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Who is Confronted to Insecure Labor Market Histories ? Some Evidence based on the French Labor Market Transitions

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Who is Confronted to Insecure Labor Market Histories ? Some Evidence based on the French Labor Market Transitions*

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Abstract

This paper presents some empirical evidence on the French labor market focusing on transitions between stable jobs, temporary work, unemployment and non-participation. The model used is based on a Markov chain mixture which allows one to distinguish labor market histories that are confined to contingent work and non-employment from the non-confined ones. This enables us to identify, quantify and characterize (conditional on observable characteristics) the workers who never accede to stable jobs and remain stuck to temporary jobs and non-employment spells. We consider quarterly labor market transitions, observed from 2003 to 2006 in the Labor Force survey (LFS). We find that on the whole, about 5% of the working age population experience *confined* transition dynamics : they cannot access to stable jobs. Confined workers are less educated and are more likely to live in distressed areas.

Key words : labor market mobility, transitions on the labor market, mover-stayer models,Markov chains.
Journal of Economic Literature classification : J21, J60, C33

Résumé

Cette étude analyse les transitions sur le marché du travail entre quatre états : les périodes d'emploi stable, d'emploi instable, de chômage et d'inactivité. Le modèle utilisé repose sur un mélange de chaînes de Markov et permet de distinguer les individus dont les trajectoires sont confinées entre l'emploi instable et le non-emploi de ceux qui peuvent accéder à un emploi stable. Ceci nous permet de dénombrer et de caractériser en fonction de caractéristiques observables ces travailleurs qui n'accèderont jamais à l'emploi stable. L'estimation repose sur les données trimestrielles de l'enquête Emploi, de 2003 à 2006.
Environ 5 % des 30-49 ans ont des trajectoires *confinées* entre des périodes d'emploi instable et des périodes de non-emploi et ne n'accèderont jamais à un emploi stable. Un très faible niveau d'éducation augmente les risques d'être confiné, habiter en ZUS aussi.

Mots clés : mobilité sur le marché du travail, transitions sur le marché du travail, modèles mover-stayer, chaînes de Markov.

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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 controversy on the "Contrat Unique", following those on the "Contrat Nouvelle Embauche" (CNE) and the "Contrat Première Embauche" (CPE) in 2005 and 2006, stressed 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 spells 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 the heterogeneity of the labor supply

[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.

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, 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 (1978), Jovanovic (1979a, 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 duality 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 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

[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.

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 duality 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.

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. 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

[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).

require to *a priori* impose the nature of types and zero-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 one 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.

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 the retirement process begins. Furthermore, we ensure stationarity of underlying processes by 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

[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.

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 $\times$ 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 a 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 unconfined

[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.

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 one 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. Duality in the labor market

First, table 4 reports the probabilities that a worker is of one of the four types.

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%

[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.

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 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 $\vert$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 predicted probabilities are expected to peak 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.

[9] *i.e.*, the share of people that never reach stable jobs during the 15 months observed.

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 seems 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.* nonparticipation 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.

A given woman (resp. man) in unconfined-mover dynamics is in employment at the stationary

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

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 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). Transitions are modeled by a dynamic multinomial logit with unobserved heterogeneity. Let y_{it} denote the labor market state occupied by the individual i at date t, then

$$y_{it} = k \quad \text{if only if} \quad y^*_{ikt} = \max_{j=1,\dots,4}(y^*_{ijt}), \quad \forall(i,t), \tag{5.1}$$

where

$$y^*_{ijt} = \sum_{j=1}^{4} \delta_{jk}\mathbb{I}_{y_{i,t-1}=j} + \alpha_{ik} + \epsilon_{ikt}, \quad \forall(i,t). \tag{5.2}$$

