as a 3x3 partitioned matrix. Therefore we get:

$$
\begin{aligned}
&\theta^I\theta^{I'}\left(\Sigma^{I,-1}\otimes I_N\right)\\
=&\begin{pmatrix}
\theta^{Y,I}\theta^{Y,I'} & \theta^{Y,I}\theta^{W,I'} & \theta^{Y,I}\theta^{M,I'}\\
\theta^{W,I}\theta^{Y,I'} & \theta^{W,I}\theta^{W,I'} & \theta^{W,I}\theta^{M,I'}\\
\theta^{M,I}\alpha^{I'} & \theta^{M,I}\theta^{W,I'} & \theta^{M,I}\theta^{M,I'}
\end{pmatrix}
\begin{pmatrix}
d_1 I_N & a_1 I_N & a_2 I_N\\
a_1 I_N & d_2 I_N & a_3 I_N\\
a_2 I_N & a_3 I_N & d_3 I_N
\end{pmatrix}
\end{aligned}
$$

When we use previously mentioned parameters to evaluate the trace of this matrix product, we get[12] :

$$
\begin{aligned}
&tr\left(\theta^I\theta^{I'}\left(\Sigma^{I,-1}\otimes I_N\right)\right)\\
=\ & d_1 tr(\theta^{Y,I}.\theta^{Y,I'}) + d_2 tr(\theta^{W,I}.\theta^{W,I'}) + d_3 tr(\theta^{M,I}.\theta^{M,I'})\\
+\ & 2a_1 tr(\theta^{Y,I}.\theta^{W,I'}) + 2a_2 tr(\theta^{Y,I}.\theta^{M,I'}) + 2a_3 tr(\theta^{M,I}.\theta^{W,I'})
\end{aligned}
\tag{A.19}
$$

What can be written:

$$
tr\left(\underbrace{\begin{pmatrix}
tr(\theta^{Y,I}\theta^{Y,I'}) & tr(\theta^{Y,I}\theta^{W,I'}) & tr(\theta^{Y,I}\theta^{M,I'})\\
tr(\theta^{W,I}\theta^{Y,I'}) & tr(\theta^{W,I}\theta^{W,I'}) & tr(\theta^{W,I}\theta^{M,I'})\\
tr(\theta^{M,I}\theta^{Y,I'}) & tr(\theta^{M,I}\theta^{W,I'}) & tr(\theta^{M,I}\theta^{M,I'})
\end{pmatrix}}_{\mathcal{A}_I}\Sigma^{I,-1}\right)
\tag{A.20}
$$

Finally the posterior conditional distribution of $\Sigma^{I,-1}$ is:

$$
\mathcal{W}_3(\rho_I + N, (R_I^{-1} + \mathcal{A}_I)^{-1})
\tag{A.21}
$$

- For Firm Effects

[12] We use the relation $tr(A) = tr(A')$

We use the same method as the one previously used.

$$\theta^E = \begin{pmatrix} \alpha^{E,Y} \\ \alpha^{E,M} \\ \theta^{E,Y} \\ \theta^{E,W} \\ \theta^{E,M} \end{pmatrix} \sim \mathcal{N}\left(0, \underbrace{\Sigma^E}_{\in\mathcal{M}(5,5)} \otimes I_J\right)$$

We have the following prior distribution:

$$\Sigma^E \quad \sim \quad \mathcal{IW}\left(\rho_E, R_E\right)$$

Finally, with analogous notations, the posterior conditional distribution of $\Sigma^{E,-1}$ is:

$$\mathcal{W}_5(\rho_E + N, (R_E^{-1} + \mathcal{A}_E)^{-1}) \tag{A.22}$$

A.8. Firm effects

There is the likelihood terms where θ^E is.

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

with

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

Some notations to ease evaluations:

1. **First term**

$$(y_{i1}^* - m_{y_{i1}^*})^2 = (A_{i1} - \Omega_{i1}^E \alpha^{E,Y})^2$$
$$A_{i1} = y_{i1}^* - XY_{i1}\delta_0^Y$$

2. **Second term**

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

3. **Third term**

$$(y_{it}^* - m_{y_{it}^*})^2 = (C_{it} - \Omega_{it}^E \theta^{Y,E})^2$$
$$C_{it} = y_{it}^* - XY_{it}\delta^Y - \gamma^Y y_{it-1} - \gamma^M m_{it-1} - \Omega_{it}^I \theta^{Y,I}$$
$$\widehat{C}_{it} = C_{it}$$
$$\widehat{\Omega}_{it}^E = \Omega_{it}^E$$

4. **Fourth term**

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

5. **Fifth term**

For $t > 1$

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

For $t=1$

$$\begin{aligned}
y_{i1}(m^*_{i1} - M_{m^*_{i1}})^2 &= y_{i1}(G_{i1} + \varOmega^E_{i1}(-\alpha_{M,E} + a\alpha^{Y,E} + b\theta^{W,E}))^2 \\
G_{i1} &= m^*_{i1} - XM_{i1}\delta^M_0 - aA_{i1} - b(w_{i1} - XW_{i1}\delta^w - \varOmega^I_{i1}\theta^{I,W}) \\
\widetilde{G}_{i1} &= y_{i1}G_{i1}
\end{aligned}$$

The posterior distribution checks:

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

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

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

Let us denote:

1. $E_1 = \sum_{i=1}^n \varOmega^{E\prime}_{i1}\varOmega^E_{i1}$
2. $\widetilde{E_1} = \sum_{i=1}^n \widetilde{\varOmega^E_{i1}}^{\prime}\widetilde{\varOmega^E_{i1}}$

3. $E_{2T} = \sum_{i=1}^{n} \underline{\Omega}_i^{E\prime} \underline{\Omega}_i^{E}$

4. $\widetilde{E_{2T}} = \sum_{i=1}^{n} \widetilde{\underline{\Omega}_i^{E}}' \widetilde{\underline{\Omega}_i^{E}}$

5. $\widetilde{E_{2,T-1}} = \sum_{i=1}^{n} \widetilde{\underline{\Omega}_i^{E,2,T-1}}' \widetilde{\underline{\Omega}_i^{E,2,T-1}}$

So we get for the variance-covariance matrix:

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

As for the posterior mean:

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

B. Results

Table 1: Participation equation for women with a vocational-technical school

Variable	Participation Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-0.2757*	*0.2340*	*-1.2000*	*0.6549*
Experience at t-1	*0.1578*	*0.0107*	*0.1175*	*0.2018*
Experience at t-1 squared	*-0.0033*	*0.0002*	*-0.0042*	*-0.0025*
Children 0 to 2 years old	*-0.2475*	*0.0598*	*-0.4601*	*0.0108*
Children 3 to 6 years old	*-0.1941*	*0.0646*	*-0.4410*	*0.0594*
Married	*0.0249*	*0.0626*	*-0.2037*	*0.2540*
Located in "Île de France"	*4.9798*	*0.3745*	*3.9270*	*6.3089*
Other than French	*-0.2427*	*0.0957*	*-0.5786*	*0.0708*
Unemployment Rate	*2.0884*	*0.6729*	*-0.6267*	*4.5066*
Mobility at t-1	*0.4510*	*0.0753*	*0.2067*	*0.7073*
Participation at t-1	*1.3286*	*0.0740*	*1.0697*	*1.5702*
Cohort Effect				
Born before 1930	*-2.7878*	*0.1693*	*-3.4321*	*-2.1655*
Born between 1930 and 1939	*-2.4906*	*0.1470*	*-2.9976*	*-1.9757*
Born between 1940 and 1949	*-2.3221*	*0.1308*	*-2.8347*	*-1.7766*
Born between 1950 and 1959	*-1.6335*	*0.1029*	*-2.0634*	*-1.2801*
Born between 1960 and 1969	*-0.9520*	*0.0650*	*-1.2211*	*-0.6995*
Time Effect				
Year 1977	*0.2434*	*0.2297*	*-0.6673*	*1.0540*
Year 1978	*0.1994*	*0.2300*	*-0.6896*	*1.0289*
Year 1979	*0.1687*	*0.2293*	*-0.8049*	*0.9822*
Year 1980	*0.1354*	*0.2301*	*-0.7490*	*0.9636*
Year 1981	*-0.1686*	*0.2290*	*-0.9924*	*0.7077*
Year 1982	*0.2749*	*0.2297*	*-0.6568*	*1.1165*
Year 1983	*-0.3926*	*0.2293*	*-1.2292*	*0.4558*
Year 1984	*0.2636*	*0.2307*	*-0.5745*	*1.1680*
Year 1985	*-0.0722*	*0.2302*	*-0.9748*	*0.8416*
Year 1986	*-0.0633*	*0.2315*	*-0.9315*	*0.7633*
Year 1987	*-0.2712*	*0.2315*	*-1.1559*	*0.6341*
Year 1988	*-0.0242*	*0.2310*	*-0.9440*	*0.7864*
Year 1989	*-0.0487*	*0.2323*	*-0.9839*	*0.8058*
Year 1990	*-1.2223*	*0.2326*	*-2.0833*	*-0.3598*
Year 1991	*0.3924*	*0.2329*	*-0.4850*	*1.3096*
Year 1992	*0.0471*	*0.2327*	*-0.8215*	*0.9383*
Year 1993	*-0.2070*	*0.2347*	*-1.0849*	*0.6890*
Year 1994	*-0.3214*	*0.2327*	*-1.2672*	*0.5511*
Year 1995	*-0.3175*	*0.2342*	*-1.2745*	*0.5814*

Table 2: Mobility equation for women with a vocational-technical school

Variable	Mobility Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*0.7082*	*0.2705*	*-0.3407*	*1.9438*
Experience at t-1	*0.0182*	*0.0154*	*-0.0406*	*0.0725*
Experience at t-1 squared	*0.0000*	*0.0004*	*-0.0012*	*0.0014*
Seniority at t-1	*0.0109*	*0.0167*	*-0.0473*	*0.0696*
Seniority at t-1 squared	*-0.0005*	*0.0008*	*-0.0033*	*0.0024*
Children 0 to 2 years old	*0.0903*	*0.0921*	*-0.2896*	*0.4017*
Children 3 to 6 years old	*0.0201*	*0.0943*	*-0.3750*	*0.3723*
Married	*0.1941*	*0.0808*	*-0.1050*	*0.4865*
Located in "Île de France"	*-0.1684*	*0.0913*	*-0.5066*	*0.1483*
Other than French	*0.0440*	*0.1121*	*-0.3555*	*0.4598*
Mobility at t-1	*0.2231*	*0.0677*	*0.0148*	*0.4341*
Part Time	*-0.3549*	*0.0638*	*-0.6168*	*-0.1291*
Unemployment Rate	*0.1756*	*0.8727*	*-3.0517*	*3.4377*
Cohort Effect				
Born before 1930	*0.5679*	*0.3973*	*-0.9454*	*2.2319*
Born between 1930 and 1939	*0.4620*	*0.2944*	*-0.5482*	*1.5944*
Born between 1940 and 1949	*0.4596*	*0.2255*	*-0.3503*	*1.2406*
Born between 1950 and 1959	*0.5350*	*0.1731*	*-0.0760*	*1.1344*
Born between 1960 and 1969	*0.3724*	*0.1280*	*-0.1141*	*0.8154*
Time Effect				
Year 1977	*-0.5008*	*0.2598*	*-1.4716*	*0.5619*
Year 1978	*-0.2364*	*0.2607*	*-1.1926*	*0.8340*
Year 1979	*-0.3133*	*0.2597*	*-1.3824*	*0.7989*
Year 1980	*0.6003*	*0.2929*	*-0.5912*	*1.6512*
Year 1981	*0.7002*	*0.3027*	*-0.4031*	*1.9807*
Year 1982	*0.7889*	*0.3051*	*-0.2625*	*2.2001*
Year 1983	*1.0297*	*0.3320*	*-0.1481*	*2.4981*
Year 1984	*-0.2188*	*0.2485*	*-1.2795*	*1.0294*
Year 1985	*-0.2280*	*0.2501*	*-1.1702*	*0.7692*
Year 1986	*-0.3585*	*0.2500*	*-1.3799*	*0.6155*
Year 1987	*-0.2173*	*0.2494*	*-1.1983*	*0.7311*
Year 1988	*-0.3067*	*0.2474*	*-1.3196*	*0.6109*
Year 1989	*0.4059*	*0.2651*	*-0.6226*	*1.3677*
Year 1990	*0.2619*	*0.2669*	*-0.7067*	*1.2404*
Year 1991	*-0.3241*	*0.2452*	*-1.2465*	*0.7196*
Year 1992	*-0.1815*	*0.2483*	*-1.1533*	*0.7049*
Year 1993	*-0.3928*	*0.2493*	*-1.3743*	*0.6486*
Year 1994	*-0.0656*	*0.2554*	*-1.1196*	*0.9569*
Year 1995	*0.0005*	*0.9985*	*-3.8312*	*3.9405*

Table 3: Wage equation for women with a vocational-technical school

Variable	Wage Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*3.2511*	*0.0489*	*3.0644*	*3.4364*
Experience at t	*0.0402*	*0.0045*	*0.0238*	*0.0575*
Experience at t squared	*-0.0006*	*0.0001*	*-0.0011*	*-0.0002*
Seniority at t	*0.0181*	*0.0041*	*0.0016*	*0.0343*
Seniority at t squared	*-0.0003*	*0.0002*	*-0.0009*	*0.0004*
Children 0 to 2 years old	*-0.0489*	*0.0289*	*-0.1677*	*0.0580*
Children 3 to 6 years old	*0.0081*	*0.0288*	*-0.1223*	*0.1082*
Married	*0.0153*	*0.0333*	*-0.1081*	*0.1478*
Unmarried Couples	*-0.0387*	*0.0428*	*-0.2205*	*0.1183*
Located in "Île de France"	*0.2681*	*0.0398*	*0.1208*	*0.4361*
Other than French	*-0.0243*	*0.0472*	*-0.2211*	*0.1574*
Part Time	*-0.5375*	*0.0237*	*-0.6220*	*-0.4368*
Cohort Effect				
Born before 1930	*0.0206*	*0.0773*	*-0.2893*	*0.3295*
Born between 1930 and 1939	*0.0957*	*0.0644*	*-0.1401*	*0.3659*
Born between 1940 and 1949	*0.1980*	*0.0542*	*-0.0035*	*0.4321*
Born between 1950 and 1959	*0.3070*	*0.0505*	*0.1308*	*0.4924*
Born between 1960 and 1969	*0.3497*	*0.0477*	*0.1352*	*0.5285*
Time Effect				
Year 1977	*0.0257*	*0.0411*	*-0.1231*	*0.2144*
Year 1978	*0.1006*	*0.0404*	*-0.0575*	*0.2459*
Year 1979	*0.0890*	*0.0396*	*-0.0954*	*0.2391*
Year 1980	*0.0795*	*0.0399*	*-0.0553*	*0.2360*
Year 1981	*0.1048*	*0.0433*	*-0.0622*	*0.2912*
Year 1982	*0.1158*	*0.0383*	*-0.0417*	*0.2668*
Year 1983	*0.1017*	*0.0432*	*-0.0779*	*0.2735*
Year 1984	*0.1253*	*0.0381*	*-0.0175*	*0.2696*
Year 1985	*0.1246*	*0.0378*	*-0.0114*	*0.2713*
Year 1986	*0.1366*	*0.0371*	*-0.0165*	*0.2778*
Year 1987	*0.0967*	*0.0367*	*-0.0368*	*0.2611*
Year 1988	*0.1364*	*0.0358*	*-0.0006*	*0.2760*
Year 1989	*0.1017*	*0.0358*	*-0.0374*	*0.2479*
Year 1990	*0.1153*	*0.0397*	*-0.0329*	*0.2598*
Year 1991	*0.1501*	*0.0358*	*0.0160*	*0.2852*
Year 1992	*0.1541*	*0.0359*	*0.0113*	*0.2811*
Year 1993	*0.1244*	*0.0361*	*-0.0057*	*0.2558*
Year 1994	*0.0523*	*0.0376*	*-0.0971*	*0.1916*
Year 1995	*0.0803*	*0.0375*	*-0.0636*	*0.2273*

Table 4: Initial participation equation for women with a vocational-technical school

Variable	Initial Participation Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-1.9266*	*0.1295*	*-2.4064*	*-1.3908*
Experience at t-1	*0.1451*	*0.0178*	*0.0827*	*0.2190*
Experience at t-1 squared	*-0.0028*	*0.0005*	*-0.0046*	*-0.0008*
Children 0 to 2 years old	*-0.0209*	*0.1776*	*-0.7166*	*0.7139*
Children 3 to 6 years old	*-0.3816*	*0.1891*	*-1.2446*	*0.4146*
Married	*0.6984*	*0.1490*	*0.1323*	*1.2761*
Located in "Île de France"	*3.1482*	*0.4425*	*1.8310*	*5.2085*
Other than French	*0.2578*	*0.1564*	*-0.3560*	*0.8248*
Unemployment Rate	*-1.1164*	*0.9767*	*-5.2166*	*2.8333*

Table 5: Initial mobility equation for women with a vocational-technical school

Variable	Initial Mobility Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*1.1737*	*0.3486*	*-0.2858*	*2.4884*
Experience at t-1	*0.0255*	*0.0331*	*-0.1035*	*0.1676*
Experience at t-1 squared	*-0.0005*	*0.0007*	*-0.0036*	*0.0022*
Seniority at t-1	*-0.0349*	*0.0542*	*-0.2990*	*0.2005*
Seniority at t-1 squared	*0.0027*	*0.0031*	*-0.0099*	*0.0163*
Children 0 to 2 years old	*1.0012*	*0.4452*	*-0.5296*	*2.8540*
Children 3 to 6 years old	*0.3369*	*0.3534*	*-0.9247*	*2.0497*
Married	*0.0192*	*0.2270*	*-1.1188*	*0.8122*
Located in "Île de France"	*-0.6363*	*0.2159*	*-1.4359*	*0.3297*
Other than French	*-0.4837*	*0.2169*	*-1.3648*	*0.3639*
Unemployment Rate	*0.0669*	*0.9901*	*-4.2351*	*3.8306*

Table 6: Variance-covariance matrix for women with a vocational-technical school

Variable	**Variance-covariance Matrix Elements for Women with a Technical Degree**			
	Mean	St. Dev.	Range	
			Min	Max
Residual Variance (Σ)				
σ^2	*0.4080*	*0.0231*	*0.3437*	*0.5516*
ρ_{wm}	*0.0620*	*0.0244*	*-0.0309*	*0.1489*
ρ_{ym}	*-0.0079*	*0.0354*	*-0.1312*	*0.1163*
ρ_{yw}	*0.0636*	*0.0320*	*-0.0609*	*0.1671*
Individual Effects (Σ_I)				
$\sigma^2_{\theta^{Y,I}}$	*0.7159*	*0.0647*	*0.5092*	*1.0069*
$\rho_{\theta^{Y,I}\theta^{W,I}}$	*0.0639*	*0.0555*	*-0.1540*	*0.2895*
$\rho_{\theta^{Y,I}\theta^{M,I}}$	*-0.1399*	*0.0816*	*-0.4397*	*0.1520*
$\sigma^2_{\theta^{W,I}}$	*0.2107*	*0.0177*	*0.1579*	*0.3012*
$\rho_{\theta^{W,I}\theta^{M,I}}$	*0.0431*	*0.0630*	*-0.1872*	*0.2796*
$\sigma^2_{\theta^{M,I}}$	*0.4106*	*0.0552*	*0.2504*	*0.6518*
Firm Effects (Σ_E)				
$\sigma^2_{\alpha^{Y,E}}$	*0.2163*	*0.0174*	*0.1590*	*0.2914*
$\rho_{\alpha^{Y,E}\alpha^{M,E}}$	*0.0356*	*0.0540*	*-0.1611*	*0.2447*
$\rho_{\alpha^{Y,E}\theta^{Y,E}}$	*0.0030*	*0.0387*	*-0.1429*	*0.1458*
$\rho_{\alpha^{Y,E}\theta^{W,E}}$	*0.0016*	*0.0383*	*-0.1413*	*0.1446*
$\rho_{\alpha^{Y,E}\theta^{M,E}}$	*0.0003*	*0.0401*	*-0.1546*	*0.1638*
$\sigma^2_{\alpha^{M,E}}$	*0.2205*	*0.0222*	*0.1475*	*0.3259*
$\rho_{\alpha^{M,E}\theta^{Y,E}}$	*0.0035*	*0.0386*	*-0.1393*	*0.1538*
$\rho_{\alpha^{M,E}\theta^{W,E}}$	*-0.0009*	*0.0382*	*-0.1546*	*0.1378*
$\rho_{\alpha^{M,E}\theta^{M,E}}$	*-0.0086*	*0.0393*	*-0.1860*	*0.1612*
$\sigma^2_{\theta^{Y,E}}$	*0.2154*	*0.0179*	*0.1529*	*0.2908*
$\rho_{\theta^{Y,E}\theta^{W,E}}$	*0.0303*	*0.0542*	*-0.1656*	*0.2326*
$\rho_{\theta^{Y,E}\theta^{M,E}}$	*0.0451*	*0.0476*	*-0.1489*	*0.2241*
$\sigma^2_{\theta^{W,E}}$	*0.2117*	*0.0183*	*0.1514*	*0.2929*
$\rho_{\theta^{W,E}\theta^{M,E}}$	*0.0274*	*0.0460*	*-0.1382*	*0.2366*
$\sigma^2_{\theta^{M,E}}$	*0.2184*	*0.0199*	*0.1473*	*0.3041*

Table 7: Summary Statistics for women with a vocational-technical school

Variable	1976-1995	Year 1976	1985	1995
Experience	*13.1909*	*8.9961*	*12.5800*	*18.4044*
	(13.4160)	*(11.5179)*	*(13.4461)*	*(13.2853)*
Seniority	*2.7086*	*2.9840*	*2.4912*	*3.3044*
	(5.6840)	*(5.3040)*	*(5.6625)*	*(6.0035)*
Log Wage	*4.1304*	*4.1002*	*4.1512*	*4.0995*
	(0.8003)	*(0.6781)*	*(0.7882)*	*(0.9073)*
Participation	*0.4447*	*0.3085*	*0.4303*	*0.5831*
	(0.4969)	*(0.4619)*	*(0.4952)*	*(0.4931)*
Mobility	*0.3257*	*0.2442*	*0.3402*	*0.0000*
	(0.4686)	*(0.4297)*	*(0.4738)*	*(0.0000)*
Children 0 to 2 years old	*0.0916*	*0.0942*	*0.0831*	*0.0759*
	(0.2884)	*(0.2922)*	*(0.2760)*	*(0.2649)*
Children 3 to 6 years old	*0.0755*	*0.0858*	*0.0837*	*0.0673*
	(0.2642)	*(0.2800)*	*(0.2770)*	*(0.2505)*
Married	*0.4563*	*0.3327*	*0.4556*	*0.5517*
	(0.4981)	*(0.4712)*	*(0.4981)*	*(0.4974)*
Unmarried Couples	*0.0507*	*0.0000*	*0.0100*	*0.1515*
	(0.2195)	*(0.0000)*	*(0.0995)*	*(0.3586)*
Located in "Île de France"	*0.1286*	*0.1115*	*0.1259*	*0.1373*
	(0.3347)	*(0.3148)*	*(0.3318)*	*(0.3442)*
Other than French	*0.0764*	*0.0666*	*0.0790*	*0.0758*
	(0.3115)	*(0.2914)*	*(0.3155)*	*(0.3122)*
Born before 1930	*0.0724*	*0.0792*	*0.0773*	*0.0434*
	(0.2592)	*(0.2700)*	*(0.2671)*	*(0.2038)*
Born between 1930 and 1939	*0.1192*	*0.1192*	*0.1192*	*0.1192*
	(0.3240)	*(0.3240)*	*(0.3240)*	*(0.3240)*
Born between 1940 and 1949	*0.1966*	*0.1966*	*0.1966*	*0.1966*
	(0.3974)	*(0.3975)*	*(0.3975)*	*(0.3975)*
Born between 1950 and 1959	*0.1771*	*0.1771*	*0.1771*	*0.1771*
	(0.3818)	*(0.3818)*	*(0.3818)*	*(0.3818)*
Born between 1960 and 1969	*0.2407*	*0.0537*	*0.3127*	*0.3127*
	(0.4275)	*(0.2255)*	*(0.4636)*	*(0.4636)*
Part Time	*0.6643*	*0.7632*	*0.6703*	*0.6002*
	(0.4722)	*(0.4251)*	*(0.4701)*	*(0.4899)*

Table 8: Initial Participation Equation for men with a Vocational Technical Degree

Variable	**Initial Participation Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-1.7185*	*0.1253*	*-2.3117*	*-1.1900*
Experience at t-1	*0.1426*	*0.0180*	*0.0717*	*0.2089*
Experience at t-1 squared	*-0.0023*	*0.0004*	*-0.0039*	*-0.0004*
Children 0 to 2 years old	*0.3230*	*0.1866*	*-0.3545*	*1.0590*
Children 3 to 6 years old	*-0.1517*	*0.1939*	*-0.9183*	*0.7070*
Married	*0.7011*	*0.1627*	*0.0755*	*1.4050*
Located in "Île de France"	*2.8640*	*0.4571*	*1.4217*	*5.1261*
Other than French	*0.1118*	*0.1432*	*-0.4433*	*0.6388*
Unemployment rate	*-1.3283*	*0.9811*	*-5.4080*	*2.2546*

Table 9: Initial Mobility Equation for men with a Vocational Technical Degree

Variable	**Initial Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*0.4267*	*0.2888*	*-0.8114*	*1.5471*
Experience at t-1	*0.0372*	*0.0310*	*-0.0765*	*0.1665*
Experience at t-1 squared	*-0.0004*	*0.0007*	*-0.0028*	*0.0023*
Seniority at t-1	*0.0014*	*0.0444*	*-0.1750*	*0.1711*
Seniority at t-1 squared	*0.0002*	*0.0022*	*-0.0078*	*0.0098*
Children 0 to 2 years old	*0.0349*	*0.2379*	*-0.8494*	*0.9663*
Children 3 to 6 years old	*0.4191*	*0.2800*	*-0.5685*	*1.6695*
Married	*0.2704*	*0.2194*	*-0.5313*	*1.1126*
Located in "Île de France"	*0.2390*	*0.2080*	*-0.5239*	*1.0316*
Other than French	*-0.4667*	*0.1866*	*-1.1438*	*0.2296*
Unemployment rate	*0.0817*	*0.9964*	*-3.8903*	*3.7749*

Table 10: Participation Equation for men with a Vocational Technical Degree

Variable	Participation Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-0.2881*	*0.2328*	*-1.2498*	*0.5703*
Experience at t-1	*0.12545*	*0.0089*	*0.0935*	*0.1694*
Experience at t-1 squared	*-0.0024*	*0.0002*	*-0.0033*	*-0.0018*
Children 0 to 2 years old	*-0.0369*	*0.0711*	*-0.3156*	*0.2362*
Children 3 to 6 years old	*-0.0264*	*0.0727*	*-0.3180*	*0.2720*
Married	*0.0285*	*0.0665*	*-0.2265*	*0.2623*
Located in "Île de France"	*4.9743*	*0.3171*	*4.0698*	*5.8838*
Other than French	*-0.3436*	*0.0820*	*-0.6398*	*-0.0637*
Unemployment Rate	*1.4712*	*0.6896*	*-2.0813*	*4.8732*
Mobility at t-1	*0.4203*	*0.0661*	*0.1860*	*0.6534*
Participation at t-1	*1.6206*	*0.0665*	*1.3378*	*1.8917*
Cohort Effect				
Born before 1930	*-2.6538*	*0.1263*	*-3.1350*	*-2.0839*
Born between 1930 and 1939	*-2.2994*	*0.1304*	*-2.7678*	*-1.7769*
Born between 1940 and 1949	*-1.9916*	*0.1174*	*-2.4204*	*-1.5751*
Born between 1950 and 1959	*-1.5877*	*0.0879*	*-1.9031*	*-1.2487*
Born between 1960 and 1969	*-0.8943*	*0.0682*	*-1.1689*	*-0.6200*
Time Effect				
Year 1977	*0.3270*	*0.2300*	*-0.5353*	*1.2124*
Year 1978	*0.2392*	*0.2299*	*-0.6544*	*1.1694*
Year 1979	*0.2477*	*0.2293*	*-0.6944*	*1.2162*
Year 1980	*0.2306*	*0.2293*	*-0.6229*	*1.0806*
Year 1981	*-0.2358*	*0.2286*	*-1.0561*	*0.7129*
Year 1982	*0.4023*	*0.2299*	*-0.5567*	*1.2852*
Year 1983	*-0.4325*	*0.2299*	*-1.4353*	*0.4025*
Year 1984	*0.4115*	*0.2307*	*-0.4944*	*1.3409*
Year 1985	*-0.0626*	*0.2309*	*-0.9155*	*0.8239*
Year 1986	*-0.0438*	*0.2330*	*-0.8842*	*0.8249*
Year 1987	*-0.2869*	*0.2322*	*-1.2051*	*0.6712*
Year 1988	*-0.1936*	*0.2323*	*-1.1344*	*0.6802*
Year 1989	*-0.0957*	*0.2322*	*-0.9275*	*0.8015*
Year 1990	*-1.2978*	*0.2334*	*-2.1516*	*-0.3210*
Year 1991	*0.4253*	*0.2329*	*-0.5541*	*1.3887*
Year 1992	*-0.2217*	*0.2336*	*-1.2413*	*0.6107*
Year 1993	*-0.2244*	*0.2341*	*-1.1692*	*0.6141*
Year 1994	*-0.3757*	*0.2346*	*-1.2434*	*0.6405*
Year 1995	*-0.5510*	*0.2350*	*-1.3905*	*0.3717*

Table 11: Mobility Equation for men with a Vocational Technical Degree

Variable	**Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*0.7131*	*0.2763*	*-0.2489*	*1.7568*
Experience at t-1	*0.02431*	*0.0152*	*-0.0390*	*0.0821*
Experience at t-1 squared	*-0.0005*	*0.0003*	*-0.0016*	*0.0009*
Seniority at t-1	*0.0145*	*0.0152*	*-0.0449*	*0.0764*
Seniority at t-1 squared	*-0.0001*	*0.0006*	*-0.0027*	*0.0024*
Children 0 to 2 years old	*0.1775*	*0.0975*	*-0.1979*	*0.5454*
Children 3 to 6 years old	*-0.0911*	*0.0939*	*-0.4372*	*0.2843*
Married	*0.2004*	*0.0958*	*-0.2193*	*0.5252*
Located in "Île de France"	*-0.1659*	*0.0922*	*-0.5074*	*0.2417*
Other than French	*0.0121*	*0.1143*	*-0.3635*	*0.6171*
Mobility at t-1	*0.0108*	*0.0647*	*-0.2486*	*0.2419*
Part time	*-0.7229*	*0.0764*	*-1.0451*	*-0.4419*
Unemployment Rate	*-0.0416*	*0.8669*	*-3.9669*	*3.1219*
Cohort Effect				
Born before 1930	*0.8046*	*0.3828*	*-0.6158*	*2.1426*
Born between 1930 and 1939	*0.6719*	*0.3076*	*-0.6456*	*1.8179*
Born between 1940 and 1949	*0.6187*	*0.2406*	*-0.2324*	*1.5728*
Born between 1950 and 1959	*0.5946*	*0.1880*	*-0.1890*	*1.2840*
Born between 1960 and 1969	*0.3360*	*0.1441*	*-0.3091*	*0.8977*
Time Effect				
Year 1977	*-0.2294*	*0.2584*	*-1.3095*	*0.8734*
Year 1978	*-0.2427*	*0.2579*	*-1.2469*	*0.7926*
Year 1979	*-0.3343*	*0.2536*	*-1.2399*	*0.7277*
Year 1980	*0.2164*	*0.2711*	*-0.7108*	*1.3638*
Year 1981	*0.4560*	*0.2808*	*-0.5451*	*1.5486*
Year 1982	*0.3208*	*0.2760*	*-0.8439*	*1.3718*
Year 1983	*0.6375*	*0.2877*	*-0.6578*	*1.6782*
Year 1984	*-0.1017*	*0.2500*	*-1.1508*	*1.0398*
Year 1985	*-0.1632*	*0.2502*	*-1.1390*	*0.8535*
Year 1986	*-0.3700*	*0.2462*	*-1.3948*	*0.5626*
Year 1987	*-0.3425*	*0.2478*	*-1.2806*	*0.5847*
Year 1988	*-0.0753*	*0.2485*	*-0.9798*	*0.8555*
Year 1989	*0.6836*	*0.2692*	*-0.2794*	*1.7781*
Year 1990	*0.3166*	*0.2611*	*-0.6588*	*1.2486*
Year 1991	*-0.2134*	*0.2465*	*-1.1536*	*0.7426*
Year 1992	*-0.0733*	*0.2495*	*-1.0076*	*0.8031*
Year 1993	*-0.0154*	*0.2525*	*-0.9637*	*0.9761*
Year 1994	*0.1703*	*0.2527*	*-0.8082*	*1.0984*
Year 1995	*0.0003*	*0.9940*	*-3.9034*	*3.5625*

Table 12: Wage Equation for men with a Vocational Technical Degree

Variable	Wage Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*3.9828*	*0.0497*	*3.7495*	*4.1652*
Experience at t	*0.0341*	*0.0045*	*0.0169*	*0.0517*
Experience at t squared	*-0.0006*	*0.0001*	*-0.0010*	*-0.0001*
Seniority at t	*0.0075*	*0.0040*	*-0.0077*	*0.0221*
Seniority at t squared	*0.0000*	*0.0002*	*-0.0005*	*0.0008*
Children 0 to 2 years old	*-0.0394*	*0.0308*	*-0.1666*	*0.0846*
Children 3 to 6 years old	*-0.0040*	*0.0292*	*-0.1197*	*0.1094*
Married	*0.1642*	*0.0371*	*0.0041*	*0.3062*
Unmarried Couples	*0.0772*	*0.0484*	*-0.1123*	*0.2759*
Located in "Île de France"	*0.0724*	*0.0380*	*-0.0692*	*0.2319*
Other than French	*0.0207*	*0.0475*	*-0.1730*	*0.1782*
Part Time	*-0.6154*	*0.0323*	*-0.7282*	*-0.4956*
Cohort Effect				
Born before 1929	*0.0347*	*0.0747*	*-0.2452*	*0.3192*
Born between 1930 and 1939	*-0.0296*	*0.0654*	*-0.2959*	*0.2079*
Born between 1940 and 1949	*0.0348*	*0.0554*	*-0.1828*	*0.2206*
Born between 1950 and 1959	*0.0230*	*0.0537*	*-0.1617*	*0.2295*
Born between 1960 and 1969	*-0.0203*	*0.0513*	*-0.2169*	*0.1811*
Time Effect				
Year 1977	*-0.0938*	*0.0374*	*-0.2488*	*0.0657*
Year 1978	*-0.0642*	*0.0376*	*-0.2055*	*0.0896*
Year 1979	*-0.0505*	*0.0370*	*-0.1932*	*0.0937*
Year 1980	*-0.0509*	*0.0368*	*-0.2185*	*0.0868*
Year 1981	*-0.0343*	*0.0407*	*-0.1915*	*0.1218*
Year 1982	*-0.0520*	*0.0370*	*-0.2055*	*0.1106*
Year 1983	*0.0026*	*0.0407*	*-0.1635*	*0.1608*
Year 1984	*0.0344*	*0.0359*	*-0.1048*	*0.1613*
Year 1985	*-0.0003*	*0.0363*	*-0.1470*	*0.1283*
Year 1986	*0.0139*	*0.0362*	*-0.1460*	*0.1606*
Year 1987	*0.0080*	*0.0366*	*-0.1377*	*0.1570*
Year 1988	*0.0483*	*0.0363*	*-0.0967*	*0.1848*
Year 1989	*0.0459*	*0.0358*	*-0.0929*	*0.1962*
Year 1990	*0.0560*	*0.0396*	*-0.0846*	*0.2155*
Year 1991	*0.0724*	*0.0359*	*-0.0632*	*0.1979*
Year 1992	*0.0883*	*0.0362*	*-0.0521*	*0.2329*
Year 1993	*0.0699*	*0.0362*	*-0.0754*	*0.2248*
Year 1994	*0.0921*	*0.0372*	*-0.0370*	*0.2363*
Year 1995	*0.0726*	*0.0388*	*-0.0857*	*0.2281*

Table 13: Variance-covariance matrix for men with a Vocational Technical Degree

Variable	**Variance-covariance Matrix Elements for Men with a Vocational-Technical School**			
	Mean	St. Dev.	Range	
			Min	Max
Residual Variance (Σ)				
σ^2	*0.4159*	*0.0220*	*0.3561*	*0.5650*
ρ_{wm}	*0.0505*	*0.0222*	*-0.0603*	*0.1373*
ρ_{ym}	*-0.0211*	*0.0286*	*-0.1232*	*0.0897*
ρ_{yw}	*-0.0211*	*0.0310*	*-0.1237*	*0.0931*
Individual Effects (Σ_I)				
$\sigma^2_{\theta^{Y,I}}$	*0.6049*	*0.0547*	*0.4244*	*0.8264*
$\rho_{\theta^{Y,I}\theta^{W,I}}$	*0.0649*	*0.0545*	*-0.1489*	*0.2846*
$\rho_{\theta^{Y,I}\theta^{M,I}}$	*-0.0187*	*0.0756*	*-0.2782*	*0.2554*
$\sigma^2_{\theta^{W,I}}$	*0.2777*	*0.0247*	*0.1977*	*0.4061*
$\rho_{\theta^{W,I}\theta^{M,I}}$	*0.0653*	*0.0622*	*-0.1773*	*0.2939*
$\sigma^2_{\theta^{M,I}}$	*0.5623*	*0.0671*	*0.3544*	*0.8806*
Firm Effects (Σ_E)				
$\sigma^2_{\alpha^{Y,E}}$	*0.2849*	*0.0276*	*0.2026*	*0.4328*
$\rho_{\alpha^{Y,E}\alpha^{M,E}}$	*0.0028*	*0.0651*	*-0.2800*	*0.2285*
$\rho_{\alpha^{Y,E}\theta^{Y,E}}$	*0.0872*	*0.0585*	*-0.1567*	*0.3304*
$\rho_{\alpha^{Y,E}\theta^{W,E}}$	*0.0009*	*0.0503*	*-0.1888*	*0.1914*
$\rho_{\alpha^{Y,E}\theta^{M,E}}$	*0.0030*	*0.0397*	*-0.1570*	*0.1446*
$\sigma^2_{\alpha^{M,E}}$	*0.2858*	*0.0256*	*0.2041*	*0.4027*
$\rho_{\alpha^{M,E}\theta^{Y,E}}$	*-0.0050*	*0.0568*	*-0.2075*	*0.1979*
$\rho_{\alpha^{M,E}\theta^{W,E}}$	*0.0838*	*0.0513*	*-0.1098*	*0.2978*
$\rho_{\alpha^{M,E}\theta^{M,E}}$	*0.0031*	*0.0392*	*-0.1321*	*0.1642*
$\sigma^2_{\theta^{Y,E}}$	*0.2835*	*0.0219*	*0.2137*	*0.3825*
$\rho_{\theta^{Y,E}\theta^{W,E}}$	*-0.0089*	*0.0465*	*-0.1642*	*0.1795*
$\rho_{\theta^{Y,E}\theta^{M,E}}$	*0.0555*	*0.0385*	*-0.1075*	*0.2092*
$\sigma^2_{\theta^{W,E}}$	*0.2738*	*0.0241*	*0.1930*	*0.3931*
$\rho_{\theta^{W,E}\theta^{M,E}}$	*0.0061*	*0.0378*	*-0.1577*	*0.1427*
$\sigma^2_{\theta^{M,E}}$	*0.2853*	*0.0291*	*0.1961*	*0.4536*

Table 14: Summary statistics for men with a Vocational Technical Degree

Variable	1976-1995	Year 1976	1985	1995
Experience	*15.5053*	*10.7550*	*14.9819*	*21.0103*
	(14.5587)	*(12.7510)*	*(14.6378)*	*(14.0915)*
Seniority	*3.5184*	*4.2806*	*3.5263*	*3.5702*
	(6.7760)	*(6.5467)*	*(6.9945)*	*(6.6418)*
Log Wage	*4.5124*	*4.4853*	*4.5380*	*4.4965*
	(0.7694)	*(0.5902)*	*(0.7557)*	*(0.8704)*
Participation	*0.4824*	*0.4105*	*0.4674*	*0.5899*
	(0.4997)	*(0.4920)*	*(0.4990)*	*(0.4919)*
Mobility	*0.3576*	*0.3275*	*0.3707*	*0.0000*
	(0.4793)	*(0.4693)*	*(0.4830)*	*(0.0000)*
Children 0 to 2 years old	*0.0787*	*0.0995*	*0.0668*	*0.0564*
	(0.2692)	*(0.2993)*	*(0.2498)*	*(0.2307)*
Children 3 to 6 years old	*0.0696*	*0.0879*	*0.0810*	*0.0484*
	(0.2544)	*(0.2832)*	*(0.2729)*	*(0.2146)*
Married	*0.5031*	*0.3966*	*0.5062*	*0.5803*
	(0.5000)	*(0.4892)*	*(0.5000)*	*(0.4936)*
Unmarried Couples	*0.0409*	*0.0000*	*0.0122*	*0.1174*
	(0.1980)	*(0.0000)*	*(0.1099)*	*(0.3219)*
Located in "Île de France"	*0.1255*	*0.1199*	*0.1293*	*0.1323*
	(0.3313)	*(0.3248)*	*(0.3355)*	*(0.3388)*
Other than French	*0.1254*	*0.1204*	*0.1284*	*0.1156*
	(0.3935)	*(0.3844)*	*(0.3971)*	*(0.3847)*
Born before 1930	*0.1060*	*0.1179*	*0.1142*	*0.0613*
	(0.3078)	*(0.3225)*	*(0.3181)*	*(0.2400)*
Born between 1930 and 1939	*0.1356*	*0.1356*	*0.1356*	*0.1356*
	(0.3424)	*(0.3424)*	*(0.3424)*	*(0.3424)*
Born between 1940 and 1949	*0.1871*	*0.1871*	*0.1871*	*0.1871*
	(0.3900)	*(0.3900)*	*(0.3900)*	*(0.3900)*
Born between 1950 and 1959	*0.1849*	*0.1849*	*0.1849*	*0.1849*
	(0.3882)	*(0.3883)*	*(0.3883)*	*(0.3883)*
Born between 1960 and 1969	*0.1979*	*0.0505*	*0.2551*	*0.2551*
	(0.3984)	*(0.2191)*	*(0.4360)*	*(0.4360)*
Part Time	*0.5719*	*0.6548*	*0.5801*	*0.4888*
	(0.4948)	*(0.4755)*	*(0.4936)*	*(0.4999)*

Table 15: Participation equation for women with a Technical College or Undergraduate University

Variable	Participation Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-0.2163*	*0.2403*	*-1.1355*	*0.7020*
Experience at t-1	*0.0870*	*0.0091*	*0.0539*	*0.1184*
Experience at t-1 squared	*-0.0020*	*0.0002*	*-0.0027*	*-0.0013*
Children 0 to 2 years old	*-0.1588*	*0.0639*	*-0.4213*	*0.0956*
Children 3 to 6 years old	*-0.0912*	*0.0670*	*-0.3603*	*0.1636*
Married	*0.1830*	*0.0667*	*-0.0593*	*0.4507*
Located in "Île de France"	*6.1529*	*0.3399*	*5.3605*	*7.4000*
Other than French	*-0.1285*	*0.0794*	*-0.3851*	*0.1551*
Unemployment rate	*2.9261*	*0.7519*	*0.1767*	*6.4721*
Mobility at t-1	*0.5265*	*0.0741*	*0.2897*	*0.8092*
Participation at t-1	*1.3033*	*0.0712*	*1.0314*	*1.5658*
Cohort Effect				
Born before 1930	*-2.7021*	*0.1992*	*-3.4142*	*-2.0403*
Born between 1930 and 1939	*-2.3237*	*0.1591*	*-2.9589*	*-1.7199*
Born between 1940 and 1949	*-2.4530*	*0.1097*	*-2.8768*	*-1.9691*
Born between 1950 and 1959	*-2.0083*	*0.0877*	*-2.3263*	*-1.6812*
Born between 1960 and 1969	*-1.6749*	*0.0930*	*-2.0025*	*-1.3128*
Time Effect				
Year 1977	*0.1305*	*0.2360*	*-0.7458*	*1.1721*
Year 1978	*0.1638*	*0.2359*	*-0.6850*	*1.0913*
Year 1979	*0.0707*	*0.2354*	*-0.8620*	*0.9740*
Year 1980	*0.1802*	*0.2356*	*-0.8249*	*1.1747*
Year 1981	*-0.5385*	*0.2349*	*-1.4579*	*0.3698*
Year 1982	*0.3014*	*0.2368*	*-0.6703*	*1.3255*
Year 1983	*-0.8893*	*0.2381*	*-1.8691*	*0.0721*
Year 1984	*0.3296*	*0.2385*	*-0.6318*	*1.2306*
Year 1985	*-0.2323*	*0.2388*	*-1.2453*	*0.6792*
Year 1986	*-0.0341*	*0.2382*	*-1.0252*	*0.9075*
Year 1987	*-0.1688*	*0.2388*	*-1.1256*	*0.6763*
Year 1988	*0.3160*	*0.2385*	*-0.7446*	*1.1637*
Year 1989	*0.1496*	*0.2365*	*-0.7864*	*1.1960*
Year 1990	*-1.0350*	*0.2409*	*-1.9747*	*-0.1713*
Year 1991	*0.3909*	*0.2373*	*-0.6069*	*1.3637*
Year 1992	*-0.0366*	*0.2395*	*-0.9843*	*0.8516*
Year 1993	*-0.0256*	*0.2404*	*-0.9780*	*0.9389*
Year 1994	*-0.1481*	*0.2401*	*-1.1698*	*0.7366*
Year 1995	*-0.2018*	*0.2406*	*-1.1626*	*0.7944*

Table 16: Mobility equation for women with a Technical College or Undergraduate University

Variable	**Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*1.0879*	*0.4620*	*-0.6375*	*2.8647*
Experience at t-1	*0.0298*	*0.0163*	*-0.0269*	*0.0877*
Experience at t-1 squared	*-0.0012*	*0.0005*	*-0.0030*	*0.0006*
Seniority at t-1	*0.0257*	*0.0198*	*-0.0542*	*0.0976*
Seniority at t-1 squared	*-0.0008*	*0.0009*	*-0.0040*	*0.0029*
Children 0 to 2 years old	*0.1426*	*0.1064*	*-0.2150*	*0.5372*
Children 3 to 6 years old	*-0.0014*	*0.1091*	*-0.4112*	*0.4214*
Married	*0.2608*	*0.1012*	*-0.0898*	*0.5873*
Located in "Île de France"	*-0.0747*	*0.1032*	*-0.4750*	*0.3253*
Other than French	*0.0428*	*0.1027*	*-0.3365*	*0.4278*
Unemployment Rate	*0.4215*	*0.9029*	*-3.5269*	*3.7134*
Part Time	*-0.2420*	*0.0719*	*-0.4966*	*0.0188*
Mobility at t-1	*0.1192*	*0.0751*	*-0.1453*	*0.3855*
Cohort Effect				
Born before 1930	*1.2292*	*0.4936*	*-0.7596*	*3.0831*
Born between 1930 and 1939	*0.4903*	*0.4340*	*-1.4241*	*2.3332*
Born between 1940 and 1949	*0.3994*	*0.4112*	*-1.1889*	*2.2124*
Born between 1950 and 1959	*-0.0911*	*0.4064*	*-1.6532*	*1.6763*
Born between 1960 and 1969	*-0.5110*	*0.4188*	*-2.1646*	*1.1206*
Time Effect				
Year 1977	*-0.5111*	*0.2655*	*-1.5279*	*0.5441*
Year 1978	*-0.3550*	*0.2621*	*-1.2824*	*0.5984*
Year 1979	*-0.4874*	*0.2616*	*-1.5874*	*0.5430*
Year 1980	*0.4637*	*0.3004*	*-0.5902*	*1.6099*
Year 1981	*0.4599*	*0.3003*	*-0.6568*	*1.6609*
Year 1982	*0.3520*	*0.2928*	*-0.8924*	*1.5651*
Year 1983	*0.5798*	*0.3074*	*-0.4411*	*1.8319*
Year 1984	*-0.1489*	*0.2576*	*-1.1466*	*0.8662*
Year 1985	*-0.2602*	*0.2533*	*-1.2240*	*0.7976*
Year 1986	*-0.1293*	*0.2530*	*-1.0590*	*0.9404*
Year 1987	*-0.3288*	*0.2495*	*-1.3029*	*0.7109*
Year 1888	*-0.1951*	*0.2485*	*-1.1994*	*0.8274*
Year 1989	*0.4423*	*0.2706*	*-0.6243*	*1.5491*
Year 1990	*0.5475*	*0.2760*	*-0.5465*	*1.7648*
Year 1991	*0.0761*	*0.2517*	*-0.9723*	*1.0994*
Year 1992	*-0.0276*	*0.2548*	*-0.9609*	*0.9154*
Year 1993	*0.2191*	*0.2578*	*-0.7269*	*1.2489*
Year 1994	*0.1727*	*0.2595*	*-0.7961*	*1.2287*
Year 1995	*0.0024*	*1.0028*	*-3.6287*	*4.5741*

Table 17: Wage equation for women with a Technical College or Undergraduate University

Variable	Wage Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*2.6811*	*0.0657*	*2.4180*	*2.9107*
Experience at t	*0.0529*	*0.0057*	*0.0301*	*0.0799*
Experience at t squared	*-0.0006*	*0.0002*	*-0.0013*	*0.0000*
Seniority at t	*0.0244*	*0.0054*	*0.0035*	*0.0439*
Seniority at t squared	*-0.0003*	*0.0002*	*-0.0012*	*0.0007*
Children 0 to 2 years old	*0.0023*	*0.0395*	*-0.1541*	*0.1600*
Children 3 to 6 years old	*0.0035*	*0.0401*	*-0.1514*	*0.1583*
Married	*0.2489*	*0.0455*	*0.0830*	*0.4120*
Unmarried Couples	*-0.0353*	*0.0558*	*-0.2471*	*0.2134*
Located in "Île de France"	*0.4266*	*0.0485*	*0.2412*	*0.6010*
Other than French	*0.0033*	*0.0549*	*-0.2256*	*0.2158*
Part Time	*-0.7208*	*0.0313*	*-0.8359*	*-0.5986*
Cohort Effect				
Born before 1930	*0.0362*	*0.0886*	*-0.3052*	*0.4191*
Born between 1930 and 1939	*0.1308*	*0.0806*	*-0.1708*	*0.4488*
Born between 1940 and 1949	*0.2960*	*0.0667*	*0.0373*	*0.5611*
Born between 1950 and 1959	*0.5308*	*0.0601*	*0.2917*	*0.7425*
Born between 1960 and 1969	*0.6800*	*0.0671*	*0.3779*	*0.9596*
Time Effect				
Year 1977	*0.0484*	*0.0560*	*-0.1807*	*0.2773*
Year 1978	*0.1284*	*0.0538*	*-0.0785*	*0.3257*
Year 1979	*0.0676*	*0.0529*	*-0.1169*	*0.2742*
Year 1980	*0.0627*	*0.0507*	*-0.1226*	*0.2578*
Year 1981	*0.0847*	*0.0594*	*-0.1603*	*0.3044*
Year 1982	*0.1018*	*0.0503*	*-0.0868*	*0.2915*
Year 1983	*0.1229*	*0.0585*	*-0.1347*	*0.3373*
Year 1984	*0.1424*	*0.0494*	*-0.0423*	*0.3234*
Year 1985	*0.0343*	*0.0486*	*-0.1333*	*0.2183*
Year 1986	*0.0440*	*0.0476*	*-0.1604*	*0.2122*
Year 1987	*0.0250*	*0.0469*	*-0.1921*	*0.2064*
Year 1988	*0.0915*	*0.0448*	*-0.0946*	*0.2475*
Year 1989	*0.0992*	*0.0445*	*-0.0696*	*0.2494*
Year 1990	*0.0823*	*0.0503*	*-0.1192*	*0.2804*
Year 1991	*0.0814*	*0.0450*	*-0.0998*	*0.2434*
Year 1992	*0.0651*	*0.0455*	*-0.1131*	*0.2418*
Year 1993	*0.0386*	*0.0456*	*-0.1291*	*0.2048*
Year 1994	*0.0283*	*0.0469*	*-0.1906*	*0.2118*
Year 1995	*0.0193*	*0.0477*	*-0.1564*	*0.2285*

Table 18: Initial Participation equation for women with a Technical College or Undergraduate University

Variable	**Initial Participation Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-1.8608*	*0.1259*	*-2.3995*	*-1.3676*
Experience at t-1	*0.0697*	*0.0192*	*-0.0082*	*0.1400*
Experience at t-1 squared	*-0.0009*	*0.0006*	*-0.0030*	*0.0016*
Children 0 to 2 years old	*0.1227*	*0.1933*	*-0.7881*	*0.8520*
Children 3 to 6 years old	*-0.1656*	*0.2133*	*-0.9721*	*0.7075*
Married	*0.7367*	*0.1520*	*0.1867*	*1.3478*
Located in "Île de France"	*3.7385*	*0.3933*	*2.4188*	*5.4842*
Other than French	*0.3345*	*0.1234*	*-0.1447*	*0.8083*
Unemployment Rate	*-0.6205*	*0.9896*	*-4.4382*	*3.0283*

Table 19: Initial Mobility equation for women with a Technical College or Undergraduate University

Variable	**Initial Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*0.6815*	*0.3129*	*-0.5931*	*1.8330*
Experience at t-1	*0.0245*	*0.0328*	*-0.1003*	*0.1571*
Experience at t-1 squared	*-0.0008*	*0.0009*	*-0.0039*	*0.0027*
Seniority at t-1	*-0.1204*	*0.0525*	*-0.3332*	*0.0757*
Seniority at t-1 squared	*0.0078*	*0.0033*	*-0.0051*	*0.0210*
Children 0 to 2 years old	*-0.3920*	*0.3183*	*-1.7958*	*1.0344*
Children 3 to 6 years old	*-0.2091*	*0.3463*	*-1.3746*	*1.5433*
Married	*0.6302*	*0.2625*	*-0.3372*	*1.7089*
Located in "Île de France"	*0.0372*	*0.2259*	*-0.8872*	*0.9015*
Other than French	*0.1172*	*0.1907*	*-0.6377*	*0.9493*
Unemployment Rate	*0.0710*	*1.0016*	*-3.6066*	*4.3921*

Table 20: Variance covariance matrix for women with a Technical College or Undergraduate University

Variable	Variance-covariance Matrix Elements for Women with Technical College or Undergraduate University			
	Mean	St. Dev.	Range	
			Min	Max
Residual Variance (Σ)				
σ^2	*0.6971*	*0.0342*	*0.6038*	*0.8544*
ρ_{wm}	*0.0605*	*0.0250*	*-0.0500*	*0.1590*
ρ_{ym}	*-0.0064*	*0.0273*	*-0.0999*	*0.1076*
ρ_{yw}	*0.0577*	*0.0274*	*-0.0586*	*0.1625*
Individual Effects(Σ_I)				
$\sigma^2_{\theta^{Y,I}}$	*0.8647*	*0.0754*	*0.6201*	*1.1716*
$\rho_{\theta^{Y,I}\theta^{W,I}}$	*0.1871*	*0.0505*	*-0.0028*	*0.3822*
$\rho_{\theta^{Y,I}\theta^{M,I}}$	*-0.0242*	*0.0729*	*-0.3124*	*0.2352*
$\sigma^2_{\theta^{W,I}}$	*0.6447*	*0.0461*	*0.4973*	*0.8522*
$\rho_{\theta^{W,I}\theta^{M,I}}$	*0.1383*	*0.0619*	*-0.1005*	*0.3781*
$\sigma^2_{\theta^{M,I}}$	*0.7780*	*0.0942*	*0.4828*	*1.2500*
Firm Effects (Σ_E)				
$\sigma^2_{\alpha^{Y,E}}$	*0.3880*	*0.0364*	*0.2752*	*0.5575*
$\rho_{\alpha^{Y,E}\alpha^{M,E}}$	*0.0307*	*0.0496*	*-0.1442*	*0.2110*
$\rho_{\alpha^{Y,E}\theta^{Y,E}}$	*0.0817*	*0.0508*	*-0.1419*	*0.2653*
$\rho_{\alpha^{Y,E}\theta^{W,E}}$	*0.0045*	*0.0394*	*-0.1760*	*0.1549*
$\rho_{\alpha^{Y,E}\theta^{M,E}}$	*0.0076*	*0.0391*	*-0.1389*	*0.1528*
$\sigma^2_{\alpha^{M,E}}$	*0.4017*	*0.0331*	*0.2872*	*0.5747*
$\rho_{\alpha^{M,E}\theta^{Y,E}}$	*0.0755*	*0.0605*	*-0.1708*	*0.3101*
$\rho_{\alpha^{M,E}\theta^{W,E}}$	*0.0049*	*0.0391*	*-0.1419*	*0.1763*
$\rho_{\alpha^{M,E}\theta^{M,E}}$	*0.0048*	*0.0400*	*-0.1526*	*0.1551*
$\sigma^2_{\theta^{Y,E}}$	*0.4068*	*0.0351*	*0.2909*	*0.6404*
$\rho_{\theta^{Y,E}\theta^{W,E}}$	*0.0225*	*0.0358*	*-0.1194*	*0.1619*
$\rho_{\theta^{Y,E}\theta^{M,E}}$	*0.0482*	*0.0380*	*-0.1080*	*0.1970*
$\sigma^2_{\theta^{W,E}}$	*0.3836*	*0.0315*	*0.2789*	*0.5478*
$\rho_{\theta^{W,E}\theta^{M,E}}$	*0.0614*	*0.0536*	*-0.1225*	*0.2728*
$\sigma^2_{\theta^{M,E}}$	*0.4102*	*0.0367*	*0.2828*	*0.5709*