δ_{jk}'s account for dependence from the lag state (state dependence), α_{ik}'s is the unobserved heterogeneity term. This unobserved propensity to move from one state to another is type-specific, $i.e.$ $\alpha_i = (\alpha_{i1}, \dots, \alpha_{i4})'$ can take T different values, $\alpha^1, \dots, \alpha^T$, where T is the number of types present in the model. In order to identify the model, some parameters are set to 0:

$$\begin{aligned} \delta_{j4} &= 0, \forall j = 1, \dots, 4, \\ \delta_{4j} &= 0, \forall j = 1, \dots, 4, \\ \alpha^l_4 &= 0, \forall l = 1, \dots, T. \end{aligned}$$

Further, the ϵ's are type-I extreme value distributed, independent across alternatives, individuals, time and independent of the α's. Then, the probability that individual i goes to state k at time t conditional on being in state j at $t-1$ is given by

$$P(y_{it} = k | y_{it-1} = j, \alpha_i = \alpha^l) = \frac{exp(\delta_{jk} + \alpha_{ik})}{\sum_{m=1}^{4} exp(\delta_{jm} + \alpha_{im})}. \tag{5.3}$$

It depends on his unobserved type l. Contrary to mover-stayer model, no *a priori* 0-constraints are imposed on the transition matrix components, but the dynamic multinomial logit model implies that the odds ratios satisfy the following constraints:

$$\frac{\frac{\mathbb{P}(SJ|State=k,Type=l)}{\mathbb{P}(SJ|State=j,Type=l)}}{\frac{\mathbb{P}(UJ|State=k,Type=l)}{\mathbb{P}(UJ|State=j,Type=l)}} = \frac{\frac{\mathbb{P}(SJ|State=k,Type=l')}{\mathbb{P}(SJ|State=j,Type=l')}}{\frac{\mathbb{P}(UJ|State=k,Type=l')}{\mathbb{P}(UJ|State=j,Type=l')}}, \quad \forall (j,k,l,l'). \tag{5.4}$$

Finally, there is no reason why the dynamic multinomial logit model would be more or less flexible than the mover-stayer approach.

This 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. The number of types is determined iteratively.

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 to be type-1 individuals (60%) or type-5 individuals (28%). Probabilities for men are not as clear cut: when they start out of the labor force, they tend to be type-1 (57%) and type-5 (18%), but also of type-2 and type-4 (11% each). Almost all individuals starting in stable jobs are 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, the types of men and women starting in unemployment are similarly distributed: mainly type-4 (around 65%), then type-3 (around 20%) and type-5 (around 15%).

Table 8 contains the estimates of the transition matrices associated to each type. These matrices and

Table 7. Types Distribution

	Initial State			
Women	SJ	UJ	U	NP
Type 1	0.002 (0.001)	0.000 (0.003)	0.009 (0.007)	0.601 (0.024)
Type 2	0.907 (0.009)	0.019 (0.008)	0.011 (0.007)	0.044 (0.005)
Type 3	0.020 (0.004)	0.831 (0.018)	0.220 (0.017)	0.024 (0.003)
Type 4	0.018 (0.003)	0.094 (0.013)	0.611 (0.021)	0.056 (0.007)
Type 5	0.053 (0.010)	0.056 (0.013)	0.148 (0.020)	0.275 (0.024)
	Initial State			
Men	SJ	UJ	U	NP
Type 1	0.000 (0.001)	0.010 (0.004)	0.000 (0.004)	0.572 (0.031)
Type 2	0.925 (0.013)	0.020 (0.009)	0.000 (0.002)	0.106 (0.018)
Type 3	0.025 (0.004)	0.839 (0.052)	0.207 (0.026)	0.030 (0.010)
Type 4	0.015 (0.004)	0.131 (0.017)	0.657 (0.037)	0.114 (0.025)
Type 5	0.035 (0.012)	0.000 (0.049)	0.136 (0.029)	0.179 (0.044)

Note: Each column sums to one. Standard errors are reported in parentheses.

the heterogeneity distribution have to be analyzed together. They are used to give an interpretation of the individual types that were found and to compare them with the types imposed in the mover-stayer approach. Standard errors are obtained by bootstrap using 70 replicates. Table 9 contains the stationary occupation probabilities for each type.