Table 21: Summary Statistics for women with a Technical College or Undergraduate University

		Year		
Variable	1976-1995	1976	1985	1995
Experience	*10.1013*	*5.9130*	*9.4643*	*15.4055*
	(9.2327)	*(7.4484)*	*(8.8420)*	*(9.4755)*
Seniority	*1.5574*	*1.8950*	*1.2973*	*2.5561*
	(4.2399)	*(4.4060)*	*(4.0910)*	*(4.9434)*
Log Wage	*4.1886*	*3.9877*	*4.1623*	*4.3309*
	(1.1883)	*(1.0424)*	*(1.1233)*	*(1.3408)*
Participation	*0.3695*	*0.2229*	*0.3589*	*0.5179*
	(0.4827)	*(0.4163)*	*(0.4798)*	*(0.4998)*
Mobility	*0.2437*	*0.1429*	*0.2488*	*0.0000*
	(0.4293)	*(0.3500)*	*(0.4325)*	*(0.0000)*
Children 0 to 2 years old	*0.1186*	*0.1262*	*0.1192*	*0.0680*
	(0.3233)	*(0.3321)*	*(0.3242)*	*(0.2518)*
Children 3 to 6 years old	*0.1006*	*0.0864*	*0.1308*	*0.0755*
	(0.3008)	*(0.2810)*	*(0.3372)*	*(0.2642)*
Married	*0.4545*	*0.2995*	*0.4591*	*0.5530*
	(0.4979)	*(0.4582)*	*(0.4985)*	*(0.4973)*
Unmarried Couples	*0.0520*	*0.0000*	*0.0213*	*0.1400*
	(0.2219)	*(0.0000)*	*(0.1445)*	*(0.3471)*
Located in "Île de France"	*0.1668*	*0.1094*	*0.1619*	*0.2350*
	(0.3728)	*(0.3123)*	*(0.3684)*	*(0.4241)*
Other than French	*0.1503*	*0.1400*	*0.1532*	*0.1526*
	(0.4423)	*(0.4288)*	*(0.4461)*	*(0.4456)*
Born before 1930	*0.0383*	*0.0426*	*0.0409*	*0.0248*
	(0.1920)	*(0.2021)*	*(0.1981)*	*(0.1555)*
Born between 1930 and 1939	*0.0806*	*0.0806*	*0.0806*	*0.0806*
	(0.2723)	*(0.2724)*	*(0.2724)*	*(0.2724)*
Born between 1940 and 1949	*0.2414*	*0.2414*	*0.2414*	*0.2414*
	(0.4279)	*(0.4280)*	*(0.4280)*	*(0.4280)*
Born between 1950 and 1959	*0.3923*	*0.3923*	*0.3923*	*0.3923*
	(0.4883)	*(0.4884)*	*(0.4884)*	*(0.4884)*
Born between 1960 and 1969	*0.1867*	*0.0478*	*0.2408*	*0.2408*
	(0.3897)	*(0.2134)*	*(0.4277)*	*(0.4277)*
Part Time	*0.7597*	*0.8514*	*0.7690*	*0.6688*
	(0.4273)	*(0.3558)*	*(0.4216)*	*(0.4708)*

Table 22: Participation Equation for Men with a Technical College or Undergraduate University degree

Variable	**Participation Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-0.4511*	*0.2428*	*-1.3845*	*0.4352*
Experience at $t-1$	*0.1309*	*0.0101*	*0.0947*	*0.1683*
Experience at $t-1$ squared	*-0.0031*	*0.0002*	*-0.0040*	*-0.0023*
Children 0 to 2 years old	*0.1457*	*0.0709*	*-0.1229*	*0.4192*
Children 3 to 6 years old	*-0.0856*	*0.0709*	*-0.3625*	*0.2005*
Married	*0.0444*	*0.0761*	*-0.2074*	*0.3503*
Located in "Île de France"	*6.2034*	*0.3286*	*5.2757*	*7.0578*
Other than French	*-0.4177*	*0.0926*	*-0.7160*	*-0.1073*
Mobility at $t-1$	*0.5425*	*0.0770*	*0.2574*	*0.8649*
Participation at $t-1$	*1.5984*	*0.0780*	*1.2218*	*1.8783*
Cohort Effect				
Born before 1929	*-2.7297*	*0.1527*	*-3.2792*	*-2.0985*
Born between 1930 and 1939	*-2.3065*	*0.1457*	*-2.9020*	*-1.7986*
Born between 1940 and 1949	*-2.0098*	*0.1206*	*-2.5336*	*-1.5481*
Born between 1950 and 1959	*-1.8795*	*0.1106*	*-2.2975*	*-1.4514*
Born between 1960 and 1969	*-1.6745*	*0.1486*	*-2.2924*	*-1.1158*
Unemployment rate	*3.5008*	*0.7591*	*0.6140*	*6.4364*
Time Effect				
Year 1977	*0.4057*	*0.2362*	*-0.4081*	*1.2599*
Year 1978	*0.4154*	*0.2351*	*-0.4749*	*1.3023*
Year 1979	*0.1770*	*0.2351*	*-0.6530*	*1.0245*
Year 1980	*0.3439*	*0.2368*	*-0.5651*	*1.1822*
Year 1981	*-0.7206*	*0.2363*	*-1.6296*	*0.2070*
Year 1982	*0.6725*	*0.2373*	*-0.2330*	*1.5864*
Year 1983	*-1.1395*	*0.2367*	*-2.0348*	*-0.2255*
Year 1984	*0.4882*	*0.2376*	*-0.3840*	*1.3718*
Year 1985	*-0.0873*	*0.2392*	*-0.9586*	*0.7859*
Year 1986	*-0.0516*	*0.2383*	*-0.9084*	*0.8288*
Year 1987	*-0.2241*	*0.2375*	*-1.1013*	*0.7002*
Year 1988	*-0.0984*	*0.2376*	*-0.9401*	*0.8109*
Year 1989	*0.0305*	*0.2373*	*-0.9065*	*0.8523*
Year 1990	*-1.0145*	*0.2372*	*-1.9160*	*0.0065*
Year 1991	*0.3278*	*0.2370*	*-0.6019*	*1.3515*
Year 1992	*-0.3164*	*0.2373*	*-1.2018*	*0.6473*
Year 1993	*-0.2735*	*0.2387*	*-1.1657*	*0.6825*
Year 1994	*-0.5378*	*0.2381*	*-1.4907*	*0.4623*
Year 1995	*-0.4354*	*0.2375*	*-1.3211*	*0.4621*

Table 23: Mobility Equation for Men with a Technical College or Undergraduate University degree

Variable	**Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*1.2519*	*0.4646*	*-0.5884*	*3.0806*
Experience at $t-1$	*0.0168*	*0.0138*	*-0.0294*	*0.0740*
Experience at $t-1$ squared	*-0.0004*	*0.0003*	*-0.0017*	*0.0006*
Seniority at $t-1$	*0.0177*	*0.0134*	*-0.0403*	*0.0672*
Seniority at $t-1$ squared	*-0.0007*	*0.0005*	*-0.0029*	*0.0013*
Children 0 to 2 years old	*-0.0055*	*0.0820*	*-0.3219*	*0.3373*
Children 3 to 6 years old	*0.1003*	*0.0793*	*-0.2451*	*0.4130*
Married	*0.0691*	*0.0881*	*-0.2517*	*0.3862*
Located in "Île de France"	*-0.2314*	*0.0797*	*-0.5027*	*0.1211*
Other than French	*-0.0650*	*0.0945*	*-0.4168*	*0.2766*
Unemployment rate	*0.7216*	*0.8763*	*-2.7283*	*4.4805*
Part time	*-0.5702*	*0.0770*	*-0.9166*	*-0.2459*
Mobility at t-1	*-0.0158*	*0.0642*	*-0.2391*	*0.2042*
Cohort Effect				
Born before 1929	*0.6455*	*0.4523*	*-1.1950*	*2.3575*
Born between 1930 and 1939	*0.5239*	*0.4212*	*-1.0196*	*2.0141*
Born between 1940 and 1949	*0.1711*	*0.4065*	*-1.3828*	*1.6220*
Born between 1950 and 1959	*-0.0401*	*0.4062*	*-1.6018*	*1.3610*
Born between 1960 and 1969	*-0.5018*	*0.4235*	*-2.1213*	*1.1517*
Time Effect				
Year 1977	*-0.3741*	*0.2525*	*-1.3989*	*0.5939*
Year 1978	*-0.3761*	*0.2507*	*-1.4304*	*0.5534*
Year 1979	*-0.2694*	*0.2498*	*-1.2755*	*0.6234*
Year 1980	*0.1553*	*0.2592*	*-0.8669*	*1.1274*
Year 1981	*0.3404*	*0.2656*	*-0.6054*	*1.3376*
Year 1982	*0.4988*	*0.2682*	*-0.6333*	*1.5334*
Year 1983	*0.4017*	*0.2645*	*-0.5763*	*1.3331*
Year 1984	*-0.2053*	*0.2457*	*-1.2118*	*0.8032*
Year 1985	*-0.1617*	*0.2461*	*-1.1447*	*0.8932*
Year 1986	*-0.2471*	*0.2461*	*-1.2260*	*0.6671*
Year 1987	*-0.2852*	*0.2457*	*-1.2616*	*0.6728*
Year 1988	*-0.0319*	*0.2470*	*-0.9226*	*0.8590*
Year 1989	*0.7744*	*0.2697*	*-0.2417*	*1.8964*
Year 1990	*0.3577*	*0.2580*	*-0.5415*	*1.3192*
Year 1991	*0.0851*	*0.2508*	*-0.8260*	*1.0606*
Year 1992	*0.0355*	*0.2518*	*-0.9659*	*1.0126*
Year 1993	*0.2987*	*0.2595*	*-0.6825*	*1.2245*
Year 1994	*0.2349*	*0.2591*	*-0.7487*	*1.2459*
Year 1995	*0.0013*	*0.9896*	*-3.9623*	*4.9080*

Table 24: Wage Equation for Men with a Technical College or Undergraduate University degree

Variable	Wage Equation			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*4.1059*	*0.0634*	*3.8450*	*4.3285*
Experience at t	*0.0430*	*0.0051*	*0.0245*	*0.0640*
Experience at t squared	*-0.0006*	*0.0001*	*-0.0010*	*0.0000*
Seniority at t	*0.0129*	*0.0043*	*-0.0024*	*0.0309*
Seniority at t squared	*-0.0002*	*0.0002*	*-0.0008*	*0.0004*
Children 0 to 2 years old	*0.0390*	*0.0338*	*-0.1260*	*0.1614*
Children 3 to 6 years old	*0.0612*	*0.0314*	*-0.0706*	*0.1758*
Married	*0.1276*	*0.0433*	*-0.0412*	*0.3116*
Unmarried Couples	*0.0745*	*0.0515*	*-0.1196*	*0.2822*
Located in "Île de France"	*0.1562*	*0.0394*	*-0.0229*	*0.3162*
Other than French	*-0.1086*	*0.0514*	*-0.3252*	*0.0728*
Part time	*-0.8948*	*0.0343*	*-1.0218*	*-0.7712*
Cohort Effect				
Born before 1929	*0.0705*	*0.0765*	*-0.2502*	*0.3997*
Born between 1930 and 1939	*-0.0113*	*0.0667*	*-0.3397*	*0.2386*
Born between 1940 and 1949	*0.0257*	*0.0602*	*-0.2308*	*0.2482*
Born between 1950 and 1959	*0.0647*	*0.0610*	*-0.1632*	*0.2842*
Born between 1960 and 1969	*0.0372*	*0.0723*	*-0.2249*	*0.3464*
Time Effect				
Year 1977	*-0.0625*	*0.0432*	*-0.2407*	*0.1043*
Year 1978	*-0.0396*	*0.0424*	*-0.1919*	*0.1271*
Year 1979	*-0.0448*	*0.0424*	*-0.2191*	*0.1160*
Year 1980	*-0.0505*	*0.0415*	*-0.2141*	*0.0990*
Year 1981	*0.0138*	*0.0448*	*-0.1681*	*0.2069*
Year 1982	*0.0128*	*0.0404*	*-0.1411*	*0.1814*
Year 1983	*0.0344*	*0.0450*	*-0.1723*	*0.2339*
Year 1984	*0.0405*	*0.0410*	*-0.1118*	*0.2179*
Year 1985	*0.0096*	*0.0410*	*-0.1358*	*0.1574*
Year 1986	*-0.0063*	*0.0409*	*-0.1675*	*0.1696*
Year 1987	*-0.0460*	*0.0408*	*-0.2382*	*0.1074*
Year 1988	*0.0689*	*0.0409*	*-0.1062*	*0.2448*
Year 1989	*0.0628*	*0.0411*	*-0.0987*	*0.2479*
Year 1990	*0.0638*	*0.0451*	*-0.1414*	*0.2304*
Year 1991	*0.0533*	*0.0426*	*-0.1132*	*0.2282*
Year 1992	*0.0552*	*0.0431*	*-0.1194*	*0.2346*
Year 1993	*0.0429*	*0.0439*	*-0.1254*	*0.2009*
Year 1994	*0.0700*	*0.0455*	*-0.1132*	*0.2441*
Year 1995	*0.0647*	*0.0467*	*-0.1109*	*0.2360*

Table 25: Initial Participation Equation for Men with a Technical College or Undergraduate University degree

Variable	**Initial Participation Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*-1.3192*	*0.1259*	*-1.8222*	*-0.8373*
Experience at t-1	*0.0664*	*0.0191*	*-0.0094*	*0.1459*
Experience at t-1 squared	*-0.0009*	*0.0006*	*-0.0033*	*0.0013*
Children 0 to 2 years old	*0.2238*	*0.1635*	*-0.4262*	*0.8726*
Children 3 to 6 years old	*0.1748*	*0.1813*	*-0.5837*	*0.9075*
Married	*0.7095*	*0.1405*	*0.1687*	*1.2251*
Located in "Île de France"	*3.4818*	*0.3943*	*2.3201*	*5.4107*
Other than French	*-0.0576*	*0.1219*	*-0.4790*	*0.3988*
Unemployment Rate	*-0.4415*	*0.9927*	*-4.5822*	*3.2558*

Table 26: Initial Mobility Equation for Men with a Technical College or Undergraduate University degree

Variable	**Initial Mobility Equation**			
	Mean	St. Dev.	Range	
			Min	Max
Constant	*0.6653*	*0.2731*	*-0.2784*	*1.7049*
Experience at t-1	*0.0018*	*0.0293*	*-0.1117*	*0.1121*
Experience at t-1 squared	*-0.0001*	*0.0008*	*-0.0031*	*0.0032*
Seniority at t-1	*-0.0934*	*0.0426*	*-0.2557*	*0.0768*
Seniority at t-1 squared	*0.0057*	*0.0023*	*-0.0044*	*0.0156*
Children 0 to 2 years old	*0.5791*	*0.2562*	*-0.4149*	*1.5705*
Children 3 to 6 years old	*0.5465*	*0.2759*	*-0.4915*	*1.6420*
Married	*0.4569*	*0.1913*	*-0.2621*	*1.1980*
Located in "Île de France"	*-0.0886*	*0.1695*	*-0.8890*	*0.6965*
Other than French	*0.1826*	*0.1871*	*-0.5271*	*0.9440*
Unemployment Rate	*0.0300*	*0.9891*	*-3.5822*	*3.7165*

Table 27: Variance-Covariance Matrix for Men with a Technical College or Undergraduate University degree

Variable	Variance-covariance Matrix Elements for Men with Technical College or Undergraduate University			
	Mean	St. Dev.	Range	
			Min	Max
Residual Variance (Σ)				
σ^2	*0.6481*	*0.0392*	*0.5204*	*0.8460*
ρ_{wm}	*0.0430*	*0.0237*	*-0.0456*	*0.1235*
ρ_{ym}	*-0.0190*	*0.0244*	*-0.1151*	*0.0728*
ρ_{yw}	*-0.0339*	*0.0272*	*-0.1274*	*0.0553*
Individual Effects(Σ_I)				
$\sigma^2_{\theta^{Y,I}}$	*1.2731*	*0.1110*	*0.9351*	*1.8381*
$\rho_{\theta^{Y,I}\theta^{W,I}}$	*0.2027*	*0.0475*	*0.0165*	*0.3782*
$\rho_{\theta^{Y,I}\theta^{M,I}}$	*-0.0656*	*0.0686*	*-0.3072*	*0.2219*
$\sigma^2_{\theta^{W,I}}$	*0.5705*	*0.0409*	*0.4203*	*0.8245*
$\rho_{\theta^{W,I}\theta^{M,I}}$	*-0.0446*	*0.0637*	*-0.2714*	*0.2064*
$\sigma^2_{\theta^{M,I}}$	*0.5933*	*0.0697*	*0.3820*	*0.8946*
Firm Effects (Σ_E)				
$\sigma^2_{\alpha^{Y,E}}$	*0.4485*	*0.0459*	*0.2993*	*0.6362*
$\rho_{\alpha^{Y,E}\alpha^{M,E}}$	*-0.0468*	*0.0503*	*-0.2193*	*0.1313*
$\rho_{\alpha^{Y,E}\theta^{Y,E}}$	*0.1004*	*0.0518*	*-0.1316*	*0.2866*
$\rho_{\alpha^{Y,E}\theta^{W,E}}$	*-0.0027*	*0.0383*	*-0.1434*	*0.1409*
$\rho_{\alpha^{Y,E}\theta^{M,E}}$	*0.0127*	*0.0389*	*-0.1569*	*0.1605*
$\sigma^2_{\alpha^{M,E}}$	*0.4122*	*0.0333*	*0.3088*	*0.5413*
$\rho_{\alpha^{M,E}\theta^{Y,E}}$	*-0.0010*	*0.0607*	*-0.2390*	*0.2503*
$\rho_{\alpha^{M,E}\theta^{W,E}}$	*-0.0015*	*0.0391*	*-0.1494*	*0.1497*
$\rho_{\alpha^{M,E}\theta^{M,E}}$	*0.0071*	*0.0392*	*-0.1299*	*0.1532*
$\sigma^2_{\theta^{Y,E}}$	*0.4421*	*0.0398*	*0.3129*	*0.6318*
$\rho_{\theta^{Y,E}\theta^{W,E}}$	*-0.0274*	*0.0363*	*-0.1638*	*0.1104*
$\rho_{\theta^{Y,E}\theta^{M,E}}$	*0.0593*	*0.0379*	*-0.0763*	*0.2105*
$\sigma^2_{\theta^{W,E}}$	*0.4056*	*0.0354*	*0.2924*	*0.5594*
$\rho_{\theta^{W,E}\theta^{M,E}}$	*-0.0215*	*0.0536*	*-0.2281*	*0.1724*
$\sigma^2_{\theta^{M,E}}$	*0.4180*	*0.0366*	*0.2942*	*0.5789*

Table 28: Descriptive Statistics for Men with a Technical College or Undergraduate University degree

Variable	1976-1995	Year		
		1976	1985	1995
Experience	*15.3394*	*9.6367*	*14.8724*	*21.4711*
	(11.1709)	*(9.5811)*	*(10.8165)*	*(10.5628)*
Seniority	*3.4495*	*4.4343*	*3.3245*	*3.3898*
	(6.7224)	*(6.6233)*	*(6.8343)*	*(6.3545)*
Log Wage	*4.8947*	*4.7004*	*4.8763*	*5.0370*
	(1.0876)	*(0.9809)*	*(1.0190)*	*(1.2383)*
Participation	*0.4916*	*0.4313*	*0.5217*	*0.5150*
	(0.4999)	*(0.4953)*	*(0.4996)*	*(0.4998)*
Mobility	*0.3636*	*0.3191*	*0.4074*	*0.0000*
	(0.4810)	*(0.4662)*	*(0.4914)*	*(0.0000)*
Children 0 to 2 years old	*0.1169*	*0.1552*	*0.1035*	*0.0462*
	(0.3213)	*(0.3621)*	*(0.3046)*	*(0.2100)*
Children 3 to 6 years old	*0.1074*	*0.1235*	*0.1441*	*0.0651*
	(0.3096)	*(0.3291)*	*(0.3513)*	*(0.2467)*
Married	*0.6033*	*0.4754*	*0.6144*	*0.6693*
	(0.4892)	*(0.4995)*	*(0.4868)*	*(0.4705)*
Unmarried couples	*0.0541*	*0.0000*	*0.0201*	*0.1517*
	(0.2262)	*(0.0000)*	*(0.1402)*	*(0.3588)*
Located in "Île de France"	*0.2170*	*0.1883*	*0.2334*	*0.2278*
	(0.4122)	*(0.3910)*	*(0.4230)*	*(0.4195)*
Other than French	*0.2272*	*0.2110*	*0.2313*	*0.2229*
	(0.5282)	*(0.5089)*	*(0.5321)*	*(0.5272)*
Born before 1930	*0.1118*	*0.1223*	*0.1174*	*0.0715*
	(0.3151)	*(0.3277)*	*(0.3220)*	*(0.2577)*
Born between 1930 and 1939	*0.1569*	*0.1569*	*0.1569*	*0.1569*
	(0.3637)	*(0.3638)*	*(0.3638)*	*(0.3638)*
Born between 1940 and 1949	*0.3095*	*0.3095*	*0.3095*	*0.3095*
	(0.4623)	*(0.4624)*	*(0.4624)*	*(0.4624)*
Born between 1950 and 1959	*0.2935*	*0.2935*	*0.2935*	*0.2935*
	(0.4554)	*(0.4554)*	*(0.4554)*	*(0.4554)*
Born between 1960 and 1969	*0.0956*	*0.0279*	*0.1162*	*0.1162*
	(0.2940)	*(0.1647)*	*(0.3206)*	*(0.3206)*
Part time	*0.5882*	*0.6661*	*0.5638*	*0.5699*
	(0.4922)	*(0.4717)*	*(0.4960)*	*(0.4952*

Figure 1: Posterior distributions - Women with a Vocational Technical Degree

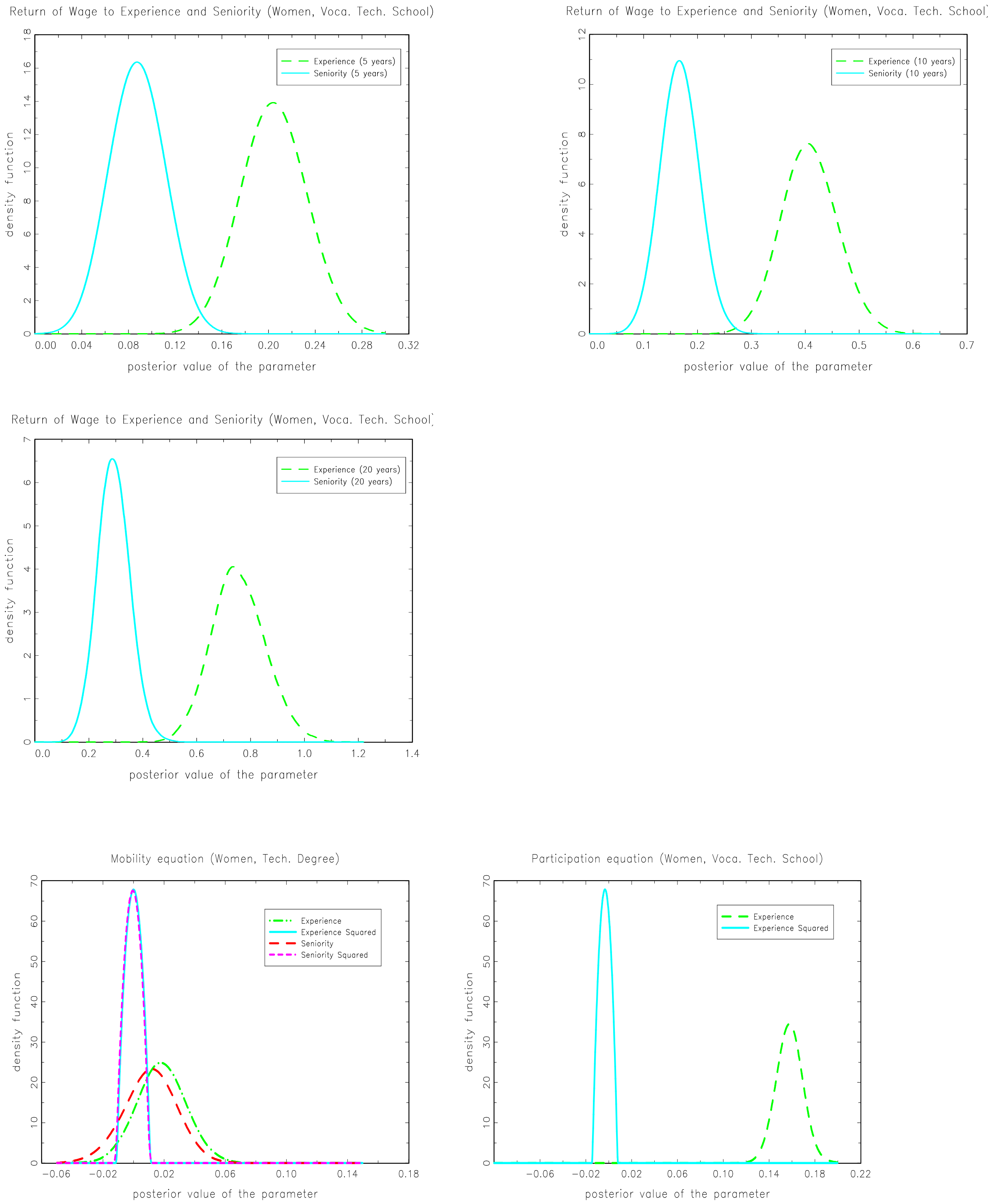


Figure 2: Posterior Distributions - Women with a Technical College or Undergraduate University degree