- Type-1 transition matrix exhibits high transition probabilities to non-participation. Moreover, individuals who are initially out of the labor market are mainly of type-1. These two points enable us to interpret quite unambiguously type-1- individual as “stayers out of the labor market”.

- The same kind of argument can 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 are often in unstable jobs. They have low conditional probabilities to accede to a stable job whatever their departing state: less than 10% when they have an unstable job the period before, and even lower for women (6%) than for men (9%); between 8% and 13% when they come from unemployment or non-participation. Thus, individuals of type-3 are close to confined movers.

- Type-4 individuals are mainly unemployed. When they get exit unemployment, they are more likely to find 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 very low around 5%, both for men and for women. Further, obtaining a stable job is unlikely, whatever the departing state: the transition probabilities never exceed 10%. And this holds also for men and women. Type 4 is the closest to the confined mover-type.

- Finally, type-5 individuals have relatively 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 job or unemployment spells. They obviously can be interpreted as unconfined movers.

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
(0.129)	(0.002)	(0.004)	(0.129)	(0.065)	(0.001)	(0.003)	(0.066)
0.031	0.074	0.024	0.871	0.000	0.000	0.009	0.991
(0.028)	(0.028)	(0.013)	(0.046)	(0.010)	(0.008)	(0.007)	(0.019)
0.015	0.019	0.034	0.931	0.000	0.000	0.014	0.986
(0.013)	(0.007)	(0.019)	(0.029)	(0.005)	(0.002)	(0.010)	(0.015)
0.006	0.005	0.009	0.980	0.000	0.000	0.003	0.997
(0.005)	(0.002)	(0.004)	(0.007)	(0.002)	(0.000)	(0.002)	(0.004)
Second type				**Second type**			
0.998	0.000	0.001	0.001	0.998	0.000	0.000	0.001
(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
0.950	0.032	0.011	0.008	0.956	0.021	0.010	0.014
(0.018)	(0.016)	(0.004)	(0.004)	(0.016)	(0.013)	(0.004)	(0.005)
0.933	0.017	0.033	0.017	0.940	0.009	0.026	0.025
(0.024)	(0.009)	(0.015)	(0.008)	(0.019)	(0.006)	(0.011)	(0.009)
0.924	0.011	0.020	0.044	0.921	0.006	0.014	0.058
(0.031)	(0.006)	(0.009)	(0.023)	(0.024)	(0.004)	(0.006)	(0.021)
Third type				**Third type**			
0.856	0.079	0.046	0.019	0.804	0.108	0.060	0.028
(0.022)	(0.016)	(0.007)	(0.004)	(0.029)	(0.020)	(0.009)	(0.004)
0.086	0.810	0.086	0.018	0.059	0.828	0.089	0.024
(0.009)	(0.008)	(0.006)	(0.003)	(0.004)	(0.007)	(0.004)	(0.002)
0.103	0.534	0.316	0.048	0.082	0.512	0.344	0.062
(0.016)	(0.028)	(0.025)	(0.009)	(0.011)	(0.022)	(0.019)	(0.006)
0.132	0.454	0.254	0.161	0.105	0.457	0.244	0.194
(0.029)	(0.046)	(0.029)	(0.028)	(0.014)	(0.027)	(0.016)	(0.019)
Fourth type				**Fourth type**			
0.710	0.027	0.213	0.050	0.726	0.023	0.196	0.054
(0.046)	(0.006)	(0.039)	(0.010)	(0.032)	(0.004)	(0.026)	(0.008)
0.089	0.346	0.507	0.058	0.094	0.312	0.513	0.082
(0.017)	(0.029)	(0.026)	(0.012)	(0.014)	(0.024)	(0.023)	(0.010)
0.046	0.097	0.790	0.067	0.052	0.077	0.788	0.006
(0.007)	(0.007)	(0.013)	(0.008)	(0.004)	(0.006)	(0.009)	(0.028)
0.058	0.083	0.635	0.224	0.070	0.072	0.585	0.273
(0.013)	(0.013)	(0.039)	(0.039)	(0.010)	(0.007)	(0.022)	(0.023)
Fifth type				**Fifth type**			
0.902	0.002	0.029	0.068	0.830	0.007	0.030	0.133
(0.033)	(0.018)	(0.013)	(0.016)	(0.020)	(0.002)	(0.004)	(0.018)
0.399	0.083	0.243	0.275	0.223	0.194	0.164	0.418
(0.083)	(0.113)	(0.041)	(0.061)	(0.028)	(0.038)	(0.013)	(0.043)
0.221	0.025	0.411	0.343	0.145	0.056	0.296	0.503
(0.052)	(0.067)	(0.048)	(0.062)	(0.017)	(0.016)	(0.021)	(0.034)
0.159	0.012	0.185	0.645	0.093	0.025	0.104	0.778
(0.039)	(0.056)	(0.039)	(0.072)	(0.011)	(0.009)	(0.009)	(0.023)