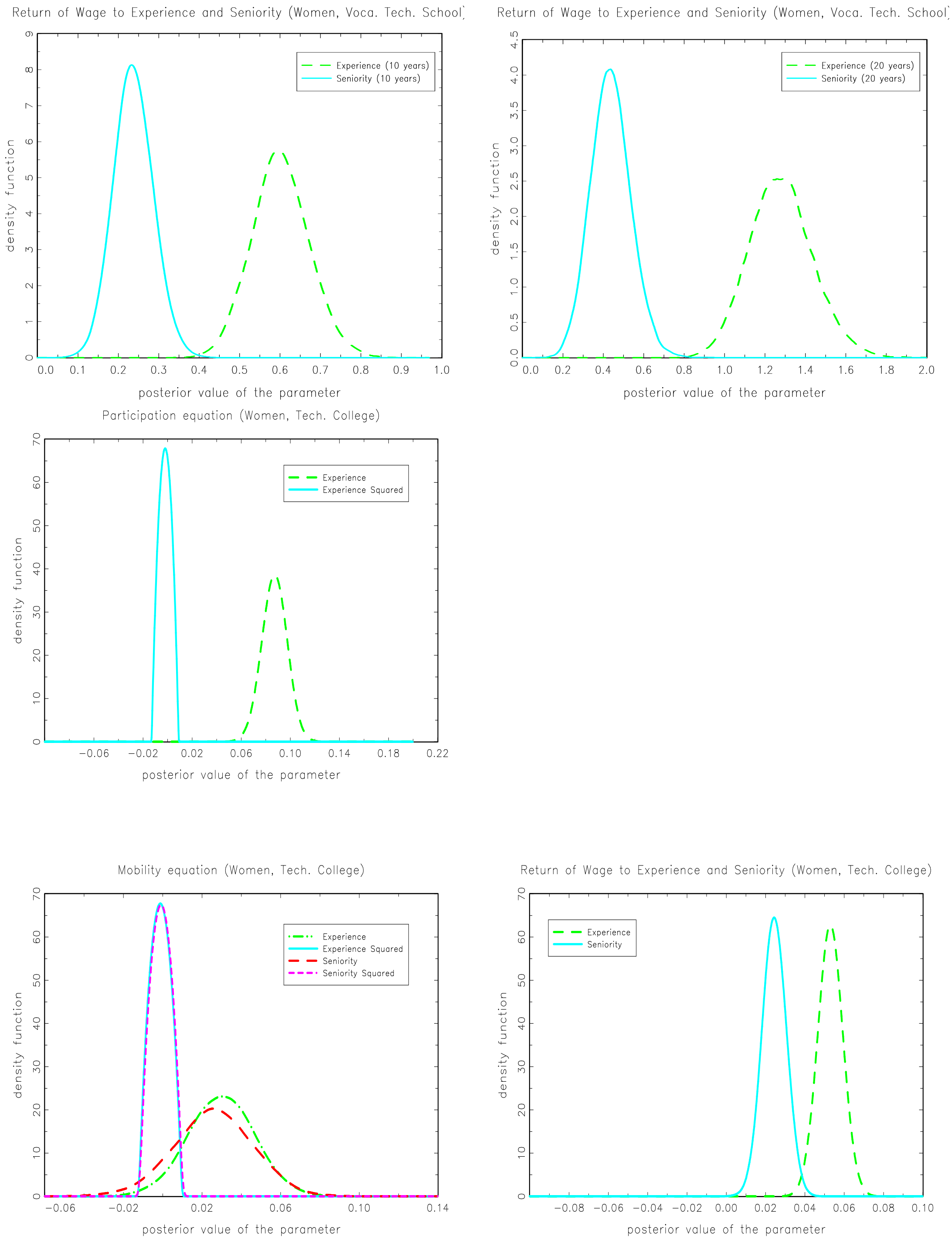


Figure 3: Posterior distributions - Men with a Vocational Technical Degree

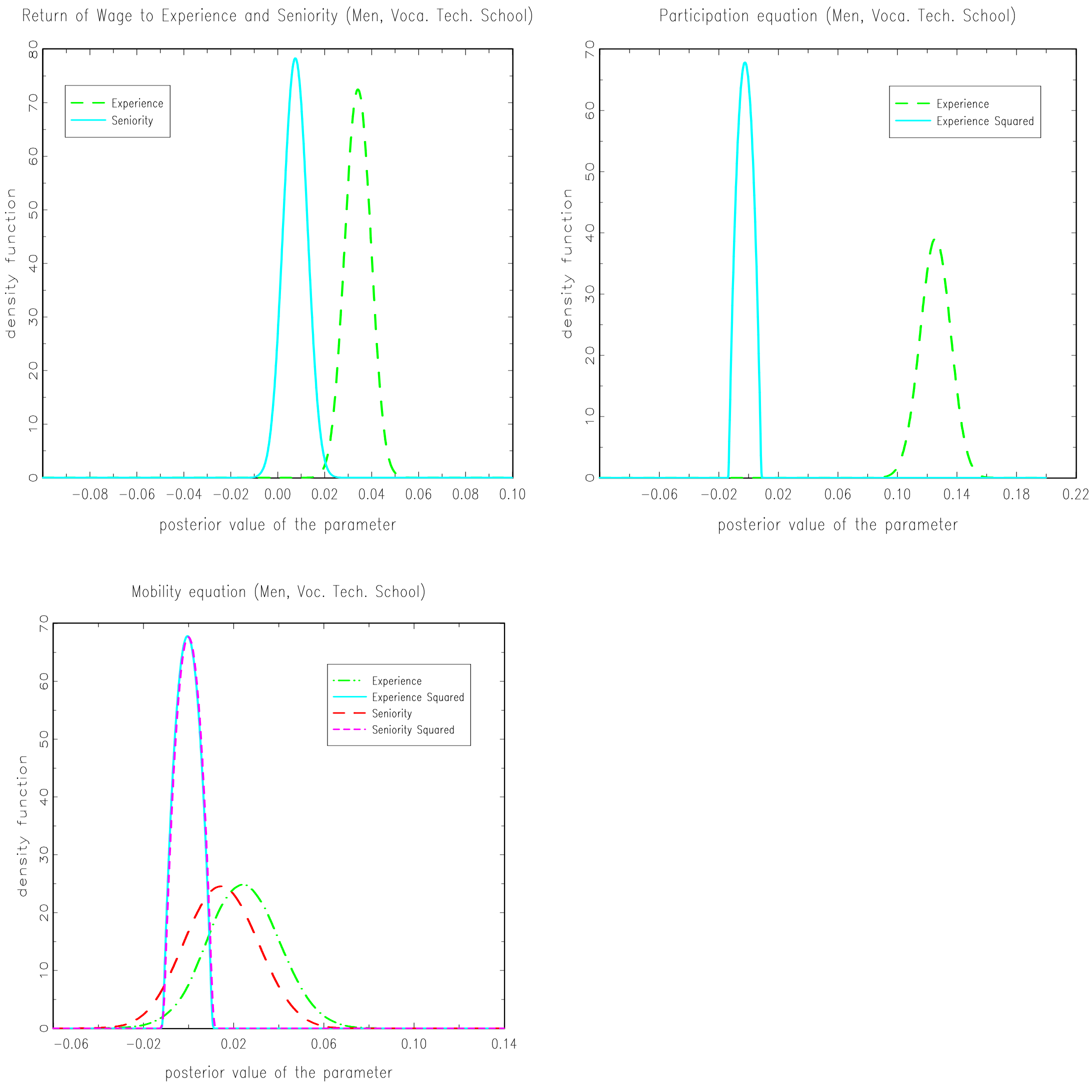
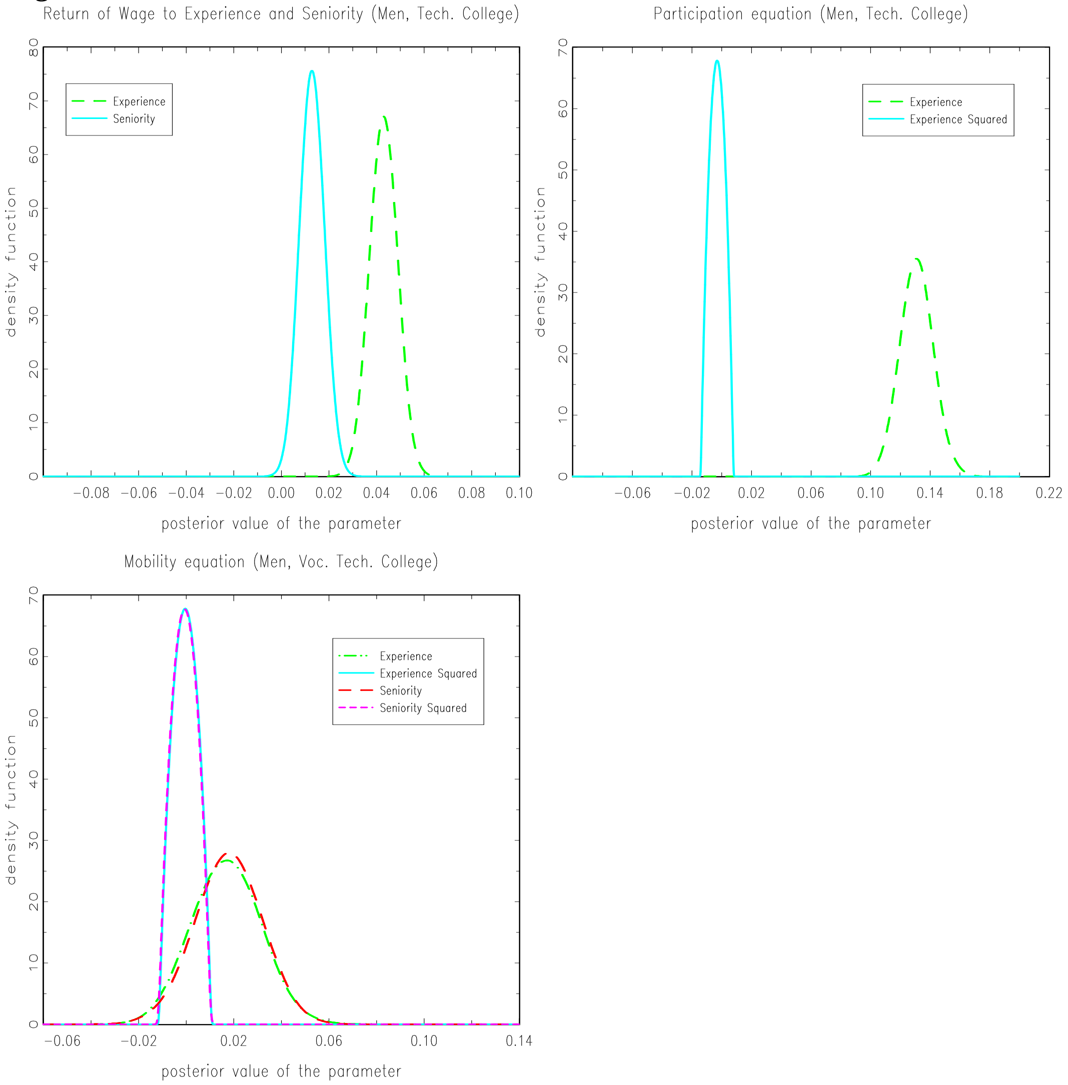


Figure 4: Posterior distributions - men with a technical college or undergraduate university degree



Chapitre 3

Is civil-servant human capital sector-specific?

1. Introduction

There has been an increasing interest in studying the public sector employment for more than two decades. This process was initiated by Smith (1977) and this is justified by the large share of public employment in total employment. Over that period of time, very few countries have seen this share decrease but for UK. For instance, in France, in 2006, this proportion amounts to one quarter of total employment, and it has been relatively stable since the beginning of the nineties (source OECD data). But this large part of the public sector employment may have adverse effects on private sector efficiency. Moreover a shortage of public sector workers can lead to difficulties, such as an excess can lead to fiscal outcomes.

In France, this interest has been renewed recently for budgetary reasons. On the one hand the French debt burden does not diminish, and on the other hand, the wage bill constitutes the largest item in the public sector spending. Furthermore the retirement of many public servants raises the following issue: should everyone departing be replaced? Is the cost of every public-servant job justified? The French government looks for efficiently spent money, hence every euro spent must be necessary and efficiently allocated. Hence public sector employment and wages come under close scrutiny. Therefore it is important to compare both public and private earnings.

However, few studies deal with the French case (Fougère and Pouget (2003), and Bargain and Melly (2008)). Fougère and Pouget (2003) concentrate on the main determinants of the entry into the public sector. Bargain and Melly (2008) focus on the public sector pay gap using quantile regressions on a short panel data set. This paper aims to contribute to the classical analysis of the public wage gap, especially in France. Do relationships between wages and wage determining factors differ by sector of work? Do public sector employees earn a premium? However usual the issue, the methods we develop extend some previous approaches.

Many recent studies rely on cross sectional switching regression, endogenous or not (see Disney and Gosling (1998) and Gyourko and Tracy (1988) for UK, Dustman and Van Soest (1998) for Germany, Hartog and Oosterbeek (1993) and Van Ophem (1993) for the Netherlands, Fougère and Pouget (2003) for France and Heitmueller (2006) for Scotland). Hartog and Oosterbeek (1993) stress that neglecting selectivity effects are likely to give a false picture of the relative earnings position of public-sector workers (see Goddeeris (1988)). Moreover, Dustman and Van Soest (1998) underlines that, even when the sector choice is controlled for, instruments must be chosen with particular care and exogeneity assumptions can lead to different results. In a different way, Heitmueller (2006) controls for participation and sector selections, but in cross-sectional analysis.

In order to overcome these potential biases, Disney and Gosling (2003) uses the natural experiment that happened in the UK in the nineties with the privatization programme. And they show that their results are robust to self-selection. Bargain and Melly (2008) use panel data to control for both sector choice and individual fixed effects, and compare the quantiles of both distributions. Raising close but different issues, Bell, Elliott, and Scott (2005) exploit the mobility between both sectors, and study the wage incentives to change sectors. They identify the wage premium after a job change. Other studies focus on the link between the wage distribution and mobility. Postel-Vinay and Turon (2007) and Cappellari (2002) focus on earnings dynamics and lifetime values of employment in both sectors. They argue that public and private sectors differ not only in their log wage distribution but also in their income mobility. They conclude, for UK and resp. for Italy, that life cycle of earnings matters in the private sector whereas it does not in the public sector.[1]

In this paper, the way we proceed is more in line with Dustman and Van Soest (1998) such as Heitmueller (2006). We extend their approach by considering a panel framework, controlling both for self-selection -people do choose to work in the public sector - and employment -people choose to participate. We question the earnings differences by modeling the double selection i.e. employment and sector choice, and we account for unobserved heterogeneity by using the method of Heckman and Singer (1984). Unobserved heterogeneity allows us to control for individual tastes, and individual abilities. Moreover, we observe each individual for 8 years, ensuring convergence properties that can not be ensured with the method used by Bargain and Melly (2008), based on quantile regressions, as the LFS surveyed identical people at most three times.

We answer the following issue: do people who work in the public sector have a different

[1]Another trend of the literature on public/private differences concerns queue models (Venti (1987), Heywood and Mohanty (1995) and Fougère and Pouget (2003)) and analysis the individual propensity to seek employment in public sectors. But these models require very detailed information about the offer and the demand for public jobs. Furthermore, they are very sensitive to the instruments chosen and it turns out difficult to share and identify the characteristics determining the search for a public job from those determining the access to a public job (more risk adverse workers in the public sector -see Bellante and Link (1981), but maybe a *taste* for public services -see Goddeeris (1988)).

propensity to get high wages or low wages given their educational level and other characteristics? Moreover we analyze the sector selection.[2] We find that mimicking the parents is determinant and as expected, that the public sector attracts more people when the local labor market is depressed.

We also find that there exists a wage public premium at the bottom of the public wage distribution, whereas it is not true at the upper tail. These results are in line with empirical observations: low-wage civil-servants are weakly mobile, whereas high-wage civil servants move more frequently from the public to the private sector.

Further, the female public-sector workers have a comparative advantage in the public sector. Their counterfactuals wages in the private sector are lower than their current wages. Unlike women, men would have higher wages in the private sector excepted at the bottom of the distribution. For men, this wage gap worsens with the education level; in the case of graduated women, the public wage premium is closer to zero. These results may reflect that motivations underlying sector choice differ between men and women.

Finally we find that wage differences between the public and the private sectors result from three factors: first the raw mean is greater in the public sector, second the returns to different observable characteristics differ between both sectors (for instance, for most of them, degrees are better rewarded in the private sector), finally the unobserved productivity civil-servants would have in the private sector is a bit inferior to the one they have in their current occupation. Unlike them, a part of the workers employed in the private sector seem to acquire specific human capital, that they could not transfer to the public sector.

The paper is structured as follows: in the next section, the structural model is presented. Section 3 reports a descriptive analysis of the data. Section 4 describes the econometric model and the estimation methods. Sections 5 and 6 discuss results and simulations. Finally section 8 concludes.

2. The Search Model

We derive a continuous time search model in a stationary labor market environment. There are three possible states: employment in the public sector, employment in the private sector and

[2] We use parental background information to ensure identification of the sector choice equation following Dustman and Van Soest (1998) advice.

nonemployment. The individuals employed in the private sector can be laid off, and they may search for a private job even when they are employed. Those employed in the public sector do not search for a job and can not be laid off. This is justified by the fact that in France, a public servant can not be laid off. A public employee can be fired only in very few cases, the rules of which greatly differ from private-sector ones (disciplinary sanctions in the public sector). Hence firings in the public sector are neglected. Finally the nonemployed may search either for a public or for a private job.

Agents are infinitely alive. At each point in time, they can be either nonemployed (denoted by n, i.e. unemployed or out of the labor force), or employed either in the private sector (denoted by Pr) or in the public sector (denoted by Pu). Unemployment and nonparticipation are assumed to be non distinct labor force states. This assumption is not restrictive since we focus on the choice between the public and the private sector and the data set is restricted to people under 60. Nonemployed individuals enjoy a real return b and receive job offers at a Poisson rate depending on the sector of research $\lambda_{n,Pr}$ and $\lambda_{n,Pu}$. b may represent unemployment benefit or private rents. Nonemployed individuals support research costs depending on the type of job they search for: c_{Pr} (resp. c_{Pu}) for private jobs (resp. for public jobs). They can decide to restrict their research to private jobs. Agents who decide to search for a job in the public sector can fail to enter public services although they get a public offer since they have to succeed the entrance exam to become a civil servant. p_S denotes the probability to succeed conditional on searching for a job in this sector, and it implicitly depends on individual covariates.

When employed in the private sector, individuals receive a real wage w, and they continue to receive private job offers at a Poisson rate $\lambda_{Pr,Pr}$. They are assumed to restrict their job research to the private sector and they face search costs c.[3] Existing private jobs are hit by idiosyncratic (productive) shocks that occur at a Poisson rate δ. The instantaneous discount rate is ρ and the horizon is infinite. This assumption implies that an individual can not transit directly from the private to the public sector, he has to go through an unemployment period.

Finally, when employed in the public sector, agents can not search for a private job. We detail later what the consequences of this assumption are.

[3]To search for a public job requires a lot of time since entrance exams need preparation.

F_{Pr} denotes the wage distribution in the private sector on $[0, \overline{w}]$, F_{Pu} in the public sector on $[0, \overline{w}]$. We assume that these distributions are different from one another but that they rely on the same finite support for sake of simplicity. But the tails of the distributions can be far different (see the empirical part for some illustration, figure 1).

In the sequel V denotes the value function.

A worker currently employed in the public sector with starting wage w receives net income w and cannot loose his job. He receives no external nor internal offer. His function value is

$$V_{Pu}(w) = \frac{w\Delta t}{1+\rho\Delta t} + \frac{V_{Pu}(w)}{1+\rho\Delta t}, \tag{2.1}$$

which yields

$$V_{Pu}(w) = \frac{w}{\rho}. \tag{2.2}$$

A worker currently employed in the private sector receives a net income $w - c$ and may be forcibly separated from his job with probability δ. He also receives private job offers at rate $\lambda_{Pr,Pr}$ which are accepted when their value exceeds the expected discounted lifetime utility stream in the current job:

$$\begin{aligned} V_{Pr}(w) &= \frac{(w-c)\Delta t}{1+\rho\Delta t} + \delta\frac{V_n\Delta t}{1+\rho\Delta t} + (1-\delta\Delta t - \lambda_{Pr,Pr}\Delta t)\frac{V_{Pr}(w)}{1+\rho\Delta t} \\ &+ \frac{\Delta t\lambda_{Pr,Pr}}{1+\rho\Delta t}\int_0^{\overline{w}} \max\left(V_{Pr}(x), V_{Pr}(w)\right) dF_{Pr}(x), \end{aligned}$$

which can be simplified in

$$\begin{aligned} V_{Pr}(w)\,(\rho+\delta) &= w - c + \delta V_n \\ &+ \lambda_{Pr,Pr}\int_w^{\overline{w}} \left(V_{Pr}(x) - V_{Pr}(w)\right) dF_{Pr}(x). \end{aligned} \tag{2.3}$$

A currently nonemployed person enjoys a net flow of income $b - c - d_{Pu}c_{Pu}$ depending on her choice to search for a public job ($d_{Pu} = 1$) or not ($d_{Pu} = 0$).

$$V_n^{d_{Pu}} = \frac{(b-c-d_{Pu}c_{Pu})}{1+\rho\Delta t}\Delta t + \frac{\Delta t}{1+\rho\Delta t}\lambda_{n,Pr}\mathbb{E}_{F_{Pr}}\left(\max\left(V_n, V_{Pr}(x)\right)\right)$$

$$+\frac{\Delta t}{1+\rho\Delta t}\lambda_{n,Pu}d_{Pu}\mathbb{E}_{F_{Pu}}\left\{\max\left(V_n, p_S V_{Pu}(x)+(1-p_S)V_n\right)\right\}$$
$$+\frac{1}{1+\rho\Delta t}\left(1-\lambda_{n,Pr}\Delta t-\lambda_{n,Pu}d_{Pu}\Delta t\right)V_n. \tag{2.4}$$

For the nonemployed, the optimal acceptance rule consists in accepting the first job, whatever the sector, that pays more than a reservation wage w^* that is specific to the sector: w^*_{Pu} for the public sector and $w^{*,d_{Pu}}_{Pr}$ for the private sector ($w^{*,d_{Pu}=1}_{Pr}$ denotes the reservation wage when the unemployed search for both public and private jobs, $w^{*,d_{Pu}=0}_{Pr}$ when the unemployed search only for private jobs).

$$\begin{aligned} d_{Pu}\in\{0,1\} \quad V_{Pr}(w^{*,d_{Pu}}_{Pr}) &= V^{d_{Pu}}_n \\ V_{Pu}(w^*_{Pu}) &= V^{d_{Pu}=1}_n. \end{aligned}$$

These reservation wages exist and are unique because the private and public value functions are continuous and increasing functions. Therefore the equation (2.4) can be rewritten:[4]

$$\begin{aligned} \rho V^{d_{Pu}}_n &= (b-c-d_{Pu}c_{Pu})+\lambda_{n,Pr}\int_{w^*_{Pr}}^{\overline{w}}\left(V_{Pr}(x)-V_n\right)dF_{Pr}(x) \\ &\quad +\lambda_{n,Pu}d_{Pu}p\int_{w^*_{Pu}}^{\overline{w}}\left(V_{Pu}(x)-V_n\right)dF_{Pu}(x). \end{aligned} \tag{2.5}$$

When does a nonemployed worker decide to search for a public job? Searching for a public job is actually costly and risky since individuals are not sure to succeed to enter public services. This cost of searching for a public job is induced by the fact that individuals have to pick up information, to prepare entrance exams, and by the fact that they anticipate private sector opportunities. Hence nonemployed will search for a public job when their expected gains, which may depend on individual characteristics and unobserved ability, exceed the cost of searching

[4]Note that $\max(x, zp+(1-p)x)=p\max(x,z)+(1-p)x$ with $p\in]0,1[$

(see figure (6)). So $d_{pu} = 1$ when:[5]

$$\begin{aligned} c_{Pu} &\leq p_S \frac{\lambda_{n,Pu}}{\rho} \int_{h(w^*_{d=0})}^{\overline{w}} \overline{F}_{Pu}(x)dx, \\ \text{where} \quad & p_S \frac{\lambda_{n,Pu}}{\rho} \int_{h(w^*_{d=0})}^{\overline{w}} \overline{F}_{Pu}(x)dx = \mathcal{U}_{pu} \\ \text{and} \quad & h(w^*_{d=0}) \text{is a function of } \left(b, \lambda_{n,Pr}, \lambda_{Pr,Pr}, \overline{w}, \rho, \delta, \overline{F}_{Pr}\right). \end{aligned} \tag{2.6}$$

$h(w^*_{d=0})$ can also be written as

$$h(w^*_{d=0}) = \frac{\lambda_{n,Pr}}{\lambda_{n,Pr} - \lambda_{Pr,Pr}} w^*_{d=0} - c - \frac{\lambda_{Pr,Pr}}{\lambda_{n,Pr} - \lambda_{Pr,Pr}} b \tag{2.7}$$

The probability to search for a public job is $\mathbb{P}\left(c_{Pu} \leq \mathcal{U}_{pu}\right)$. When the cost of searching for a public job is greater than $\mathcal{U}_{pu}$, the nonemployed had rather search for a private job only. $\mathcal{U}_{pu}$ depends on individual characteristics, on the probability of passing the exam and finally, on the reservation wage via $h(w^*_{d=0})$.

Equation (2.6) entails that the value of the threshold, determining the search for a public job, is lower when the probability to succeed the entrance exams decreases or when the public offer is lower. $\mathcal{U}_{pu}$ depends on $\lambda_{n,Pu}$ and p_S in a multiplicative way, since $h(w^*_{d=0})$ does not depend on these variables.

The model teachings

First, the higher the probability to pass the exam, the higher the probability to search for a public job. This feature is empirically illustrated by the fact that individuals with higher degree are more likely to pass the exam. For instance, among individuals who take the "*CAPES*" exam (entrance exam for high-school and secondary school) in 2006, 53.2% have a "*licence*" degree and 44.0% a "*maîtrise*" (which requires an additional year of studies). And when considering those who pass the exam, the proportions switch: 57.8% who pass the exam have a maîtrise and 40.7% a licence. Similar features hold for other public-sector exams.

An unemployment growth is captured by the parameter δ. And $h(w^*_{d=0})$ depends on δ

[5] Details are in appendix A

only by the way of $w^*_{d=0}$, and $w^*_{d=0}$ diminishes when δ grows (see equation (2.7)). Hence the probability to search for a public job increases with δ.

The possible limits of the model

This model presents several limits: unemployed and nonparticipants are not distinguished. As the sample is composed of people aged between 17 and 59, largely economically active, this assumption is not very restrictive. Furthermore, the model assumes that public workers can not search for a private job. This assumption is made for sake of simplicity but if relaxed, our core results would not be modified. The function value associated to the public sector would be larger, since more flexible as the French civil servants would be able to work a few years in the private sector and get back to public services. Henceforth they could not suffer from their private-job experience: even if laid off, they could recover a job in public services. In such a case, their wage would be the wage they had when departing for a private experience.

Finally the model does not take into account possible parental or sabbatic leaves for civil servants. Moreover we do not enable direct transitions from the public to the private sector, and vice versa. These limits would modify both the public and the private function values but the core results would not change.

3. The data

3.1. A brief description

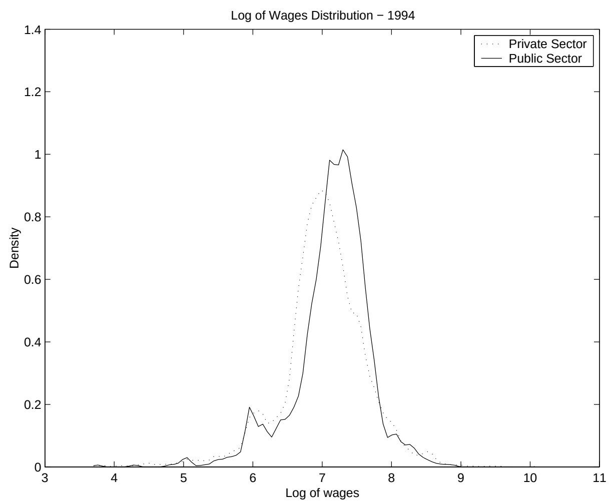
The data used are taken from the French European Household Survey which was set up by the European Union via Eurostat. This survey analyzes and follows the wage and employment dynamics. Individuals were interviewed annually over 8 years, from 1994 to 2001.

In the following, we consider a balanced panel. The individuals who work, but for whom the wage is not declared, are excluded. Self-employed workers and unpaid workers in a family business are also excluded. Finally the data consist in $5,092$ individuals, between 16 and 59, who are followed from 1994 to 2001.

Further, we consider the highest education degree instead of the educational level. In France, civil-servant exams are actually conditional on degrees and not on a certain number of years of studying. The activity sector is declared by individuals. We consider that they work in the public sector when they answered that they work for state or local governments. Otherwise, they are said to work in the private sector, namely that they are employed by national or private firms, or by their own firm.[6]

The French European Household survey provides annual wage earnings and a monthly description of the occupation but it does not provide the specific wage of the job occupied during the month of the interview. We divide the annual wage earnings by the total number of months employed during the year. In order to get an accurate estimate for this monthly wage, cautiousness is required when people had two jobs or more in a given year, but this actually concerns less than 5% of the employed people in a given year. Hence, for these people, we divide the annual wage earnings by the number of months they are employed whatever the number of jobs they got throughout the year. When there is a single employment spell in a year, no problem arises, since the data set distinguishes benefits from wages. Finally, monthly wages are assessed in euros at 1994 prices.

Figure 1 Density of the log of wages in 1994.



3.2. Some descriptive statistics on balanced data

The initial sample (without age restriction) contains half nonemployed people and half employed people. Logically the sample restricted to people aged less than 60 over-represents

[6]There is no cross-validation of their employment status as in Card (1996) and the different public services can not be distinguished.

employed people (table (1)). In the data set, the public sector is over represented compared to usual national statistics. The public sector amounts to one third of employed people, versus one fourth for national statistics. This can be due to the fact that short-term jobs in public services may be occupied by individuals who declare themselves as civil servants, and who are not. And this over representation of civil-servants is not due to the balanced panel, as this proportion is also higher when assessed on the non balanced data set.

The proportion of female is traditionally higher in the public than in the private sector, since it is easier to conciliate professional and family lives while employed in public sectors (table (2)). Few foreigners work in the public sector because entrance exams often require French citizenship. Entrance exams also require a minimum level of degree and a certain age, so degree distribution differs within sectors. There are less graduates in the private sector compared to the public one, and there are less high-school drop-outs. The same remarks hold for the age distribution.

The log monthly wage variance is lower in the public sector than in the private one whatever the degree considered. The log monthly wage mean is also higher in the public sector when degree is not controlled for, see (figure (1), appendix B). When degree is controlled for, this still holds for high-school dropouts and vocational technical degrees, but this mean wage is roughly equivalent in both sectors for high-school graduates, and university degrees seem to be less rewarded in the public sector. The public sector would play an insurance role for lower degrees, it would protect them from too low wages and it would guarantee them a lower variance. As descriptive statistics do not control for selectivity, the model we estimate goes one step further. It controls for participation selection and sector choice, such as unobserved and observed heterogeneity: age, experience,[7] region, number of children less than 3 years old, between 3 and 6...

Finally consider some figures about transitions. From 1994 to 2001, 816 individuals are nonemployed, and $2,384$ are employed. Over these $2,384$ individuals, 775 are employed in public services, and $1,544$ are employed in the private sector. Moreover, $4,276$ individuals are employed at least once throughout this period. Few direct transitions from the public to the private sectors and from the private to the public sectors are observed: 93 transitions from the public to the private sector over the whole period (experienced by 92 individuals), against

[7]Experience can not be precisely measured in the data set. Hence it is assessed by age minus age at the end of studies. It is a proxy for general experience and not for sector-specific experience.

67 from the private to the public sector (experienced by 67 individuals). 217 individuals are employed at least one period in the public sector and at least one period in the private sector. 334 individuals previously employed in the public sector become non-employed, which confirms that very few individuals transit from public employment to nonparticipation.

Table 1 Nonemployment, employment in public and private sectors.

Activity status	1994	1995	1996	1997	1998	1999	2000	2001
Non Employed	1,692	1,653	1,663	1,671	1,655	1,637	1,692	1,740
	(33%)	(32%)	(33%)	(33%)	(32%)	(32%)	(33%)	(34%)
Employed	3,400	3,439	3,429	3,421	3,437	3,455	3,400	3,352
	(67%)	(68%)	(67%)	(67%)	(68%)	(68%)	(67%)	(66%)
Sector								
Public	1,061	1,084	1,086	1,057	1,052	1,042	1,014	993
	(31%)	(32%)	(32%)	(31%)	(31%)	(30%)	(30%)	(30%)
Private	2,339	2,355	2,343	2,364	2,385	2,413	2,386	2,359
	(69%)	(68%)	(68%)	(69%)	(69%)	(70%)	(70%)	(70%)

Source: French European Household.

4. Econometric model and estimation principles

4.1. Model

The structural model described above confirms that the sector choice equation can be modeled by a binary variable: nonemployed search for both public and private jobs when $c_{Pu} \leq \mathcal{U}_{pu}$. And this threshold depends on explanatory variables such as individuals covariates and local unemployment rate.

In addition to the sector choice equation, we consider an employment equation, and a switching wage equation. Hence the reduced form model is composed of four equations. The first one describes employment, namely the fact that the individual works or not ($y_{it} = 1$ if the individual works). The second one describes the sector choice: public versus private ($z_{it} = 1$ when the individual works in the private sector, $z_{it} = 0$ otherwise). Finally, the third (resp. fourth) equation is the log monthly wage in the private sector w_{it}^{Pr}(resp. public sector w_{it}^{Pu}).

$$y_{it} = \mathbb{I}\left(X_{it}^{Y}\beta^{Y} + \theta_{i}^{Y} + u_{it}^{Y} > 0\right) \quad (4.8)$$

Table 2 General descriptive statistics

	Whole Sample		Private Sector		Public Sector	
	Number	Percent	Number	Percent	Number	Percent
Gender						
Women	2,750	54.01	955	40.83	628	59.19
Men	2,342	45.99	1,384	59.17	433	40.81
Nationality						
French	4,887	95.97	2,220	94.91	1,053	99.25
Not French	205	4.03	119	5.09	8	0.75
Region						
Paris	698	13.71	351	15.01	170	16.02
Out of Paris	4,394	86.29	170	84.99	891	83.98
Age						
16-29	1,442	28.32	555	23.73	170	16.02
30-39	1,395	27.40	742	31.72	340	32.05
40-49	1,378	27.06	741	31.68	372	35.06
50-59	877	17.22	301	12.87	179	16.87
Highest diploma						
No secondary degree	1,838	36.10	742	31.72	276	26.01
Vocational technical school (Basic)	1,449	28.46	851	36.38	242	22.81
High school degree (general or vocational)	745	14.63	308	13.17	143	13.48
Technical College, undergraduate university, or *Licence*, *Maitrise*	765	15.02	299	12.78	270	25.45
Graduates	295	5.79	139	5.94	130	12.25
Part-time	541	15.9	360	15.4	181	17.1

The statistics given above are assessed on the first year 1994.
Source: French European Household.

And if the individual works,

$$z_{it} = \mathbb{I}\left(X_{it}^{Z}\beta^{Z} + \theta_i^{Z} + u_{it}^{Z} > 0\right) \quad (4.9)$$

$$w_{it}^{Pr} = z_{it}\left(X_{it}^{Pr}\beta^{Pr} + \theta_i^{Pr} + u_{it}^{Pr}\right) \quad (4.10)$$

$$w_{it}^{Pu} = (1 - z_{it})\left(X_{it}^{Pu}\beta^{Pu} + \theta_i^{Pu} + u_{it}^{Pu}\right) \quad (4.11)$$

where

$\theta = \left(\theta^{Y}, \theta^{Z}, \theta^{Pr}, \theta^{Pu}\right)$ denotes the vector of the unobserved heterogeneity components,

$X = \left(X^{Y}, X^{Z}, X^{Pr}, X^{Pu}\right)$ denotes the vector of the observable characteristics,

$\beta = \left(\beta^Y, \beta^Z, \beta^{Pr}, \beta^{Pu}\right)$ denotes the vector of parameters,

$u = \left(u^Y, u^Z, u^{Pr}, u^{Pu}\right)$ denotes the vector of residuals, which are assumed to be independent and normally distributed across time and individuals, with variance σ^2_{Pr} (resp. σ^2_{Pu}).[8]

As unobserved heterogeneity is crucial to understand different economic behaviors and unobserved productivity, we integrate unobserved terms in each equation. And following the method of Heckman and Singer (1984), we model unobserved heterogeneity θ via a discrete random variable whose distribution has a given number of support points and has to be estimated. The model is estimated using an EM algorithm and standard errors are obtained by a parametric bootstrap. The effects of unobservables on wages vary between public and private sectors. It means that an individual may have a sector specific ability and his unobserved ability will be differently rewarded.

The model does not include lagged dependent variables. It could be included to capture state dependence. In such a case, the introduction of initial conditions could be solved using the method proposed by Wooldridge (2005) or the one proposed by Heckman (1981). This would entail to compute the likelihood recursively, conditional on the initial conditions. Finally, the model is estimated on a balanced panel, it could have been estimated easily on an unbalanced one.

4.2. Likelihood and estimation principles

We do not use *Simulated Maximum Likelihood* to estimate the model, since it is too time consuming and presents convergence failures. Even with precise and accurate initial conditions, the program fails to converge quickly and it seems to get trapped in some regions.

Instead of that, as previously mentioned, we follow the method proposed by Heckman and Singer (1984) and we consider a discrete distribution for the heterogeneity terms. The heterogeneity is modeled by K distinct types $(\theta_1, \theta_2, ..., \theta_K)$ with $\theta_k = \left(\theta_k^Y, \theta_k^Z, \theta_k^{Pr}, \theta_k^{Pu}\right)'$. Let π_k denote the unconditional probability that an individual belongs to the type k. As it is usual for finite mixture distributions, we rely on the Expectation-Maximization (EM) algorithm (Dempster, Laird, and Rubin (1977)) to estimate the model.

[8] The assumption of independence across residuals is not restrictive since we follow Heckman and Singer (1984) to model the unobserved heterogeneity, see also Cameron and Heckman (1998) and Arcidiacono (2005).

This algorithm iterates the two following steps until the stability of the log-likelihood (for detailed explanations, see appendix C). At each iteration n of the algorithm, we use the values π_k^n and the values $(\theta_1^n, \theta_2^n, ..., \theta_K^n)$ of the mixture distribution, and the values $\left(\beta^n, \sigma_{Pu}^{2,n}, \sigma_{Pr}^{2,n}\right)$ of the parameters of interest.

E-step

For each type $k = 1, ..., K$ and each individual i, the posterior probability of type k is:

$$\mathbb{P}\left(T_i = k | \underline{y}_i, \underline{z}_i, \underline{w}_i\right) = \frac{\pi_k \mathbb{P}(\underline{y}_i, \underline{z}_i, \underline{w}_i | T_i = k)}{\sum_{l=1}^K \pi_l \mathbb{P}(\underline{y}_i, \underline{z}_i, \underline{w}_i | T_i = l)}. \tag{4.12}$$

where T_i is the random variable representing the type of the individual i. $\pi_{ik}^{(n)}$ denotes these posterior probabilities.

M-step

The expected completed log likelihood is maximized:

$$\max_{\substack{\beta, \sigma_{Pu}^2, \sigma_{Pr}^2, \\ (\pi_k)_{k=1,...,K}, \\ (\theta_k)_{k=1,...,K}}} \sum_{i=1}^N \sum_{k=1}^K \pi_{ik}^{(n)} \ln l \left(\underline{y}_i, \underline{z}_i, \underline{w}_i | T_i = k, \beta, \sigma_{Pu}^2, \sigma_{Pr}^2, (\pi_k)_{k=1}^K, (\theta_k)_{k=1}^K\right) \tag{4.13}$$

First $\pi_k^{(n)}$ is updated such that:

$$\pi_k^{(n+1)} = \frac{\sum_{i=1}^N \pi_{ik}^{(n)}}{\sum_{l=1}^K \sum_{i=1}^N \pi_{il}^{(n)}} \tag{4.14}$$

Second the following three optimization problems are solved separately, thanks to the separability of the conditional completed log-likelihood (see Appendix C).

1. Optimization on the employment equation parameters

$$\begin{aligned} \max_{\beta^Y, (\theta_k^Y)_{k=1}^K} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T \quad & \pi_{il}^{(n)} \mathbb{I}_{y_{it}=0} \ln \Phi\left(-X_{it}^Y \beta_Y - \theta_k^Y\right) \\ + \quad & \pi_{il}^{(n)} \mathbb{I}_{y_{it}=1} \ln \Phi\left(X_{it}^Y \beta_Y + \theta_k^Y\right), \end{aligned}$$

2. Optimization on the sector choice equation parameters

$$\max_{\beta^Z,(\theta_k^Z)_{k=1}^K} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T \quad \pi_{il}^{(n)} \mathbb{I}_{y_{it}=1,z_{it}=0} \ln \Phi\left(-X_{it}^Z \beta_Z - \theta_k^Z\right) + \pi_{il}^{(n)} \mathbb{I}_{y_{it}=1,z_{it}=1} \ln \Phi\left(X_{it}^Z \beta_Z + \theta_k^Z\right),$$

3. Optimization on the wage equations parameters

$$\min_{\beta^{Pr},\sigma_{Pr},(\theta_k^{Pr})_{k=1}^K} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T \quad \pi_{il}^{(n)} \mathbb{I}_{y_{it}=1,z_{it}=1} \ln \sigma_{Pr} + \frac{\pi_{il}^{(n)}}{2\sigma_{Pr}^2} \mathbb{I}_{y_{it}=1,z_{it}=1} (w_{it}^{Pr} - X_{it}^{Pr} \beta_{Pr} - \theta_k^{Pr})^2,$$

and

$$\min_{\beta^{Pu},\sigma_{Pu},(\theta_k^{Pu})_{k=1}^K} \sum_{k=1}^K \sum_{i=1}^N \sum_{t=1}^T \quad \pi_{il}^{(n)} \mathbb{I}_{y_{it}=1,z_{it}=0} \ln \sigma_{Pu} + \frac{\pi_{il}^{(n)}}{2\sigma_{Pu}^2} \mathbb{I}_{y_{it}=1,z_{it}=1} (w_{it}^{Pu} - X_{it}^{Pu} \beta_{Pu} - \theta_k^{Pu})^2.$$

Standard errors estimates are obtained by a parametric bootstrap procedure, instead of a non parametric one, since this last method is unstable when applied to the EM algorithm. The parametric bootstrap consists first in obtaining reliable parameter estimates for the whole set of unknown parameters denoted $\widehat{\chi}$. $\widehat{\chi}$ is obtained by replicating the previously described EM algorithm with different random initial values for the parameters. The iteration process is necessary to ensure that a global maximum is obtained. Then, given X and $\widehat{\chi}$, we generate H vectors of the endogenous variables $\left(y_i^h, z_i^h, w_i^h\right)_{h=1...H}$. For each newly generated data set, we estimate the whole set of unknown parameters. Final parameters and standard error estimates are computed as

$$\overline{\beta^*} = \frac{1}{H} \sum_{h=1}^H \beta_h^* \tag{4.15}$$

$$\sigma_{\beta^*} = \frac{1}{H-1} \sum_{h=1}^H (\beta_h^* - \overline{\beta^*})^2. \tag{4.16}$$

5. Results

5.1. Identification

The model identification does not only rely on functional assumptions, imposed on the residual distributions, but on exclusion restrictions. On the one hand, in the nonemployment/employment equation, we include the number of children between 0 and 3, and the number of children between 3 and 6. These variables are crucial for explaining female participation (see Hyslop (1999) and Edon and Kamionka (2008)). These variables are excluded from the sector choice and the wage equation. The fertility of a woman may influence the sector choice but this component is captured by the unobserved heterogeneity specific to the sector choice equation.

On the other hand, in the sector choice equation, a proxy of the father status as a proxy of the mother status at the end of the individual studies, is included. This is known to be a determinant of civil servant status (Audier (2000)). The status of the parents occupation is not directly observed, a proxy is built from the two-digit classification of their occupation. Hence we consider the father (resp. mother) was a civil servant when he (resp. she) was either *'senior civil servants, information professionals or creative and performing artists'* or *'middle-level health and teaching workers, middle-level civil servants'* or finally *'middle-level civil servants'*. These variables are excluded from the rest of the model.[9]

5.2. Estimations

5.2.1. Estimation results

Employment

As expected, gender negatively affects employment, as well as children under 3 and 6 do. Women choose to get out of the labor market to bring up their children, and usually wait for their entrance into nursery or primary school to look for a job. In France, some children part-time attend nursery school. The marriage is not determinant for the employment decision. The effect of age on employment is quadratic. The employment probability first increases, and then decreases with age.

[9]In 1994, among women who work, 13.3% of them have a father who was civil-servant, and 10.9% a mother who was civil-servant. For men, these percentage are respectively 12.4% and 8.1%.

Moreover, the higher the degree, the higher the probability to be employed. Graduate degrees are the most rewarding ones in terms of employment probabilities.

Individuals who live in the region around Paris or in Paris have a greater probability to be employed because of job offer opportunities. Finally, as expected, local unemployment rate has a negative effect on the probability to be employed.

Sector Choice

Our theoretical model teaches us that, given risk aversion, a higher unemployment rate diminishes the cost of searching for a public job when unemployed. The return associated to the private sector drops when the unemployment rate rises. This is confirmed by our estimations: the local unemployment rate favors the choice of public sector (Table 3). Fougère and Pouget (2003) also find that the number of candidates for a public job and the macroeconomic cycle go along. Hence the local unemployment rate is a core variable to understand public sector attractiveness.

The father's position directly influences his children sector choice. A son would prefer public services if his father is a civil-servant. This confirms empirical observations: civil servants' children are over-represented in the public sector (Audier (2000)). But women whose father is a civil-servant would prefer private sector compared to women whose father is not a civil-servant.

Moreover, as expected, women have a higher propensity than men to work in public services. This would be enforced thanks to the wage analysis. This result is in line with Bell, Elliott, and Scott (2005), who find, for UK, that the gains to staying in the public sector are greater for women than for men, and that women tend to gain by joining the public sector, almost irrespective of their position in the earnings distribution. We find similar results for France (see following sections). Fougère and Pouget (2003) also find that the length of queue for public sector is longer for female.

Individuals with lower degree tend to work in the private sector unlike individuals with post-secondary education. Two reasons may explain this effect: first, French public jobs are more qualified on the whole than jobs in private sector (teaching, executive...). And many public jobs require to pass an exam which is conditional on a given degree.

Wages

Usual results are obtained in terms of effects of different variables, such as age, experience, degree... The comparison between private and public wages is more instructive.

Unlike empirical results, the residual variance is slightly higher in the public sector (0.11) than in the private one (0.08). And, the constant associated to public wages is higher (5.82 against 5.08), what people usually call "the public raw wage premium". For most degrees (except for graduates) we can not conclude that education is less rewarded in public services. But for graduates, the returns to education are statistically different and greater in the private sector.

Worth to be pointed out is the worst returns to gender in the private sector. As Gregory and Borland (1999) underlined, public sector wage inefficiency may counterbalance wage discriminations. That seems to be the case in France. Nonetheless, to be a woman has also a negative effect on public wages. Indeed women have lower probabilities to be promoted than men with similar characteristics (Bessière and Pouget (2007)). But in public services, wage increases are closely linked to grade promotions. Thus career differences may explain wage differences between men and women in public services.

Finally, living around Paris and in Paris gives a positive premium for wages.

We give further details on wages in the following section thanks to simulations.

Table 3. Employment equation

Variables	*Estimates*	*Standard Error*
Constant	-5.515	0.092
Not French	0.137	0.048
French	-	-
Not Married	0.032	0.017
Married	-	-
Women	-0.546	0.015
Men	-	-
Children under 3	-0.237	0.021
Children between 3 and 6	-0.259	0.021
Age/10	4.556	0.567
Age/10 squared	-5.651	0.673
No secondary degree	-	-
Vocational degree	0.217	0.021
High School degree	0.264	0.026
College and Under Graduate	0.335	0.023
Graduate	0.706	0.035
Paris	0.206	0.027
Local unemployment rate	-0.012	0.003

Source: French European Household.

Table 4. Private sector choice

Variables	*Estimates*	*Standard Error*
Intercept	1.067	0.251
Women	-0.604	0.041
Men	-	-
Age/100	3.024	1.483
Age/100 squared	-5.594	1.795
Not Married	0.032	0.042
Vocational degree	0.160	0.050
High School degree	0.317	0.055
College and Under Graduate	-0.122	0.041
Graduate	-0.109	0.063
Women times Father civil servant	0.406	0.080
Men times Father civil servant	-0.361	0.061
Women times Mother civil servant	0.070	0.085
Men times Mother civil servant	-0.109	0.083
Local unemployment rate	-0.047	0.006

Source: French European Household.

Table 5. Public wage equation

Variables	*Estimates*	*Standard Error*
Intercept	5.822	0.041
Women	-0.185	0.007
Paris	0.118	0.009
Age/100	4.919	0.271
Age/100 squared	-4.152	0.327
Age of end of study/100	0.308	0.205
Age of end of study/100 squared	-1.560	0.689
Vocational degree	0.068	0.010
High School degree	0.339	0.016
College and Under Graduate	0.459	0.015
Graduate	0.667	0.015
Part-time	-0.436	0.010
Variance of residuals	0.110	0.002

Source: French European Household.

Table 6. Private wage equation

Variables	*Estimates*	*Standard Error*
Intercept	5.075	0.028
Women	-0.385	0.005
Paris	0.287	0.007
Age/100	8.935	0.188
Age/100 squared	-9.284	0.232
Age of end of study/100	1.806	0.131
Age of end of study/100 squared	-1.787	0.358
Vocational degree	0.106	0.006
High School degree	0.351	0.008
College and Under Graduate	0.428	0.008
Graduate	0.800	0.010
Part-time	-0.494	0.007
Variance of residuals	0.083	0.001

Source: French European Household.

5.2.2. Types

Four types were chosen instead of three because of the insufficient fit we had and the peculiar results we got. Three were not sufficient to capture heterogeneity. Why not five? For computational reasons, since four types are already heavy to implement.

In a first step, we compute the individual posterior probability to be of a given type at the initial date 1994. We consider that an individual is of type k when the individual posterior probability associated to type k is the highest. Results show that a clear type-partition exists. At the initial date, type-2 people are mainly nonemployed (85.9%) whereas type-1, type-3 and type-4 individuals are employed. These latter groups differ according to the sector choice. 85.1% of type-3 individuals are employed in public services in 1994, whereas 88.4% of type-1 individuals and 74.1% of type-4 individuals are employed in the private sector. Thus employment and sectors distinctly partition individuals in our sample.

Considering the values of unobserved heterogeneity for different types, remark that *type-1* and *type-3* individuals have an unobserved ability roughly similar in both sectors (for type 1: $\theta^{W_{Pr}} = 0.184$ and $\theta^{W_{Pu}} = 0.014$; for type 3: $\theta^{W_{Pr}} = -0.247$ and $\theta^{W_{Pu}} = 0.007$), whereas type-4 individuals would have a different unobserved productivity in both sectors. These individuals clearly have chosen the sector in which they are the most productive. Type-4 individuals are clearly more efficient in the private sector than in the public sector ($\theta^{W_{Pr}} = -0.468$ and $\theta^{W_{Pu}} = -1.031$).They may have sorted themselves into the sector that pays them more.

6. Simulations

6.1. Model fit

This section presents a brief fit analysis of the statistical model presented above. Table (8) presents the predicted probabilities for nonemployment, public jobs and private jobs. The frequencies of nonemployment and of employment in either sector are well replicated whatever the date considered.

Further the model replicates well the cross sectional distribution. Figure (2) plots the observed and predicted log of monthly wage densities for the two sectors separately, which are quite close.

Table 7. Other parameters

Variables	*Estimates*	*Standard Error*
Probability of different types		
Type 1	0.208	0.006
Type 2	0.218	0.006
Type 3	0.225	0.006
Type 4	0.349	0.006
Type-specific heterogeneity parameters		
	Type 1	
θ^{Y}	-1.051	0.027
θ^{Z}	1.972	0.101
$\theta^{W_{Pr}}$	0.014	0.011
$\theta^{W_{Pu}}$	0.184	0.030
	Type 2	
θ^{Y}	-3.788	0.036
θ^{Z}	0.046	0.086
$\theta^{W_{Pr}}$	-1.199	0.013
$\theta^{W_{Pu}}$	-0.555	0.020
	Type 3	
θ^{Y}	-1.235	0.033
θ^{Z}	-2.581	0.087
$\theta^{W_{Pr}}$	-0.247	0.016
$\theta^{W_{Pu}}$	0.007	0.016
	Type 4	
θ^{Y}	-1.924	0.032
θ^{Z}	1.630	0.087
$\theta^{W_{Pr}}$	-0.468	0.011
$\theta^{W_{Pu}}$	-1.031	0.024

Source: French European Household.

Table 8. Model Fit

Variables	*Year*	*Predicted probability* %	*Observed probability* %
Nonemployed	1994	34.379	33.229
	1995	33.522	32.463
	1996	33.160	32.659
	1997	32.840	32.816
	1998	32.711	32.502
	1999	32.765	32.148
	2000	33.035	33.229
	2001	33.800	34.171
Public sector	1994	20.105	20.837
	1995	20.356	21.288
	1996	20.605	21.328
	1997	20.647	20.758
	1998	20.586	20.660
	1999	20.355	20.463
	2000	20.033	19.914
	2001	19.804	19.501
Private sector	1994	45.516	45.935
	1995	46.122	46.249
	1996	46.235	46.013
	1997	46.513	46.426
	1998	46.703	46.838
	1999	46.880	47.388
	2000	46.932	46.858
	2001	46.396	46.328

Source: French European Household

6.2. What private wages would civil servants have? Counterfactual distributions

We derive the counterfactual distribution of the log monthly wages for the individual employed in the public sector. Which log of wages would public servants have if they were employed in the private sector?

We use bootstrapping methods: we draw H independent replicates drawn from the empirical distribution of the explanatory variables of people working in the public sector at date t. For each replicate, we draw a type $t(i)$ in the following posterior distribution

$$\mathbb{P}\left(T_i = k | y_{it} = 1, z_{it} = 0, X_{it}\right) = \frac{\pi_k \mathbb{P}(y_{it} = 1, z_{it} = 0 | T_i = k, X_{it})}{\sum_{l=1}^{K} \pi_l \mathbb{P}(y_{it} = 1, z_{it} = 0 | T_i = l, X_{it})}, \quad (6.17)$$

where T_i is the random variable representing the type of the individual i. Then we compute the corresponding fitted value of the log monthly wages in both sectors:

$$w_{it}^{s,Pr} = X_{it}\widehat{\beta^{Pr}} + \widehat{\theta_{t(i)}^{Pr}}, \quad (6.18)$$

$$w_{it}^{s,Pu} = X_{it}\widehat{\beta^{Pu}} + \widehat{\theta_{t(i)}^{Pu}}. \quad (6.19)$$

Finally we add a sector-specific residual term that is i.i.d normally distributed with a sector-specific variance.

In figure 3, we observe that the counterfactual distribution remains close to the log of wage public distribution. But this hides different effects according to gender and degrees. The counterfactual distribution for men is rather stable except for the upper tail, whereas the one for women shifts left.

In order to precisely evaluate the public wage premium, let us derive and compare quantiles of the former distributions: the public log of wage distribution and the counterfactual distribution. Further details are given in appendix E. Figures 5 and 8 plot the difference of quantiles between the current and the counterfactual distributions according to gender and degrees. The term "public wage premium" seems to be justified at the bottom of the distribution, whereas it is not anymore for upper wages. But when detailed by degree and gender, we find that the public sector actually gives a premium to women, whereas men would be better paid in the private sector except for those at the lower tail of the distribution. As expected given previous estimations, male graduates would be far better paid in the private sector. So we find similar results as Disney and Gosling (1998) and Bell, Elliott, and Scott (2005): public sector premium is higher for women than for men, and this premium differs across the pay distribution. The lower part of the distribution gains from staying in the public sector.

Figure 2 Predicted log of monthly wages - 1994

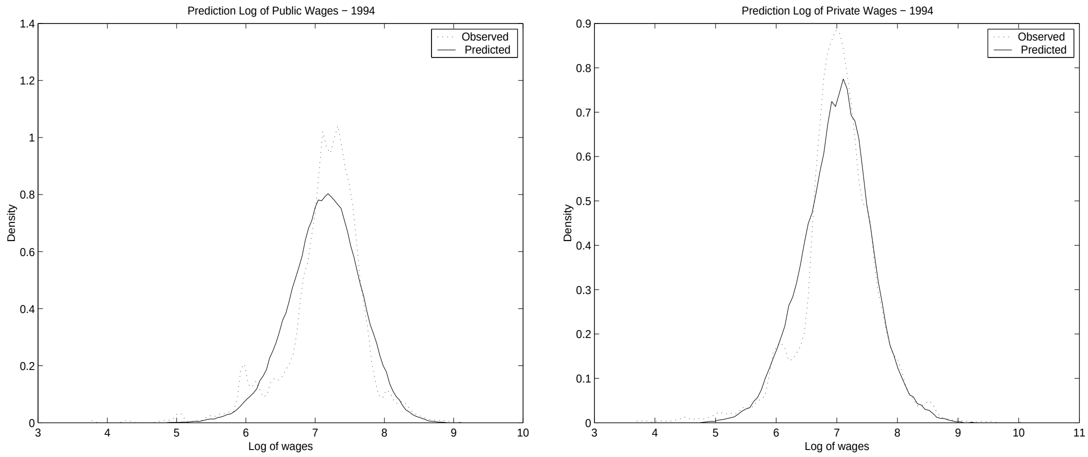


Figure 3 Counterfactual log of monthly wages for civil servants - 1994

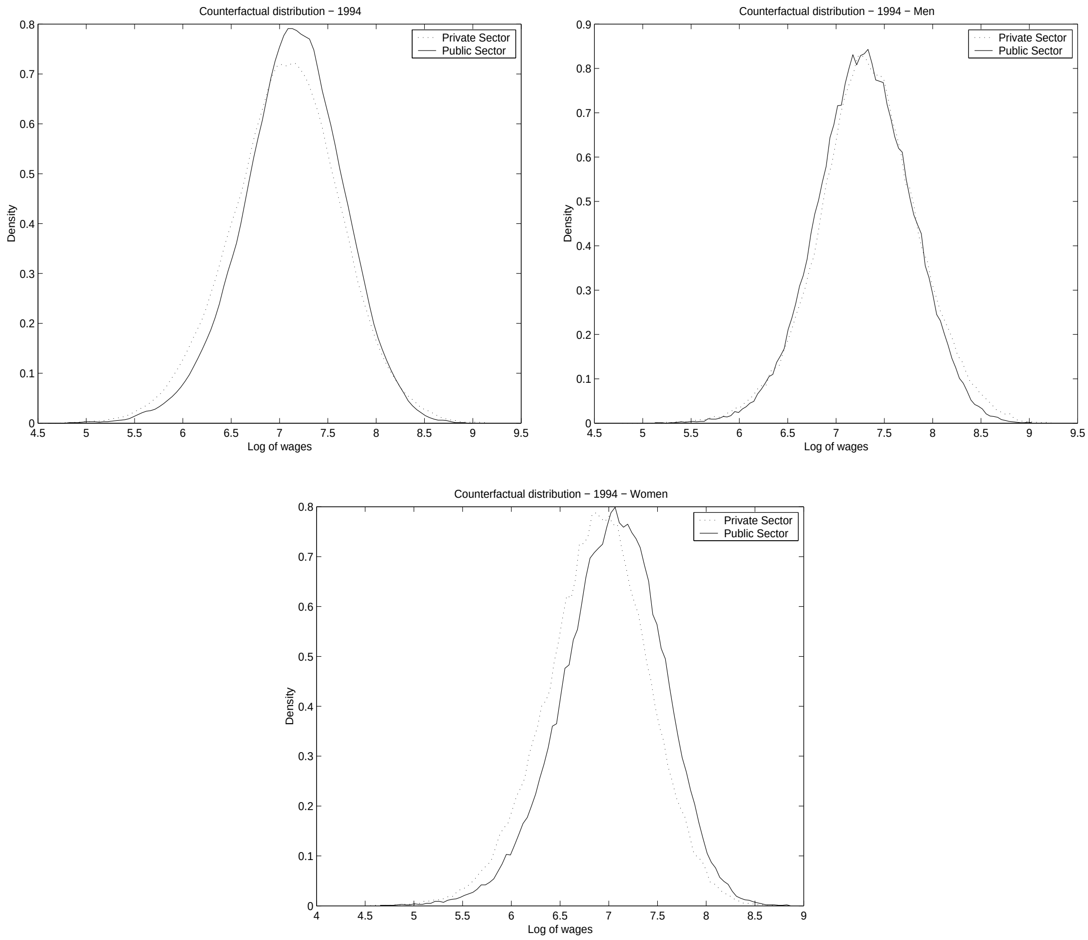
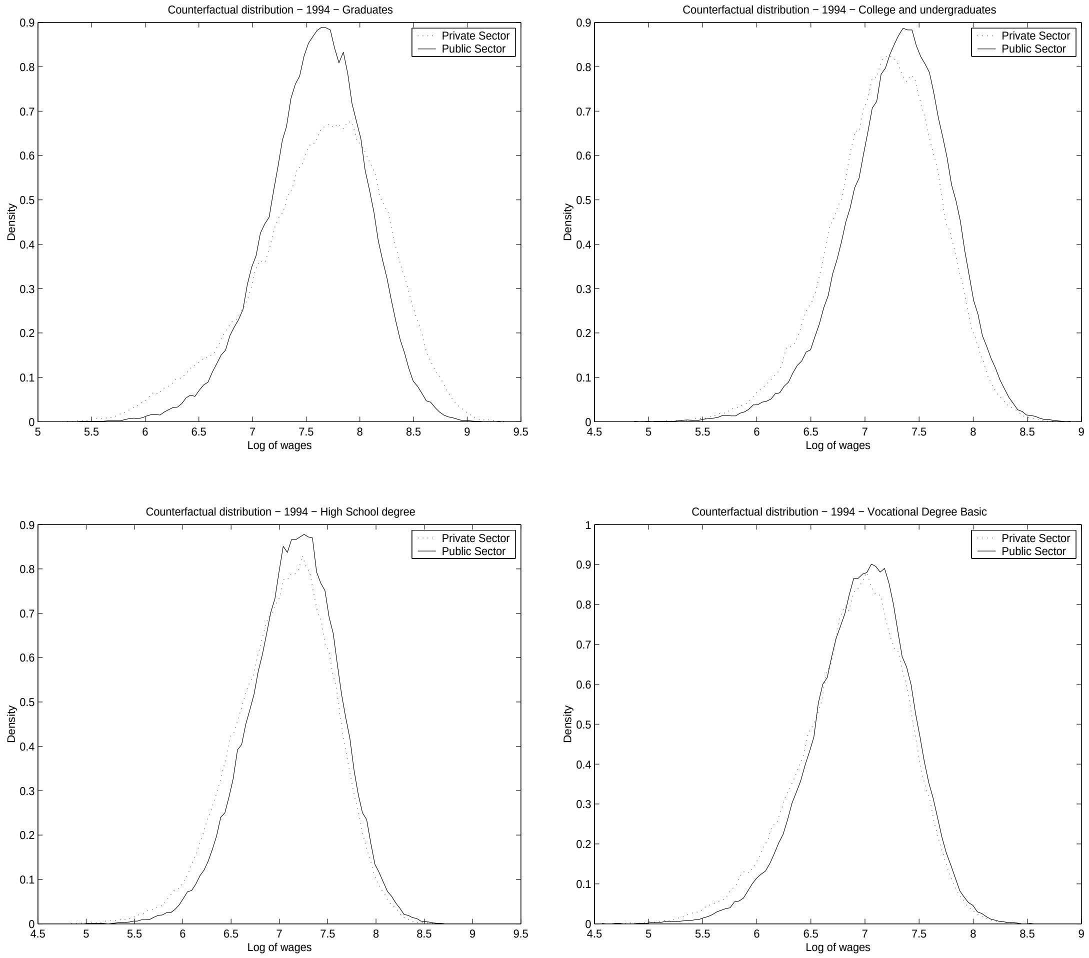


Figure 4 Counterfactual log of monthly wages according to degrees



7. Conclusion

This paper presents new evidence on the public-private pay gap. The model estimates sector-specific wage equations controlling both for sector choice and employment selection. Thanks to panel data, it captures unobserved heterogeneity which differs between equations. It is modeled using the method of Heckman and Singer (1984) via a discrete distribution.

We find that, when choosing the sector, mimicking the parents has a great importance. But only sons imitate their father's choice. As expected, the public sector attracts more people when the local labor market is depressed. We observe that the wage public premium is effective at the bottom of the public wage distribution. But it turns out to be false at the upper tail. This is in line with empirical observations: low-wage civil-servants are weakly mobile, whereas high-wage civil servants move more frequently from the public to the private sector.

However these results are mitigated when gender is distinguished. The female public sector workers have a comparative advantage in the public sector. Their counterfactual wages in the private sector would be lower. Graduated men would have higher wages in the private sector; in the case of graduated women, the public wage premium is close to zero.

Finally we find that wage differences between the public and the private sectors result from three factors: first the raw mean is greater in the public sector, second the returns to different observable characteristics differ between both sectors, finally the unobserved productivity civil-servants would have in the private sector is roughly equal, though inferior, to the one they have in their current occupation. Unlike them, a part of workers employed in the private sector seem to acquire specific human capital, that they could not transfer to the public sector.

A. Structural model

From (2.3), differentiating this latter equation with respect to w yields:

$$\begin{aligned} \rho V_{Pr}'(x) &= 1 - \delta V_{Pr}'(x) - \lambda_{Pr,Pr} V_{Pr}'(x)\overline{F}(x) \\ \Rightarrow V_{Pr}(x) - V_{Pr}(\overline{w}) &= -\int_x^{\overline{w}_{Pr}} \frac{1}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(y)} dy \end{aligned}$$

Let us consider both cases.

- Case 1: $d_{Pu} = 0$

  When the individual does not search for a public job, if he receives an offer with a wage w greater than $w^*_{d=0}$, he accepts this offer. The reservation wage $w^*_{d=0}$ checks: $V_n^{d=0} = V_{Pr}(w^*_{d=0})$. Henceforth:

$$\begin{aligned} V_n^{d=0}\rho &= (b-c) + \lambda_{n,Pr} \int_{w^*_{Pr,d=0}}^{\overline{w}} \left(V_{Pr}(x) - V_n\right) dF_{Pr}(x) \\ &= (b-c) + \lambda_{n,Pr} \int_{w^*_{Pr,d=0}}^{\overline{w}} V_{Pr}'(x)\overline{F}_{Pr}(x) dx \\ &\Rightarrow \begin{pmatrix} \rho V_n^{d=0} &=& (b-c) + \lambda_{n,Pr} \int_{w^*_{Pr,d=0}}^{\overline{w}} V_{Pr}'(x)\overline{F}_{Pr}(x)dx \\ \rho V_n^{d=0} &=& w^*_{Pr,d=0} - c + \lambda_{Pr,Pr} \int_{w^*_{Pr,d=0}}^{\overline{w}} V_{Pr}'(x)\overline{F}_{Pr}(x)dx \end{pmatrix} \end{aligned}$$

  And:

$$\begin{aligned} w^*_{Pr,d=0} &= b \\ &+ (\lambda_{n,Pr} - \lambda_{Pr,Pr}) \int_{w^*_{Pr,d=0}}^{\overline{w}} \frac{\overline{F}_{Pr}(x)}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)} dx \end{aligned} \tag{A.20}$$

- Case 2: $d_{Pu} = 1$

  Let us proceed the same way thus we get:

$$\rho V_n^{d=1} = (b - c - c_{Pu}) + \lambda_{n,Pr} \int_{w^*_{Pr,d=1}}^{\overline{w}} V_{Pr}'(x)\overline{F}_{Pr}(x) dx \lambda_{n,Pr}$$

$$
\begin{aligned}
& + \quad p\lambda_{n,Pu} \int_{w^*_{Pu}}^{\overline{w}} V'_{Pu}(x)\overline{F}_{Pu}(x)dx \\
\rho V_n^{d=1} &= w^*_{Pr,d=1} - c + \lambda_{Pr,Pr} \int_{w^*_{Pr,d=1}}^{\overline{w}} V'_{Pr}(x)\overline{F}_{Pr}(x)dx \\
V_n^{d=1} &= V_{Pr}(w^*_{Pr,d=1}) = V_{Pu}(w^*_{Pu}) = \frac{w^*_{Pu}}{\rho}
\end{aligned}
$$

Hence:

$$
\begin{aligned}
w^*_{Pu} &= w^*_{Pr,d=1} - c + \lambda_{Pr,Pr} \int_{w^*_{Pr,d=1}}^{\overline{w}} \frac{\overline{F}_{Pr}}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)}(x)dx \\
w^*_{Pr,d=1} &= (b - c_{Pu}) + (\lambda_{n,Pr} - \lambda_{Pr,Pr}) \int_{w^*_{Pr,d=1}}^{\overline{w}} \frac{\overline{F}_{Pr}(x)}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)}dx \\
&+ \frac{\lambda_{n,Pu}p}{\rho} \int_{w^*_{Pu}}^{\overline{w}} \overline{F}_{Pu}(x)dx
\end{aligned}
$$

The values we have to compare to determine whether the individual searches for a public job, are $V_n^{d=0}$ and $V_n^{d=1}$, i.e. $V_{Pr}(w^*_{Pr,d=0})$ and $V_{Pr}(w^*_{Pr,d=1})$:

$$
\begin{aligned}
& V_{Pr}(w^*_{Pr,d=1}) - V_{Pr}(w^*_{Pr,d=0}) \\
= & \int_{w^*_{Pr,d=0}}^{\overline{w}} \frac{1}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}(x)}dx - \int_{w^*_{Pr,d=1}}^{\overline{w}} \frac{1}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}(x)}dx
\end{aligned}
$$

$$
\begin{aligned}
& V_{Pr}(w^*_{Pr,d=1}) = V_{Pr}(w^*_{Pr,d=0}) \Leftrightarrow w^*_{Pr,d=1} = w^*_{Pr,d=0} \\
\text{and} \quad & V_{Pr}(w^*_{Pr,d=1}) \geq V_{Pr}(w^*_{Pr,d=0}) \Leftrightarrow w^*_{Pr,d=1} \geq w^*_{Pr,d=0}
\end{aligned}
$$

The nonemployed person searches for both public and private jobs when $w^*_{Pr,d=1} \geq w^*_{Pr,d=0}$.

From equations ($w^*_{Pr,d=0}$), ($w^*_{Pr,d=1}$) and (w^*_{Pu}), we get:

$$
\begin{aligned}
w^*_{Pr,d=0} &= f(w^*_{Pr,d=0}) \\
w^*_{Pr,d=1} &= f(w^*_{Pr,d=1}) + g(w^*_{Pr,d=1})
\end{aligned}
$$

with

$$\begin{aligned} f(x) &= b + (\lambda_{n,Pr} - \lambda_{Pr,Pr}) \int_x^{\overline{w}} \frac{\overline{F}_{Pr}(x)}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)} dx \\ \text{and } g(x) &= -c_{Pu} + \frac{\lambda_{n,Pu} p}{\rho} \int_{h(x)}^{\overline{w}} \overline{F}_{Pu}(x) dx \\ \text{and } h(x) &= x - c + \lambda_{Pr,Pr} \int_x^{\overline{w}} \frac{\overline{F}_{Pr}(x)}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)} dx \end{aligned}$$

h is an increasing and bounded function with first derivative:

$$h^{'}(x) = \frac{\rho + \delta}{\rho + \delta + \lambda_{Pr,Pr}\overline{F}_{Pr}(x)}$$

Hence g is a decreasing and bounded function and three different cases are possible. Indeed, $\forall x \in [0, \overline{w}]$, $0 \geq f'(x) \geq f'(x) + g'(x)$.

- $f(0) + g(0) \leq f(0)$: it means that a nonemployed person never searches for a public job for $w^*_{d=0} > w^*_{d=1}$.
- $f(0) + g(0) \geq f(0)$ and $f(\overline{w}) + g(\overline{w}) \geq f(\overline{w})$: it means that a nonemployed person always searches for both public and private jobs.
- $f(0) + g(0) \geq f(0)$ and $f(\overline{w}) + g(\overline{w}) < f(\overline{w})$: it means that a nonemployed person may search for a public job depending on $g(w^*_{d=0})$. If $g(w^*_{d=0}) \geq 0$ the nonemployed person will search for a public job, whereas she won't.

  We show that

  $$w^*_{d=0} \leq w^*_{d=1} \quad \Leftrightarrow \quad g(w^*_{d=0}) \geq 0$$

  Indeed,

  ♢ On one hand,

  $$\begin{aligned} & w^*_{d=0} \leq w^*_{d=1} \Rightarrow f(w^*_{d=0}) + g(w^*_{d=0}) \geq f(w^*_{d=1}) + g(w^*_{d=1}) \\ \text{And} \quad & w^*_{d=0} \leq w^*_{d=1} \Rightarrow f(w^*_{d=0}) \leq f(w^*_{d=1}) + g(w^*_{d=1}) \\ \text{Thus} \quad & f(w^*_{d=0}) \leq f(w^*_{d=0}) + g(w^*_{d=0}) \Rightarrow g(w^*_{d=0}) \geq 0 \end{aligned}$$

$\diamondsuit$ On the other hand

$$g(w^*_{d=0}) \geq 0 \Rightarrow f(w^*_{d=0}) \leq f(w^*_{d=0}) + g(w^*_{d=0})$$

Thus $\quad w^*_{d=0} \leq f(w^*_{d=0}) + g(w^*_{d=0})$

And $\quad f(x) + g(x) - x$ is a decreasing function such as

$$\left\{ \begin{array}{l} f(w^*_{d=1}) + g(w^*_{d=1}) - w^*_{d=1} = 0 \\ f(w^*_{d=0}) + g(w^*_{d=0}) - w^*_{d=0} \geq 0 \end{array} \right\}$$

$$\Rightarrow \quad w^*_{d=1} \geq w^*_{d=0}$$

Proposition A.1 *Search for a public job*

The nonemployed agent decides to search for both public and private jobs when:

$$c_{Pu} \quad \leq \quad p_S \frac{\lambda_{n,Pu}}{\rho} \int_{h(w^*_{d=0})}^{\overline{w}} \overline{F}_{Pu}(x)dx$$

where $h(w^*_{d=0})$*is a function of* $\left(b, \lambda_{n,Pr}, \lambda_{Pr,Pr}, \overline{w}, \rho, \delta, \overline{F}_{Pr}\right)$

with:

– c_{Pu} *the cost to search for a public job*

– $\lambda_{n,Pu}$ *the public job offer arrival rate*

– p_S *the individual probability to succeed public entrance exam*

– $h(w^*_{d=0}) = \frac{\lambda_{n,Pr}}{\lambda_{n,Pr} - \lambda_{Pr,Pr}} w^*_{d=0} - c - \frac{\lambda_{Pr,Pr}}{\lambda_{n,Pr} - \lambda_{Pr,Pr}} b$

He only searches for private jobs when:

$$c_{Pu} \quad > \quad p_S \frac{\lambda_{n,Pu}}{\rho} \int_{h(w^*_{d=0})}^{\overline{w}} \overline{F}_{Pu}(x)dx$$

Figure 5 Quantile differences between counterfactual and public log of wage distribution.

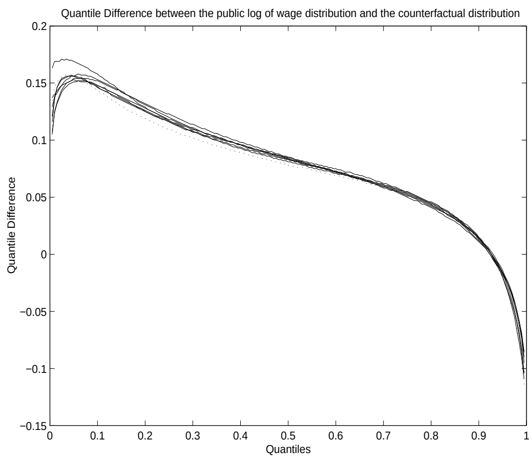
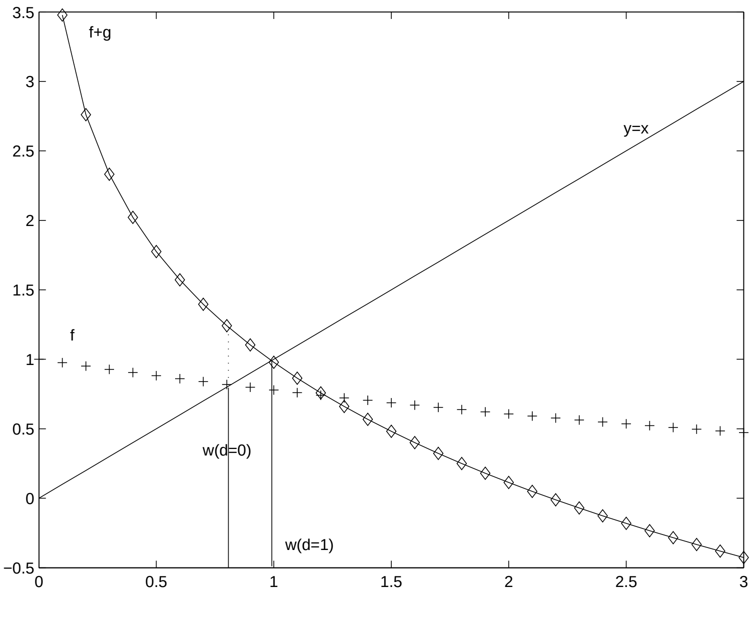


Figure 6: Function value comparison



B. Descriptive Statistics

C. Implementation

Let me describe precisely the implementation of the M-step.

$$l\left(\underline{y}_i, \underline{z}_i, \underline{w}_i | T_i = k\right) = \prod_{t=1}^{T} \left(\mathbb{P}\left(y_{it} = 0 | T_i = k\right)\right)^{y_{it}=0} \left(\mathbb{P}\left(y_{it} = 1, z_{it} = 1, w_{it}^{Pr} | T_i = k\right)\right)^{y_{it}=1, z_{it}=1} \left(\mathbb{P}\left(y_{it} = 1, z_{it} = 0, w_{it}^{Pu} | T_i = k\right)\right)^{y_{it}=1, z_{it}=0} \tag{C.21}$$

Given the individual type, for a given date, residuals are independent, hence:

$$l\left(\underline{y}_i, \underline{z}_i, \underline{w}_i | T_i = k\right) = \prod_{t=1}^{T} \left(\mathbb{P}\left(y_{it} = 0 | T_i = k\right)\right)^{y_{it}=0} \left(\mathbb{P}\left(y_{it} = 1 | T_i = k\right)\right)^{y_{it}=1} \prod_{t=1}^{T} \left(\mathbb{P}\left(z_{it} = 1 | T_i = k\right)\right)^{y_{it}=1, z_{it}=1} \left(\mathbb{P}\left(z_{it} = 0 | T_i = k\right)\right)^{y_{it}=1, z_{it}=0} \prod_{t=1}^{T} \left(\mathbb{P}\left(w_{it}^{Pu} | T_i = k\right)\right)^{y_{it}=1, z_{it}=0} \prod_{t=1}^{T} \left(\mathbb{P}\left(w_{it}^{Pr} | T_i = k\right)\right)^{y_{it}=1, z_{it}=1} \tag{C.22}$$

Therefore, we can maximize separately each equation once we condition on the individual type.

D. Cross-section results

Figure 7 Wages according to degrees in 1994

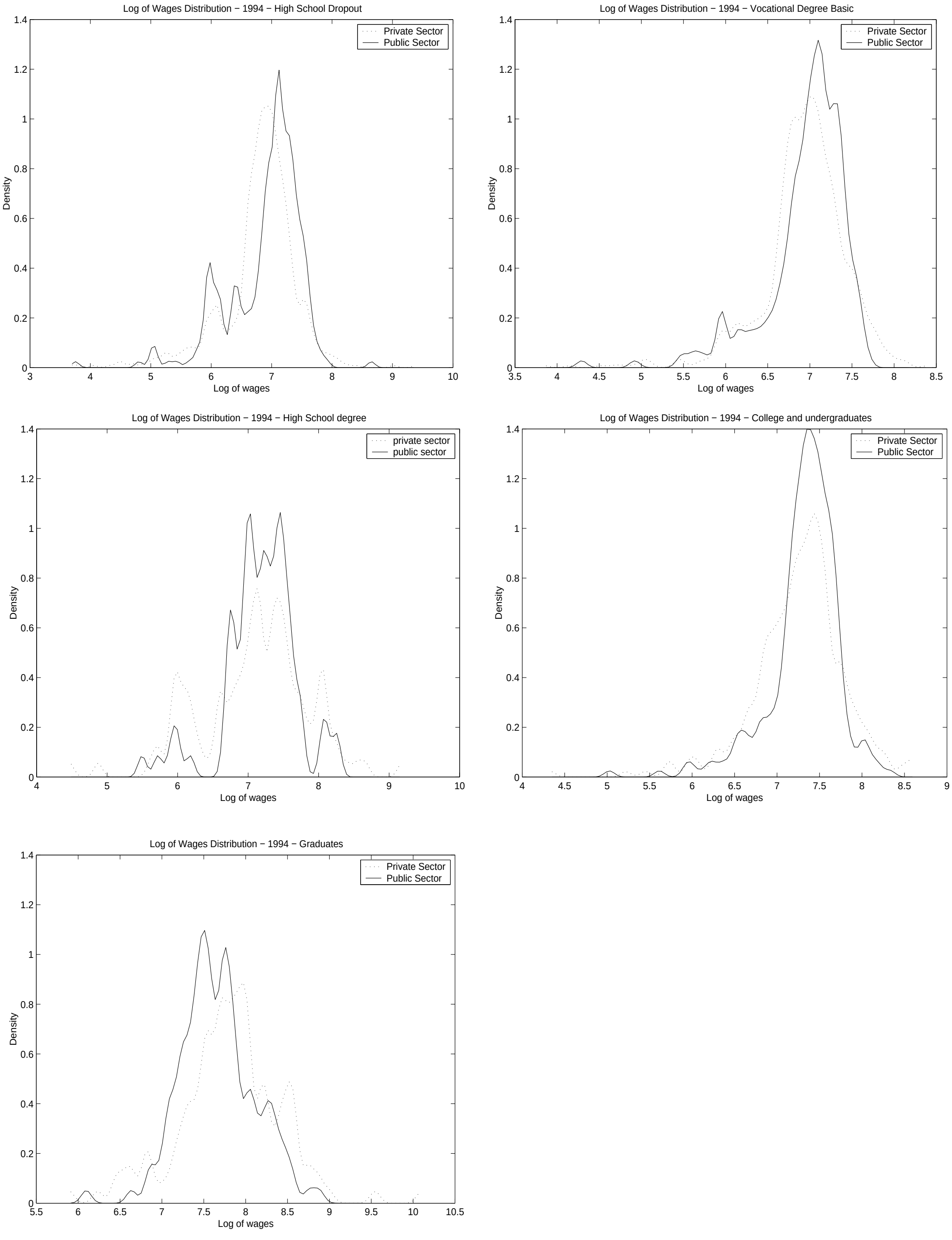


Table 9. Public wage equation without selection - 1994

Variables	*Estimates*	*Standard Error*
Intercept	4.568	0.329
Women	-0.183	0.025
Paris	0.133	0.033
Age/100	5.692	1.016
Age/100 squared	-5.162	1.259
Age of end of study/100	11.644	2.508
Age of end of study/100 squared	-27.296	5.949
Vocational degree	-0.019	0.033
High School degree	0.244	0.053
College and Under Graduate	0.323	0.034
Graduate	0.590	0.043
Part-time	-0.609	0.033

Source: French European Household

Table 10. Private wage equation without selection - 1994

Variables	*Estimates*	*Standard Error*
Intercept	4.785	0.178
Women	-0.252	0.020
Paris	0.234	0.026
Age/100	7.903	0.685
Age/100 squared	-8.384	0.887
Age of end of study	4.622	1.207
Age of end of study squared	-8.349	2.792
Vocational degree	0.076	0.021
High School degree	0.307	0.036
College and Under Graduate	0.382	0.033
Graduate	0.698	0.044
Part-time	-0.687	0.027

Source: French European Household

Table 11. Switching regression model with sector selection - 1994

Variables	*Estimates*	*Standard Error*
Private wage equation		
Intercept	4.787	0.178
Women	-0.256	0.023
Paris	0.234	0.026
Age/100	7.872	0.690
Age/100 squared	-8.361	0.887
Experience/100	4.618	1.204
Experience/100 squared	-8.344	2.785
Vocational degree	0.077	0.022
High School degree	0.307	0.036
College and Under Graduate	0.379	0.034
Graduate	0.693	0.046
Part-time	-0.687	0.027
Variance of residuals	0.432	0.006
Public wage equation		
Intercept	5.817	0.322
Women	-0.365	0.031
Paris	0.138	0.030
Age/100	3.092	1.189
Age/100 squared	-2.725	1.482
Experience/100	12.772	2.088
Experience/100 squared	-30.091	4.918
Vocational degree	0.039	0.038
High School degree	0.202	0.062
College and Under Graduate	0.107	0.042
Graduate	0.353	0.053
Part-time	-0.508	0.031
Variance of residuals	0.592	0.021

Source: French European Household

Table 12: Switching regression model with sector selection - 1994 - continued

Variables	*Estimates*	*Standard Error*
Sector choice equation		
Intercept	1.767	0.373
Women	-0.466	0.049
Men	-	-
Age/100	-3.316	1.871
Age/100 squared	2.329	2.345
Married	0.098	0.040
Vocational degree	0.169	0.057
High School degree	0.069	0.095
College and Under Graduate	-0.377	0.066
Graduate	-0.474	0.086
Women times Father civil servant	-0.248	0.073
Men times Father civil servant	-0.229	0.072
Women times Mother civil servant	-0.044	0.079
Men times Mother civil servant	-0.203	0.088
Local unemployment rate	-0.005	0.007

Source: French European Household

E. Quantile differences between the public log of wage distributions and the counterfactual distribution

Figure 8. Quantile differences between the public log of wage and the counterfactual distributions given sex and degrees.

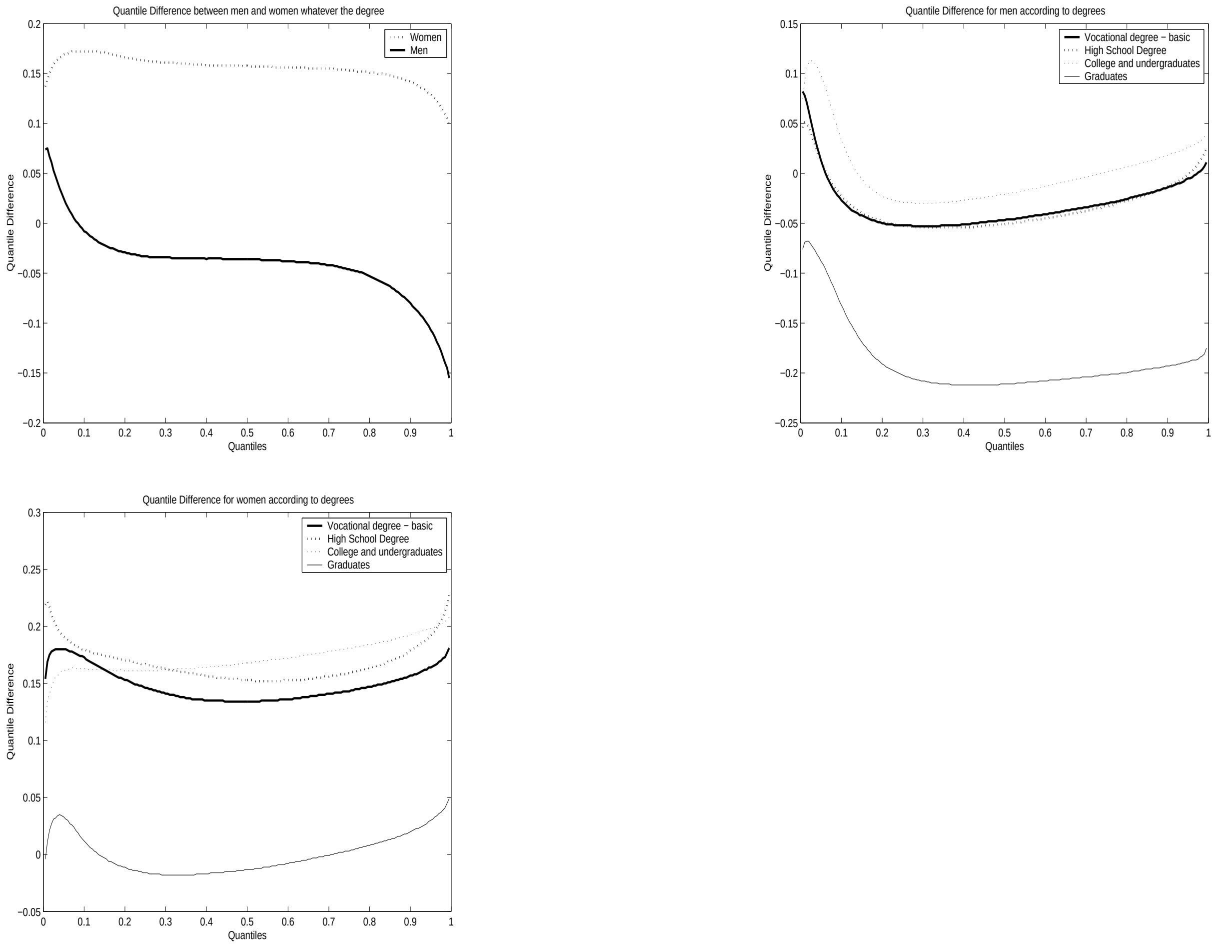


Table 13. Quantile differences between the public log of wage and the counterfactual distributions.

	1994	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
Quantiles				*Estimates*				
				Standard Errors				
0.050	0.156	0.168	0.155	0.155	0.153	0.154	0.155	0.157
	0.018	0.021	0.019	0.019	0.019	0.019	0.019	0.019
0.100	0.144	0.157	0.152	0.150	0.153	0.150	0.146	0.148
	0.017	0.019	0.018	0.017	0.018	0.018	0.018	0.018
0.150	0.130	0.142	0.143	0.138	0.142	0.140	0.136	0.136
	0.019	0.018	0.017	0.017	0.018	0.018	0.018	0.018
0.200	0.118	0.128	0.130	0.126	0.132	0.129	0.127	0.125
	0.019	0.018	0.017	0.017	0.018	0.018	0.017	0.018
0.250	0.109	0.117	0.120	0.116	0.122	0.120	0.119	0.116
	0.019	0.019	0.018	0.017	0.018	0.018	0.017	0.018
0.300	0.102	0.108	0.111	0.108	0.113	0.111	0.111	0.109
	0.019	0.018	0.018	0.017	0.017	0.017	0.017	0.018
0.350	0.095	0.100	0.102	0.100	0.106	0.103	0.104	0.102
	0.018	0.018	0.018	0.017	0.017	0.018	0.018	0.018
0.400	0.090	0.093	0.095	0.094	0.099	0.096	0.097	0.096
	0.019	0.017	0.018	0.018	0.017	0.017	0.018	0.018
0.450	0.084	0.087	0.088	0.088	0.092	0.090	0.091	0.090
	0.018	0.018	0.018	0.018	0.017	0.018	0.018	0.018
0.500	0.079	0.082	0.083	0.083	0.085	0.084	0.085	0.085
	0.018	0.018	0.018	0.018	0.017	0.018	0.018	0.018
0.550	0.074	0.077	0.077	0.077	0.078	0.078	0.079	0.079
	0.018	0.018	0.018	0.018	0.018	0.019	0.018	0.019
0.600	0.070	0.072	0.072	0.072	0.072	0.073	0.073	0.074
	0.018	0.018	0.018	0.019	0.018	0.019	0.018	0.019
0.650	0.064	0.067	0.067	0.067	0.066	0.067	0.066	0.068
	0.018	0.019	0.019	0.019	0.018	0.019	0.019	0.019
0.700	0.059	0.061	0.061	0.061	0.059	0.060	0.059	0.062
	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
0.750	0.053	0.054	0.053	0.054	0.052	0.052	0.051	0.054
	0.018	0.019	0.019	0.019	0.019	0.020	0.019	0.019
0.800	0.044	0.045	0.044	0.045	0.042	0.044	0.041	0.044
	0.018	0.020	0.020	0.019	0.019	0.020	0.019	0.019
0.850	0.032	0.033	0.033	0.033	0.030	0.032	0.029	0.031
	0.019	0.020	0.019	0.019	0.019	0.019	0.019	0.019
0.900	0.014	0.015	0.015	0.014	0.013	0.014	0.012	0.013
	0.020	0.021	0.020	0.020	0.020	0.019	0.020	0.019
0.950	-0.019	-0.020	-0.017	-0.018	-0.018	-0.015	-0.017	-0.018
	0.021	0.019	0.021	0.022	0.021	0.021	0.021	0.020

Source: French European Household

Chapitre 4

Who is confronted to insecure labor market histories?
Some evidence based on the French labor market transitions.

1. Introduction

Flexible employment has drastically increased in France since the introduction of short-term contracts (*Contrats à Durée Déterminée, CDD*) and temporary work (*mission d'intérim*) in the early 1980's. Short-term contracts represent 66% of hirings in 2005 while 60% of the transitions from employment to non-employment concern a short-term job ending. These flexible devices, which may be justified by the need to maintain the competitiveness of the firms, induce a higher frequency of labor market transitions. The transition rate between employment and nonemployment has significantly increased between 1975 and 2000 (Behaghel (2003)). Risks of involuntary job loss were higher in the 1990's than in the 1980's (Givord and Maurin (2003)). In this context, studying transitions on the labor market and the distribution of mobilities within the workforce is of first interest.

The nature of the job contract occupies an important place in the French debate on labor market and labor legislation. The current controversy on the "Contrat Unique", following those on the "Contrat Nouvelle Embauche" (CNE) and the "Contrat Première Embauche" (CPE) in 2005 and 2006, stresses indeed that the nature of the job contract is a crucial feature of job quality.[1] Then, it is interesting to distinguish job spells in long-term contract and job spell in short-term contract. Hence, four states stand out on the French labor market: stable employment, which contains long-term contract jobs and self-employed; contingent work, which refers to short-term contracts and temporary or seasonal jobs; unemployment and nonparticipation. The scope of this paper is to analyze and quantify the different kinds of labor market histories entailed by the transition dynamics between those states.

Short-term jobs may be a stepping stone in an integration process or a trap into insecurity. The economic literature supports both aspects. On the one hand, theories of imperfect information (Spence (1973)), transaction costs (Williamson (1975)) and insider-outsider (Lindbeck and Snower (1986, 2002)) give some explanations of a dual labor market which either rely on

[1]On the one hand, the pros of a "Contrat Unique" advocate for standardizing the multiple kinds of jobs contract in a single form. On the other hand, in recent years, the government made two attempts to introduce new forms of job contracts: the CNE, introduced in August 2005, was a long-term contract with simplified and lightened termination rules only available for firms with at most 20 employees; the CPE was an attempt of generalization of the CNE available only for young workers (under 26). These two attempts aborted: the CPE was canceled due to tough demonstrations in spring 2007; the CNE was declared unconstitutional just two years after its introduction.

the heterogeneity of the labor supply productivity or on the existence of negotiation power in a context of imperfect information.[2] These theories stress the role of signalling in perpetuating a vicious circle. Employers may consider a long history through unemployment and contingent work as a bad signal on a worker's ability and then they may offer him or her insecure positions rather secure ones (Katz (1986)).[3] Further, Cahuc and Postel-Vinay (2002) and Blanchard and Landier (2002) relate the labor market duality to the coexistence of short-term jobs and highly protected long-term ones. Besides, theories of segmented labor markets stress the outstanding role of firms in shaping the labor market duality with the existence of internal labor markets and human resources' management or human capital investment which differ according to the job sector; see for instance the seminal work of Doeringher and Piore (1971). On the other hand, temporary jobs, more precisely short job spells, can be viewed as opportunities, especially for young workers but also for people out of the labor force, to accumulate general human capital. Temporary job spells may also provide a worker with enough time and/or information to find out the best firm match; see Burdett (1978b),Jovanovic (1979a),Jovanovic (1979b), Mortensen (1988), Topel and Ward (1992).

Cross-sectional studies on labor market duality (see L'Horty (2004), Gazier and Petit (2007)) do not take into account the (complete) labor market histories. Here, we adopt a totally different strategy. The identification of the sectorisation structure relies only on the observed transitions between the different positions/states on the labor market. More precisely, we use a mover-stayer approach (Blumen, Kogan, and MacCarthy (1955), Kamionka (1996)), which distinguishes workers who remain stuck to contingent work (typically those alternating nonemployment spells with short-term jobs) from those who may access to stable jobs and benefit in a sense from an integration process. The approach proposed is conditional on individual characteristics, which extends Kamionka (1996). Hence, this method enables us to separate labor market histories which are confined to contingent work and non-employment from those which are not and to characterize the individuals who experience them.

The discrete time mover-stayer model was first introduced by Blumen, Kogan, and

[2] Lindbeck and Snower (1986, 2002) summarize theoretical breakthroughs and list key references.

[3] Blanchard and Landier (2002) provide some semantic advice: whereas the French have a specific word designating a succession of short-term jobs and unemployment spells (*précarité*), there does not exist an equivalent expression in English. We follow Blanchard and Landier's suggestion to use *insecurity* instead.

MacCarthy (1955) to study industrial mobility on the labor market; see also Anderson and Goodman (1957), Goodman (1961), Spilerman (1972), Singer and Spilerman (1976) and Frydman (1984). This model relies on a mixture of Markov chains which accounts for different dynamic patterns among individuals. Its most basic version assumes that two kinds of workers coexist on the labor market: while the *movers* can move from unemployment to employment, the *stayers* remain indefinitely in the state they initially occupy.[4]

In the version proposed by Kamionka (1996), some workers, named *unconfined movers*, can have access to any kind of jobs whereas some others, called *confined movers*, can only transit between unemployment, short-term jobs and non-participation. The introduction of different individual types allows one to account for the so-called partially observed heterogeneity. We use the same partition but we explicitly let the mixture probabilities (being a mover, confined or unconfined, or being a stayer) depend on observed characteristics, (*conditional confined-unconfined model*). This allows us to investigate which individual characteristics are correlated with specific dynamic patterns on the labor market. In other words, the version that we propose enables us to highlight who the stayers, the unconfined movers and the confined movers are. Further, the share of *unconfined movers* in the economy and amongst the movers may provide an indicator of the labor market sectorisation level.

Apart from the mover-stayer models, labor market transitions are usually studied using discrete choice models and/or duration models. *Discrete-choice models* explain the individual status given his/her past (and notably his/her past status) and covariates; see for instance Card and Sullivan (1988), Magnac (2000) or Havet (2006). *Duration models* explain the duration of a spell in a given state by the past and a set of individual characteristics; see for example in the French labor market context, Bonnal, Fougère, and Sérandon (1997) and Magnac and Robin (1994). Duration models capture state and duration dependence whereas Markov-chain-based approaches account for state dependence and partially observed heterogeneity. So our study completes previous studies of the French labor market by focusing on partially observed heterogeneity.

[4]Mover-stayer models have also been adapted to continuous time Fougère and Kamionka (1992a, 1992b, 2003, 2008) such as other Markov chain models Kalbfleish and Lawless (1985), Geweke, Marshall, and Zarkin (1986a, 1986b).

The discrete time mover-stayer-type model proposed in this paper aims to separate histories when individuals never accede to stable jobs from histories when individuals have a potential access to both unstable and stable jobs. This partition is chosen in response to the sectorisation issue in the French labor market. The population who experiences confined mover histories is of first interest for policy concerns. Moreover, a statistical approach *à la* Heckman and Singer (1984), which does not require to *a priori* impose the nature of types and nonzero-constraints on the transition matrix components, does not reject the relevance of the partition postulated here. In this alternative approach, the form and the number of the transition matrices are let free but more structure is imposed on the state dependence. Transitions are actually modeled by a dynamic multinomial logit with unobserved heterogeneity - which entails restrictions; see Magnac (2000) and Brodaty (2007).

The model is estimated by maximum likelihood on a sample composed of 30-49 years old people who finished their studies. The data come from the French Labor Force Survey. We focus on middle-aged people to avoid life-cycle effects that may violate stationarity requirements of Markov Chain models (labor market entrance of youth, retiring). Our main findings are the following. Individuals trapped into confined mover histories represent about 5% of the total population. This is much less than the 13% computed in summary statistics, showing the relevance of our model to handle heavily censored data. Individuals falling into the *confined-mover* category are more likely to be less educated, younger and single. At stationary equilibrium, 30% of them occupy unstable jobs, nearly a half are unemployed, while the remaining do not participate.

The paper is organized as follows. The data and summary statistics are presented in section 2, and the model in section 3. Section 4 is dedicated to the estimation results. Section 5 contains the results of the Heckman-Singer approach and some specification tests. Section 6 concludes.

2. Data

The data come from the French Labor Force survey (LFS), 2003-2007, undertaken by Insee, the French national statistical office. The LFS is a rolling panel in which individuals are interviewed on their labor market status, once per quarter, six times. This scheme enables one to construct individual labor market histories over 15 months. Each quarter, one surveyed individual out of six is replaced. In this paper, we use the LFS answers of the 30-49 years old individuals who entered the survey from 2003Q1 to 2005Q4, who finished their studies and who were interviewed 6 times. This panel consists in 33,206 individuals. The LFS contains information on labor market states - employment, unemployment and nonparticipation - as well as a detailed description of the job occupied by the employed. Long-term contracts, short-term contracts, temporary jobs, internships are distinguished. In what follows, we consider four labor market states: nonparticipation (NP), unemployment (U), unstable job state (UJ) which contains public and private short-term contracts, temporary jobs and seasonal jobs, and a stable job state (SJ) which contains private long-term contracts, self-employed and civil-servant positions. Unemployment refers to the ILO definition: unemployed are nonemployed, available to work within two weeks and actively search for a job. So, non-employed who search for a job are classified as nonparticipants if they do not satisfy the availability criterion.[5] Finally, the panel contains information on individual characteristics, age, gender, educational level, residential location, family characteristics, etc..

2.1. Summary statistics and representativeness

First, we briefly describe the current French labor market. In 2006, the average participation rate amounted to 69% for 15-64 years old, 74.5% for men and 63.8% for women; see Attal-Toubert and Lavergne (2006). The French labor market is characterized by a weak participation rate of youth and the oldest compared to other European countries. This feature is often linked to the fact that in the 1980's and the 1990's the government and social partners answered to a growing mass unemployment by promoting early retirements and longer studies. In 2006, around 10% of the 15-64 participants were unemployed, nearly half of them having been unemployed for more than one year.[6] Higher unemployment risk is correlated with: a low level of education, youth, female gender, and blue-collar occupation. 13.5% of the employed occupied an unstable job that is training, apprenticeship, fixed-duration or temporary contract jobs.

[5]See Jones and Riddel (2006) for a deep analysis of the frontiers between nonparticipation and ILO unemployment; see also Flinn and Heckman (1983).

[6]The definition of unemployment and the estimation method of the unemployment rate changed in 2007 in France. The definition used here is the one prevailing before 2007.

We focus on 30-49 years old people who finished their studies, because we are interested in rather stable labor market histories, once integration is completed and before that the retirement process begins. Furthermore, we ensure stationarity of underlying processes when concentrating on individuals aged between 30 and 49. The descriptive statistics assessed on the panel data on the one hand, and on the pooled LFS 2003Q1-2007Q1 on the other hand, are quite close; see Table 1. Nonetheless, a slight under-representation of men and of unemployed people can be observed in the balanced panel. This is due to attrition. Unemployed people usually move more often and they are less likely to be interviewed six times. The results presented in the sequel are those holding for the panel.

Table 1. Descriptive statistics

	Panel subsample (obs. 33,206 × 6)	LFS whole sample* (obs. 395,077) (30-49 years old) (Studies finished)
Population		
% women	52.3	50.4
% men	47.8	49.6
Participation rate %		
Women	81.2	82.3
Men	95.6	95.4
Total	88.1	88.8
Unemployment rate %		
Women	7.5	7.8
Men	5.8	6.4
Total	6.7	7.1
Employment rate %		
Women	73.7	74.5
Men	89.9	88.9
Total	81.4	81.7
Share of long-term contracts %		
Women	86.2	86.2
Men	92.9	91.5
Total	89.8	89.1

* pooled analysis.

2.2. Descriptive statistics on transitions

The transitions between nonparticipation, unemployment, unstable jobs and stable jobs observed in the balanced panel are described in Table 2. First, 75% of the sample sojourn within long-term jobs or do not participate during the whole observation period, while only 25% experience in-sample transitions. Second, 19% of men and 27% of women experience one or more transition within the observation period. Half of them accede to long-term contract job and half of them transit without acceding to a CDI. So the apparent ratio of individuals trapped into "contingent work" is 9% for men and 15% for women. Labor market histories greatly differ between men and women. Women are more likely to be nonparticipant during the whole observation period than men (13% versus 20%) and men are more likely to occupy a stable job during the whole observation period.

Table 2. Data description

	Men		Women	
Individuals...	15,847	100%	17,359	100%
sojourning in long-term jobs	12,497	79%	10,495	60 %
staying nonparticipants	382	2%	2,188	13%
moving between long-term, short-term jobs and without job spells	1,571	10%	2,065	12%
moving between short-term jobs and without job spells only	1,397	9%	2,611	15%

A simple Markov-chain model also provides some insightful summary statistics, see Table 3.

Table 3. Four-state Markov transition matrices

	Men				Women			
$T \rightarrow T+1$	SJ	UJ	U	NP	SJ	UJ	U	NP
SJ	0.989	0.002	0.005	0.004	0.983	0.003	0.005	0.009
	(0.000)*	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
UJ	0.084	0.759	0.128	0.029	0.062	0.785	0.113	0.040
	(0.004)	(0.008)	(0.007)	(0.003)	(0.003)	(0.007)	(0.005)	(0.002)
U	0.067	0.147	0.696	0.090	0.059	0.136	0.669	0.137
	(0.004)	(0.006)	(0.008)	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)
NP	0.074	0.024	0.112	0.791	0.037	0.016	0.059	0.887
	(0.005)	(0.003)	(0.006)	(0.009)	(0.002)	(0.001)	(0.002)	(0.003)

* bootstrapped standard deviations with 50 replicates.

Stable jobs and nonparticipation are the most persistent states: 99% and 79% of persistence within three months for men, and 98% and 89% for women. Around 75% of workers with unstable jobs and 66% of unemployed remain in the same state three months later.

The propensity to accede to stable jobs is more state-dependent for women than for men. 6.7% of male unemployed, 8.4% of male temporary workers and 7.4% of male nonparticipants obtain a stable job within three months whereas 5.9% of female unemployed, 6.2% of female temporary workers and only 3.7% of female nonparticipants obtain a stable job within three months. Female nonparticipants are further away from the labor market than men are.

About 75% of unemployed individuals, whether male or female, transit to employment via a temporary job (15% versus 6% for stable jobs). On the one hand, this underlines the potentially integrating nature of temporary jobs. Before finding a long-term job, a large part of the unemployed go through temporary jobs. On the other hand, this may also suggest a dual labor market. Unemployed people have more frequently access to unstable jobs rather than to stable positions. The relationship between unemployment and non-participation is asymmetric for women: 14% of the unemployed leave the labor force each quarter, whereas only 6% of the non-participants become unemployed. For men, these proportions are quite the same: 9% of male unemployed exit the labor force, 11% of male nonparticipants become unemployed.

3. Methodology: the conditional confined-unconfined worker model

The former Markov-chain model assumes that labor market transitions are generated by the same underlying process for all individuals. This approach is restrictive in that it does not provide information on coexisting different dynamic processes. To cover a potential labor market heterogeneity, we turn to mover-stayer-like models. Mover-stayer models rely on a mixture of Markov chains; see Blumen, Kogan, and MacCarthy (1955), Goodman (1961), Spilerman (1972), Singer and Spilerman (1976), Frydman (1984). The model developed in this section extends the version of Kamionka (1996)

Let us consider N individuals $i = 1, \ldots, N$, observed at dates $t = 0, \ldots, T$. These individuals can transit between K states relating to their labor market situation ($K = 4$ in what follows) - *stable jobs* (1), *short-term jobs* (2), *unemployment* (3) and *nonparticipation* (4). The individual i experiences a sequence of states denoted by the T-vector $(e_{i0}, \ldots, e_{iT})$. C_i denotes the kind of dynamic process generating the transitions experienced by individual i. Four dynamic processes are assumed to exist: *stable-job stayer* (S_1), *nonparticipant stayer* (S_K), *unconfined mover* (M), *confined mover* (I). The two *stayer* processes generate histories sojourning indefinitely in the same state and the two *mover* processes generate histories with transitions.

- The *unconfined-mover* process corresponds to labor-market histories where individuals can access to any of the K states, and in particular to stable jobs. Those histories are associated to an unconstrained Markov chain with transition matrix $M = \{m_{ij}\}$.

- The *confined-mover* process corresponds to labor-market histories where workers cannot have access to stable jobs. Formally, the underlying stochastic process is a degenerated Markov chain with transition matrix $Q = \{q_{ij}\}$, in which the row and the column components related to the stable-job state are set to zero.

Furthermore, individual i is endowed with characteristics X_i. The dynamic heterogeneity which is taken into account by the random variable C_i is not observed but is assumed to depend on observables.[7] Then,

- $p_{S_1}(X_i)$ is the probability to be a stayer in stable jobs (state 1), conditional on starting in state 1 and covariates X_i;

- $p_{S_K}(X_i)$ is the probability to be a stayer out of the labor market (state K) , conditional on starting in state K and covariates X_i;

- $p_I(X_i)$ is the probability to be a confined mover, conditional on not starting in state 1 and covariates X_i, *i.e.*, whether the individual starts in state $2, 3, \ldots,$ or K.

The contribution of individual i to the likelihood conditional on the initial state depends on the observed history.

1. When individual i is observed to start in state 1, stable job, alternatives cases may occur. If a transition is observed during the observation period, individual i is, for sure, an un-

[7] Kamionka (1996) describes this dynamic heterogeneity as a partially observed heterogeneity since the labor market histories, partially observed, provide information on the individual types, in contrast with other unobserved individual heterogeneity methods.

confined mover. His or her contribution to the likelihood is thus:

$$\big(1 - p_{S_1}(X_i)\big) \prod_{t=1}^{T} m_{i_{t-1}i_t}.$$

If no transition is observed, individual i may either be a stayer in state 1 or an unconfined mover. His/her contribution is:

$$p_{S_1}(X_i) + \big(1 - p_{S_1}(X_i)\big) \prod_{t=1}^{T} m_{i_{t-1}i_t}.$$

2. When individual i starts in states 2 or 3, there are also two options.

   If individual i occupies a stable job at least once, then he or she is an unconfined mover. His or her contribution is:

$$(1 - p_I(X_i)) \prod_{t=1}^{T} m_{i_{t-1}i_t}.$$

   If individual i does not occupy a stable job during the observation period, then he or she may either be a confined mover or an unconfined mover. His or her contribution is:

$$p_I(X_i) \prod_{t=1}^{T} q_{i_{t-1}i_t} + (1 - p_I(X_i)) \prod_{t=1}^{T} m_{i_{t-1}i_t}.$$

3. When individual i starts by a nonparticipation spell, three cases may occur.

   If individual i occupies once a stable job, then he or she is an unconfined mover. His or her contribution is:

$$(1 - p_{S_K}(X_i))(1 - p_I(X_i)) \prod_{t=1}^{T} m_{i_{t-1}i_t}.$$

   When individual i does not occupy a stable job during the period, then he or she may be a confined mover or an unconfined mover. His or her contribution is:

$$(1 - p_{S_K}(X_i)) \left[p_I(X_i) \prod_{t=1}^{T} q_{i_{t-1}i_t} + (1 - p_I(X_i)) \prod_{t=1}^{T} m_{i_{t-1}i_t} \right].$$

   If individual i remains in state K, then he or she may be stayer, confined mover or unconfined mover. His or her contribution is:

$$p_{S_K}(X_i) + (1 - p_{S_K}(X_i)) \left[p_I(X_i) \prod_{t=1}^{T} q_{i_{t-1}i_t} + (1 - p_I(X_i)) \prod_{t=1}^{T} m_{i_{t-1}i_t} \right].$$

Finally, the conditional likelihood is the product of the N individual contributions. The model is identified if the number of periods of observation is at least 3. The identification relies on the fact that the stayer transition matrices are set to be the identity matrix and that the individuals who move at least once in the stable job state are known to be unconfined movers. If they are observed at least three times, they are supposed to experience the 4×4 kinds of transitions, which enables the identification. The model is estimated by a standard maximum likelihood method. For a more detailed discussion on identification and consistency of ML estimators, see Kamionka (1996) and Frydman (1984). In practice, the model is reparameterized to take into account that, in the transition matrices, the exit probabilities belong to $[0, 1]$ and sum to unity by row. The conditional probabilities of being of a given type are modeled by logit models.

4. Results

The conditional confined-unconfined model is estimated separately on men and women, in order to take into account gender heterogeneity of labor market dynamics. This approach is justified by a specification analysis presented in section 5.2.[8] The covariates used to explain the conditional probabilities of being of a given kind are the following: age, marital status, having children, education, residence location (in Paris region vs. outside, in a distressed area (ZUS) vs. outside). In what follows, a discussion of the main results is presented. The detailed figures are reported in Appendix C (see Tables 11-15 and Figures 1 and 2).

4.1. Sectorisation in the labor market

First, table 4 reports the probabilities that a worker is of one of the four types.

Around 63% of women and 73% of men are stayers, either in stable jobs or out of the labor market, while the remaining are movers. Confined movers are around 5% of the whole

[8] In section 5.2, we investigate whether the labor market dynamics can be modeled by the same processes for both gender. Tests confirm that transition matrices differ across gender groups.

Table 4. Marginal probabilities for each type, given gender and age.

	stayer in stable job	unconfined mover	confined mover	stayer out of the labor market
Women 30-49	51.0%	32.1%	5.2%	11.7%
Men 30-49	70.6%	22.5%	4.3%	2.5%

population, but around 15% of the movers.

The 5% figure of confined movers has to be compared to the empirical ratio of confined movers found without accounting for truncation, which amounts to 13% [Tables 11 and 14].[9] So the model structure is successful in controlling for the truncation induced by the 15 months of observation.

Table 5. Average Type-probabilities conditional on initial states.

	confined mover	stayer in stable job	nonparticipant stayer	% confined movers $|2,3,4$
Women 30-49	0.153	0.771	0.610	23%
	(0.033)	(0.014)	(0.012)	
Men 30-49	0.285	0.832	0.546	36%
	(0.043)	(0.012)	(0.018)	

* st. errors obtained by bootstrap, using 100 sample replicates.

Table 5 reports the marginal probabilities of being of a given type conditional on the initial state. This table sums up the last rows of tables 12 and 15 for readability.

4.1.1. The confined movers

The confined-mover population keeps on alternating nonemployment spells with short-term jobs without being able to accede to a stable position. The confined-mover labor-market histories concern approximately 29% of the 30-49 men and 15% of the 30-49 women who do not start in a stable job [Table 5].

Figures 1 and 2 report the densities of the individual probabilities of being of a given type estimated on the sample. Their spread provides some insight about the way the included covariates explain the propensity of being of that type. In a sense it gives an indication on the goodness-of-fit of the model. When the covariates are poor predictors, the distributions of the

[9] *i.e.*, the share of people that never reach stable jobs during the 15 months observed.

predicted probabilities are expected to be peaked around the mean value. Here, on the contrary, they stretch over $[0, 1]$, which indicates that a notable part of the heterogeneity is explained by the observables.

The effects of the covariates on the probability of being a confined mover are reported in the first column of Tables 13 and 16. Education is the only relevant variable we find to explain females probability to be confined movers: lower degrees tend to be correlated with higher probabilities. Not surprisingly, for males, education is relevant as well. But family variables also enter significantly: men with lower probabilities to be confined movers are more likely to be married and to have children. They are also less likely to live in more distressed areas (ZUS).

4.1.2. The nonparticipant stayers

55% of men who were initially out of the labor market are nonparticipant stayers versus 62% for women (table 5). This illustrates the fact that French women are further from the labor market than are men. After a nonparticipation spell, women are more likely to stay nonparticipant than men; after a long-term job spell, they are more likely to move to short-term jobs or nonemployment.

The effects of the covariates on the probability of being stayers out of the labor market are reported in the third column of tables 13 and 16. Non participants stayers are rather older (being over than forty is significant for both gender groups), and less educated. However, the degree stratification does not look the same across groups. Among men, the distinction is between having a degree or no degree at all: the quality of the degree is not correlated with the probability to stay out of the labor force. Among women, on the other hand, there looks to exist a strict hierarchy in degrees: women with university degree are less likely to be non participant than high school graduates, who themselves are less likely than women with some elementary or no degree at all. For men, having children is correlated with lower probabilities to be non participants. The effect of children is more complex for women. Of course, having a 0 to 3 year old child is correlated with higher probabilities to stay our of the labor market. However, having a 4 to 6 years old child is correlated with lower probabilities to stay our of the labor market. The fact of being married and living outside the Paris regions are two characteristics of women who are further away from the labor market. These results illustrate that family variables affect the female labor market histories and dynamics whereas their impacts are smaller and more subtle on male ones. They directly refer to the traditional separation of roles between men and women.

4.1.3. The stable-job stayers

Between 30 and 49, 83% of men starting in stable jobs are stayers in stable jobs versus 77% of women. The education level has a noticeable impact both for women and for men. Having no degree or a basic vocational degree seriously reduces the chances of being a stayer in stable jobs. Then, age has a strong positive effect, indicating that older workers enjoy more stable histories. A distressed local labor market has a significant negative impact: living in a ZUS reduces the probability of being a stayer in a stable job both for 30-49 men and women. Finally, family variables have some, yet less important than for other probabilities, impact on the probability of being a stayer in stable jobs. Being married is more frequent for men who are stayers in stable jobs. As expected, having a child aged 0 to 6 is correlated with not being a stayer in a stable jobs.

4.2. Dynamics on the labor market

Four different processes generating labor market transitions are estimated. Two of them are stayer processes. People experiencing them remain indefinitely in their initial state, *i.e.* non-participation or long-term job. The two other processes generate labor market transitions. The unconfined-mover process generates histories in which individuals can access to the four states without restriction. The confined-mover process generates histories in which individuals cannot access to stable jobs. In this section, the estimated dynamics are compared.

4.2.1. Confined and unconfined mover transitions

The unconfined-mover-transition process and the confined-mover-transition process clearly describe different labor market histories. The unconfined-mover-transition process generates histories which refer much more often to employment states than the confined-mover-transition one. This holds whatever the gender category.

Table 6 reports the stationary occupation probabilities for each state depending on the underlying dynamic. This table sums up the results of tables 13 and 16.

Table 6. Stationary equilibria

	Unconfined equilibrium				Confined equilibrium		
	SJ	UJ	U	UNP	UJ	U	UNP
Women 30-49	0.585	0.143	0.134	0.138	0.299	0.403	0.297
	(0.023)	(0.009)	(0.011)	(0.013)	(0.059)	(0.044)	(0.069)
Men 30-49	0.680	0.143	0.122	0.055	0.289	0.541	0.169
	(0.026)	(0.012)	(0.014)	(0.006)	(0.054)	(0.042)	(0.032)

*bootstrap standard errors using 100 sample replicates

A given woman (resp. man) in unconfined-mover dynamics is in employment at the stationary equilibrium with a probability of 73% (resp. 82%). For a woman (resp. man) in confined-dynamics, this probability is only 30% (resp. 29%). Therefore, being employed is twice as likely for individuals in unconfined dynamics than for those in confined ones. Furthermore, the unconfined-mover-transition process generates histories which refer slightly more often to participation than the confined-mover one. At equilibrium, unconfined males (resp. females) are 94% (resp. 86%) to participate, versus 83% (resp. 70%) of confined males (females).

These results suggest that the main part of the difference between the unconfined and the confined-mover dynamics cannot be explained by an underlying difference in participation behaviors. This difference is rather explained by the fact that people in confined-mover dynamics more often experience difficult episodes on the labor market such as unemployment than people in unconfined-mover dynamics. This is obvious when the unemployment probability is examined (around 12% for unconfined movers versus 40% to 54% for confined movers).

The parameters in transition matrices stress the unemployment risk faced by individuals with confined-mover histories. Around 30% of individuals initially in unstable jobs and with a confined-mover dynamic would experience unemployment three months later versus around 7% of those with unconfined-mover dynamics. 38% of nonparticipant men with a confined-mover history would become unemployed three months later versus 20% of those with a unconfined-mover history. These remarks hold also for women.

The male and the female unconfined-mover dynamics are significantly different, as shown by specification tests. Men in confined dynamics tend to be less mobile than women and display, for example, higher persistence in unemployment. The picture is rather different for unconfined dynamics. Unconfined males are more mobile than women and they more often get access to employment, both to stable and unstable jobs.

5. Robustness analysis

5.1. Heckman-Singer approach

In mover-stayer-type models, the form of the heterogeneity is imposed *ex ante* by the model (*i.e.*, stayers, unconfined movers, confined movers). In this section, we adopt a more agnostic approach and we consider an alternative model, which does not require to fix *a priori* the nature of types and constraints on transition matrices, in order to see whether the entailed partition shares common features with the one we proposed. We follow the approach of Brodaty (2007) which is inspired by Magnac (2000) and Heckman and Singer (1984). The number of the transition matrices is let free but more structure is imposed on the state dependence (δ_{jk}). Transitions are modeled by a dynamic multinomial logit with unobserved heterogeneity (α_{ik}). This unobserved propensity to move from one state to another is type-specific. If y_{it} denotes the labor market state occupied by the individual i,

$$y_{it} = k \quad \text{if only if} \quad y^*_{ikt} = \max_{j=1,\dots,4}(y^*_{ijt}) \quad \forall(i,t)$$
$$y^*_{ijt} = \sum_{j=1}^{4} \delta_{jk}\mathbb{I}_{y_{i,t-1}=j} + \alpha_{ik} + \epsilon_{ikt} \quad \forall(i,t)$$

Constraints exist in the following methodology, the odds ratios satisfy the following constraints:

$$\forall(j,k,l,l'), \quad \frac{\frac{\mathbb{P}(SJ|State=k,Type=l)}{\mathbb{P}(SJ|State=j,Type=l)}}{\frac{\mathbb{P}(UJ|State=k,Type=l)}{\mathbb{P}(UJ|State=j,Type=l)}} = \frac{\frac{\mathbb{P}(SJ|State=k,Type=l')}{\mathbb{P}(SJ|State=j,Type=l')}}{\frac{\mathbb{P}(UJ|State=k,Type=l')}{\mathbb{P}(UJ|State=j,Type=l')}}$$

Hence this model does not turn to be more flexible than the mover-stayer approach.

The model is estimated sequentially. The first step consists in a conditional maximum likelihood estimation that yields consistent estimates of the state dependence parameters. The type-specific terms are estimated in a second step using an EM algorithm, given the first-stage estimates. The number of types is determined iteratively. The initial condition problem is tackled by using a likelihood conditional on initial states (Brodaty (2007)). Hence, the probability of being of type r depends on the individual initial state.

For men as well as for women, the iterative procedure suggests to retain a partition in five categories. Table 7 details the probabilities of these five types conditional on the four possible initial states. Women who are initially out of the labor force have a high probability (60%) to be type-1 individuals or type-5 individuals (28%). This is not as clear cut for men: when they start out of the labor force, they tend to be rather in types 1 (57%) and 5 (18%), but also in 2 and 4 (11% each). Almost all individuals starting in stable jobs are in type 2. Conditional on starting in unstable jobs, men are mainly type-3 (84%) and type-4 (13%). Women, apart from type-3 (83%) and type-4 (10%) are, in fewer cases, type-5 (6%). Finally, men and women starting in unemployment have similar distributions across types: mainly 4 (around 65%), 3 (around 20%) and 5 (around 15%).

Table 8 contains the transition matrices associated to each type. These matrices and the heterogeneity distribution that may be analyzed together, are used to give an interpretation of the individual types that were found. Table 9 contains the stationary occupation probabilities for each type.

- High transition probabilities leading to non-participation, as well as the fact that individuals who are initially out of the labor market are mainly of type-1, lead us to conclude quite unambiguously that type-1 individuals are close to be "stayers out of the labor market".

- The same kind of argument may be used to assert that individuals following type-2 process are stayers in stable jobs.

- The three last types are more intricate. Individuals of type-3 spend most of their time in unstable jobs. Their probability to accede to a stable job from an unstable job, during a given quarter, is low and even lower for women (6%) than for men (9%). These may be considered as confined movers.

- Type-4 individuals are mainly unemployed. From unemployment, the most likely for them is to find a unstable jobs if they are male (10%) and to exit the labor market if they are female (8%). Their probability to exit unemployment obtaining a stable job is as weak for men and women (5%). They are also good candidates to be confined movers.

- Finally, individuals belonging to type 5 have strong probabilities to accede to a stable job, whatever the state they start in (around 25% for men, and 15% for women). However, they almost never pass through unstable jobs and not frequently in unemployment. They are obviously unconfined movers.

This analysis does support the relevance of the mover-stayer-confined partition. First, non-participant stayers and stayers in stable jobs appear clearly. Results are less clear-cut for the mover categories, since all have a chance to get a stable job. This may be induced by the equality constraint on the odds ratios. But for two types, this probability turns to be rather small. Hence the results obtained here underline that clear differences exist in the transition dynamics, and that the confined/unconfined movers difference matters.

5.2. Specification tests: stability of transition matrices across gender

In section 4 we focused on the results of separate estimations on sub-samples by gender. This was justified by the results of the present section, in which we test whether, once controlling for conditional heterogeneity, the transition dynamics on the labor market are the same for men and women. To do this, we consider three testing hypotheses.

- H_0^1: both confined and unconfined-mover transition matrices are stable across gender,
- H_0^2: the unconfined-mover transition matrix is stable across gender,
- H_0^3: the confined-mover transition matrix is stable across gender.

H_0^1 can be tested by a classical LR test: we estimate the model on men and women separately (M1) and simultaneously with adequate covariates (M0), and compute a LR statistic. For testing H_0^2 and H_0^3, we use a χ^2-statistic (denoted DA, hereafter) based on the difference of the estimates between the two groups which are assumed to be independent (the method is described in details in appendix B). Results are reported in Table 10. The stability of the labor market dynamics across gender is rejected due to different unconfined-mover dynamics whereas the stability of the confined-mover dynamics cannot be rejected. For the latter, labor market histories differences can be explained conditionally, by differences in covariates.

Table 7. Types Distribution

Women	Initial State				**Men**	Initial State			
	SJ	UJ	U	NP		SJ	UJ	U	NP
Type 1	0.002	0.000	0.009	0.601	Type 1	0.000	0.010	0.000	0.572
Type 2	0.907	0.019	0.011	0.044	Type 2	0.925	0.020	0.000	0.106
Type 3	0.020	0.831	0.220	0.024	Type 3	0.025	0.839	0.207	0.030
Type 4	0.018	0.094	0.611	0.056	Type 4	0.015	0.131	0.657	0.114
Type 5	0.053	0.056	0.148	0.275	Type 5	0.035	0.000	0.136	0.179

Note: Each column sums to unity.

Table 8. Transition matrices according to types

Men					**Women**				
First type					First type				
	0.243	0.006	0.010	0.741		0.000	0.000	0.005	0.995
	0.031	0.074	0.024	0.871		0.000	0.000	0.009	0.991
	0.015	0.019	0.034	0.931		0.000	0.000	0.014	0.986
	0.006	0.005	0.009	0.980		0.000	0.000	0.003	0.997
Second type					Second type				
	0.998	0.000	0.001	0.001		0.998	0.000	0.000	0.001
	0.950	0.032	0.011	0.008		0.956	0.021	0.010	0.014
	0.933	0.017	0.033	0.017		0.940	0.009	0.026	0.025
	0.924	0.011	0.020	0.044		0.921	0.006	0.014	0.058
Third type					Third type				
	0.856	0.079	0.046	0.019		0.804	0.108	0.060	0.028
	0.086	0.810	0.086	0.018		0.059	0.828	0.089	0.024
	0.103	0.534	0.316	0.048		0.082	0.512	0.344	0.062
	0.132	0.454	0.254	0.161		0.105	0.457	0.244	0.194
Fourth type					Fourth type				
	0.710	0.027	0.213	0.050		0.726	0.023	0.196	0.054
	0.089	0.346	0.507	0.058		0.094	0.312	0.513	0.082
	0.046	0.097	0.790	0.067		0.052	0.077	0.788	0.084
	0.058	0.083	0.635	0.224		0.070	0.072	0.585	0.273
Fifth type					Fifth type				
	0.902	0.002	0.029	0.068		0.830	0.007	0.030	0.133
	0.399	0.083	0.243	0.275		0.223	0.194	0.164	0.418
	0.221	0.025	0.411	0.343		0.145	0.056	0.296	0.503
	0.159	0.012	0.185	0.645		0.093	0.025	0.104	0.778

Table 9 Limiting Probabilities

Men	SJ	UJ	U	NP	**Women**	SJ	UJ	U	NP
Type 1	0.008	0.006	0.009	0.977	Type 1	0.000	0.000	0.003	0.997
Type 2	0.998	0.000	0.001	0.001	Type 2	0.998	0.000	0.001	0.001
Type 3	0.386	0.492	0.097	0.025	Type 3	0.247	0.600	0.117	0.036
Type 4	0.154	0.114	0.658	0.075	Type 4	0.176	0.087	0.640	0.097
Type 5	0.650	0.007	0.108	0.234	Type 5	0.384	0.025	0.096	0.495

Note: Each row has to sum to unity.

Table 10. Tests for stability of dynamics across gender (p-values).

Null hypothesis	H_0^1	H_0^2	H_0^3
30-49	0.000	0.000	0.513

Note: Test statistics LR is the first column and DA for the second and the third ones. p-values are computed using χ^2 distributions. Degrees of freedom are resp. 18 (24 and 12) for the first (second and third) columns.

6. Conclusion

This paper proposes to model labor market transitions accounting specifically for individual heterogeneity in the ability to accede to stable jobs. The model used is based on a Markov-chain mixture of four types of transition dynamics: the *stayers in stable-jobs*, the *stayers in nonparticipation*, the *unconfined movers*, and the individuals stuck on *confined* states and who cannot accede to stable jobs. Conditional heterogeneity is allowed. The probabilities of being of a certain type depend on observable individual characteristics. Estimation is done focusing on a population already well inserted in the labor market but yet not ready to retire: men and women aged 30 to 49.

Our main results are the following. Individuals trapped in confined mover histories represent 5% of the population under study (versus 13% apparently observed). Unconfined-mover dynamics depend on gender, whereas male and female confined movers cannot be proved to experience different dynamics. At equilibrium, an individual whose labor market history is generated by the confined mover process has between 3 and 4 times more chances to be unemployed than a confined mover. Participation, however, is not different across the two categories. The probability to be a confined mover decreases with the quality of education. For men, a high probability is also correlated with being single, and living in a distressed area.

A. Stationary occupation probabilities

Confined-unconfined models, just like mover-stayer models, satisfy the Markov assumption conditional on the initial state. The stationary occupation probability vector represents the probabilities associated to each state once the process converged to the steady state and can be defined for any Markov-chain process. Let us consider a Markov-chain process with transition matrix A. The stationary occupation probability vector, denoted a^*, is defined such that it is invariant by pre-multiplication by the transition matrix:

$$A'a^* = a^*. \tag{A.1}$$

Moreover, it is a vector of probabilities. Hence, its components remain in $[0, 1]$ and sum to one. The stationary occupation probability vector is a useful tool to describe the labor market segmentation.

Stationary occupation probabilities (conditional on the initial values) are easily extended to mixtures of Markov chains by:

$$p^M m^* + p^Q q^* + p^{S_1} s_1^* + p^{S_K} s_K^*,$$

where m^*, q^*, s_1^* and s_K^* are the stationary probability vectors (as defined in A.1) relating to each elementary Markov chain, and p^M, p^Q, p^{S_1}, and p^{S_K}, the mixture coefficients relating to each elementary Markov chain. In the conditional confined-unconfined model, sample stationary occupation probability vector can be estimated by the sample average of the weighted sum of the stationary probability vectors of each elementary Markov process composing the mixture.

$$\frac{1}{N}\sum_{i=1}^{N} p_i^M m^* + p_i^Q q^* + p_i^{S_1} s_1^* + p_i^{S_K} s_K^*,$$

where m^*, q^*, s_1^* and s_K^* are the stationary probability vectors (as defined in A.1) relating to each elementary Markov chain, and p_i^M, p_i^Q, $p_i^{S_1}$, and $p_i^{S_K}$, the individual probabilities of following each elementary Markov chain. Note that p_i^M, p_i^Q, $p_i^{S_1}$, $p_i^{S_K}$ sum to one.

B. Darmois-type test for coefficient equality across subsamples

The idea is the same as the the classical Darmois test for testing the equality of the means in two subsamples with unknown different variances; see Darmois (1954). Data is composed of two samples: sample 1, with n_1 observations $\{\mathcal{Y}_i^1\}_{i=1,\ldots,n_1}$ whose distribution is function of the parameter of interest $\beta_1 \in \mathbb{R}^k$; and sample 2, with n_2 observations $\{\mathcal{Y}_i^2\}_{i=1,\ldots,n_2}$ whose distribution is function of $\beta_2 \in \mathbb{R}^k$. $\{\mathcal{Y}_i^1\}_{i=1,\ldots,n_1}$ and $\{\mathcal{Y}_i^2\}_{i=1,\ldots,n_2}$ are independent and both composed of $i.i.d.$ observations. $\hat{\beta}_1$ (resp. $\hat{\beta}_2$) denotes the estimate of β_1 (resp. β_2) based on sample 1 (resp. sample 2). Consider testing $H_0 : \beta_1 = \beta_2 = \beta_0$ against $H_1 : \beta_1 \neq \beta_2$. Assume that CLT theorems apply for β_1 and β_2, *i.e.* under H_0:

$$\sqrt{n_1}(\hat{\beta}_1 - \beta_0) \quad \rightarrow \quad \mathcal{N}(0, \text{Vas}(\hat{\beta}_1)) \tag{B.2}$$

$$\sqrt{n_2}(\hat{\beta}_2 - \beta_0) \quad \rightarrow \quad \mathcal{N}(0, \text{Vas}(\hat{\beta}_2)) \tag{B.3}$$

and $\hat{\beta}_1$ and $\hat{\beta}_2$ are independent. Hence, it follows that under H_0,

$$DA = (\hat{\beta}_1 - \hat{\beta}_2)' \left(\frac{1}{n_1}\text{Vas}(\hat{\beta}_1) + \frac{1}{n_2}\text{Vas}(\hat{\beta}_2) \right)^{-1} (\hat{\beta}_1 - \hat{\beta}_2) \rightarrow \chi^2(2k). \tag{B.4}$$

A test for H_0 with asymptotic level α rejects H_0 when $DA > c_{1-\alpha}$, where $c_{1-\alpha}$ is the 1-α quantile of a χ^2 distribution with $2k$ degrees of freedom.

C. Detailed results

C.1. Women between 30 and 49

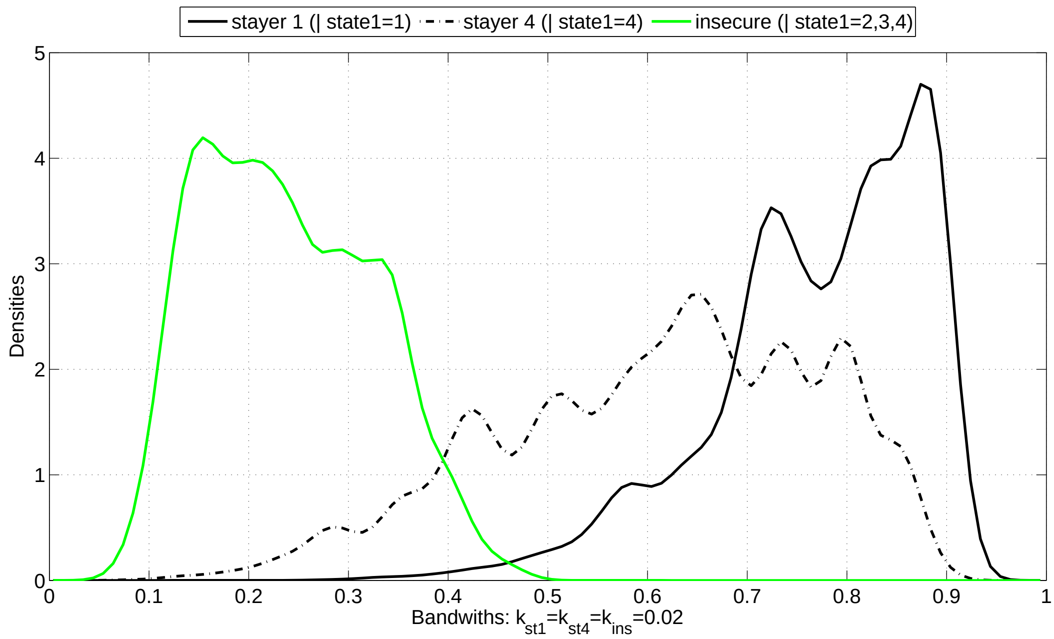
Women between 30 and 49, 4 states : out of the labor market (4), unemployed (3), short-term contract (2), long-term contract (1). Asymptotic standard-errors are obtained by bootstrap (design matrix bootstrap centered around the sample estimate) with 100 sample replicates.

Table 11 describes the observed histories.

Table 11. Data : women between 30 and 49.

Individuals...	17,359	100%
staying in 1	10,495	60 %
staying in 4	2,188	13%
moving between 1, 2, 3 and 4	2,065	12%
moving between 2, 3 and 4 only	2,611	15%

Figure 1. Densities of individual probabilities of being stayer in 1, stayer in 4 and confined conditional on initial states



C.2. Men between 30 and 49

Men between 30 and 49, 4 states : out of the labor market (4), unemployed (3), short-term contract (2), long-term contract (1). Asymptotic standard-errors are obtained by bootstrap (design matrix bootstrap centered around the sample estimate) with 100 sample replicates.

Table 14 describes the observed histories.

Table 12. Coefficients: women between 30 and 49.

	Estimates - MLE		
Covariates	confined mover	stayer in stable job	stayer in non-participation
intercept	-1.244	0.931	-1.187
	(1.409)	(0.359)	(0.626)
30-39	-	-	-
	-	-	-
40-49	0.124	0.640	0.576
	(0.179)	(0.101)	(0.108)
married	-0.234	0.125	0.627
	(0.188)	(0.096)	(0.096)
university degree	0.386	0.172	-0.453
(bac+3 and more)	(0.357)	(0.218)	(0.211)
college degree or more	0.141	0.174	-0.229
(bac+2 and more)	(0.475)	(0.172)	(0.213)
completed high school	-	-	-
(bac)	-	-	-
basic vocational degree	0.622	-0.359	0.096
	(0.299)	(0.142)	(0.141)
elementary high school	0.236	0.054	0.504
	(0.380)	(0.211)	(0.165)
no degree	1.081	-0.994	0.835
	(0.326)	(0.139)	(0.154)
ZUS	0.262	-0.421	0.190
	(0.385)	(0.231)	(0.121)
Paris	-0.416	-0.153	-0.312
	(0.288)	(0.135)	(0.135)
one 0-18 year-old child or more	0.258	-0.154	-0.395
	(0.205)	(0.104)	(0.111)
one 3- 6 year-old child or more	-0.038	-0.601	0.607
	(0.643)	(0.155)	(0.137)
one 0- 3 year-old child or more	-0.114	-0.282	-0.365
	(0.252)	(0.126)	(0.121)
Experience above 7 years	-0.636	0.397	0.905
	(1.336)	(0.307)	(0.632)
Average conditional	0.153	0.771	0.610
probability	(0.033)	(0.014)	(0.012)

Asymptotic standard errors estimates are obtained by design matrix bootstrap centered around the sample estimate with 100 sample replicates.

Table 13. Transition matrices: women between 30 and 49.

Unconfined transition matrix:

$T \to T+1$	SJ	UJ	U	NP
SJ ($k=1$)	0.931	0.011	0.023	0.036
	(0.005)	(0.001)	(0.002)	(0.003)
UJ ($k=2$)	0.079	0.836	0.061	0.023
	(0.006)	(0.033)	(0.024)	(0.008)
U ($k=3$)	0.082	0.099	0.720	0.099
	(0.009)	(0.025)	(0.030)	(0.019)
NP ($k=4$)	0.133	0.029	0.113	0.724
	(0.014)	(0.008)	(0.016)	(0.019)

boot. st. err. : 100 replicates

Confined transition matrix:

$T \to T+1$	SJ	UJ	U	NP
SJ ($k=1$)	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000
UJ ($k=2$)	0.000	0.600	0.302	0.098
	0.000	(0.090)	(0.074)	(0.025)
U ($k=3$)	0.000	0.227	0.540	0.233
	0.000	(0.076)	(0.070)	(0.058)
NP($k=4$)	0.000	0.094	0.320	0.586
	0.000	(0.080)	(0.063)	(0.096)

boot. st. err. : 100 replicates

Stationary equilibria:

	SJ	UJ	U	UNP
Unconfined equilibrium	0.585	0.143	0.134	0.138
	(0.023)	(0.009)	(0.011)	(0.013)
Confined equilibrium	0.000	0.299	0.403	0.297
	(0.000)	(0.059)	(0.044)	(0.069)
Total equilibrium	0.698	0.062	0.064	0.177
	(0.004)	(0.002)	(0.002)	(0.003)

boot. st. err. : 100 replicates

Table 14. Data : men between 30 and 49.

Individuals...	15,847	100%
staying in 1	12,497	79%
staying in 4	382	2%
moving between 1, 2, 3 and 4	1,571	10%
moving between 2, 3 and 4 only	1,397	9%

Figure 2. Densities of individual probabilities of being stayer in 1, stayer in 4 and confined conditional on initial states

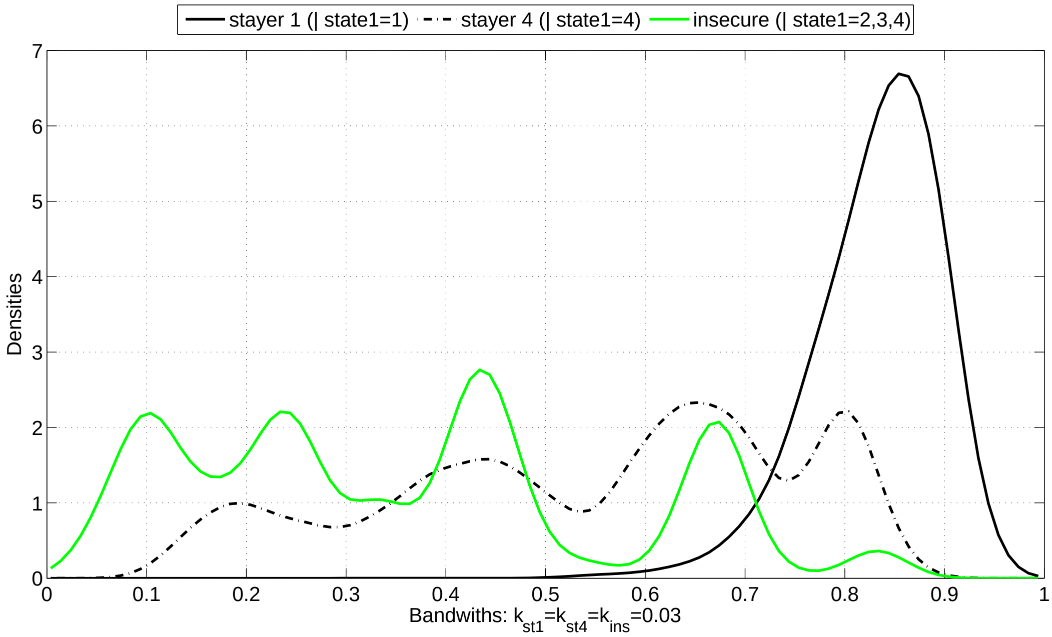


Table 15. Coefficients: men between 30 and 49.

	Estimates - MLE		
Covariates	confined mover	stayer in stable job	stayer in non-participation
intercept	-0.480	1.141	0.892
	(3.666)	(0.391)	(0.826)
30-39	-	-	-
	-	-	-
40-49	0.028	0.475	0.832
	(0.233)	(0.094)	(0.182)
married	-0.870	0.347	0.038
	(0.245)	(0.096)	(0.209)
university degree	-0.019	0.089	-0.146
(bac+3 and more)	(1.930)	(0.175)	(0.415)
college degree or more	0.270	0.306	-0.281
(bac+2 and more)	(0.484)	(0.243)	(0.446)
completed high school	-	-	-
(bac)	-	-	-
basic vocational degree	0.361	-0.145	0.179
	(0.447)	(0.146)	(0.306)
elementary high school	1.257	-0.049	0.481
	(0.616)	(0.220)	(0.353)
no degree	1.391	-0.448	0.784
	(0.486)	(0.162)	(0.314)
ZUS	0.872	-0.644	0.312
	(0.311)	(0.211)	(0.285)
Paris	-0.564	-0.123	-0.210
	(0.494)	(0.132)	(0.332)
one 0-18 year-old child or more	-0.957	-0.062	-1.053
	(0.253)	(0.108)	(0.225)
one 0- 3 year-old child or more	0.069	0.057	-0.312
	(0.374)	(0.138)	(0.408)
Experience above 7 years	-0.187	0.216	-1.108
	(3.533)	(0.370)	(0.747)
Average conditional	0.285	0.832	0.546
probability	(0.043)	(0.012)	(0.018)

Asymptotic standard errors estimates are obtained by design matrix bootstrap centered around the sample estimate with 100 sample replicates.

Table 16. Transition matrices: men between 30 and 49.

Unconfined transition matrix:

$T \rightarrow T+1$	SJ	UJ	U	NP
SJ ($k = 1$)	0.934	0.014	0.029	0.023
	(0.005)	(0.001)	(0.002)	(0.002)
UJ ($k = 2$)	0.115	0.800	0.069	0.016
	(0.011)	(0.032)	(0.028)	(0.005)
U ($k = 3$)	0.118	0.136	0.670	0.076
	(0.012)	(0.025)	(0.024)	(0.009)
NP ($k = 4$)	0.256	0.045	0.197	0.502
	(0.023)	(0.012)	(0.020)	(0.030)

boot. st. err.: 100 replicates

Confined transition matrix:

$T \rightarrow T+1$	SJ	UJ	U	NP
SJ ($k = 1$)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
UJ ($k = 2$)	0.000	0.650	0.286	0.064
	(0.000)	(0.098)	(0.091)	(0.016)
U ($k = 3$)	0.000	0.163	0.729	0.108
	(0.000)	(0.052)	(0.044)	(0.018)
NP($k = 4$)	0.000	0.077	0.378	0.545
	(0.000)	(0.037)	(0.065)	(0.079)

boot. st. err.: 100 replicates

Stationary equilibria:

	SJ	UJ	U	UNP
Unconfined equilibrium	0.680	0.143	0.122	0.055
	(0.026)	(0.012)	(0.014)	(0.006)
Confined equilibrium	0.000	0.289	0.541	0.169
	(0.000)	(0.054)	(0.042)	(0.032)
Total equilibrium	0.860	0.045	0.051	0.045
	(0.003)	(0.002)	(0.002)	(0.002)

boot. st. err.: 100 replicates

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