Note: bootstrapped standard errors are reported in parentheses.

Table 9 Limiting Probabilities

Men	SJ	UJ	U	NP	**Women**	SJ	UJ	U	NP
Type 1	0.008 (0.014)	0.006 (0.002)	0.009 (0.005)	0.977 (0.017)	Type 1	0.000 (0.003)	0.000 (0.001)	0.003 (0.002)	0.997 (0.005)
Type 2	0.998 (0.001)	0.000 (0.000)	0.001 (0.000)	0.001 (0.000)	Type 2	0.998 (0.001)	0.000 (0.000)	0.001 (0.000)	0.001 (0.000)
Type 3	0.386 (0.049)	0.492 (0.040)	0.097 (0.010)	0.025 (0.004)	Type 3	0.247 (0.035)	0.600 (0.031)	0.117 (0.007)	0.036 (0.003)
Type 4	0.154 (0.042)	0.114 (0.012)	0.658 (0.038)	0.075 (0.010)	Type 4	0.176 (0.025)	0.087 (0.008)	0.640 (0.022)	0.097 (0.009)
Type 5	0.650 (0.107)	0.007 (0.088)	0.108 (0.041)	0.234 (0.056)	Type 5	0.384 (0.049)	0.025 (0.009)	0.096 (0.009)	0.495 (0.051)

Note: each row sums to one. Bootstrapped standard errors are reported in parentheses.

This alternative analysis does support the relevance of the mover-stayer-confined partition. First, nonparticipant stayers and stayers in stable jobs appear clearly. Results are less clear-cut for the mover categories, since individuals of all categories have a chance to obtain a stable job. This could be a consequence of the structure imposed by the model. But for two types, probabilities to obtain a stable job turns out to be rather small. Hence the results obtained here underline that clear differences exist in the transition dynamics, and that splitting movers into confined/unconfined categories is relevant.

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

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.

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.

6. Conclusion

The model used in this paper 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. This partition enables us to specifically account for heterogenous abilities to accede to stable jobs. The probabilities of being of a given type also depend on observable individual characteristics. The data come from the French Labor Force Survey, the model is estimated on the 30-49 years old individuals.

The main results are the following. Individuals who are trapped in confined mover histories represent around 5% of the 30-49 years old population (versus 13% apparently observed). At equilibrium, participation rates of the confined and the unconfined populations are similar but 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. The probability to be a confined mover decreases with the education level. Male confined movers are also more likely to be single, and to live in a distressed area whereas for women, only the education seems to matter. Finally, unconfined-mover dynamics depend on gender, whereas male and female confined mover dynamics are not significantly different.

APPENDIX

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:

$$A'a^* = a^*. \tag{A.5}$$

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 how much labor market histories generated by a given dynamic are confined in some states.

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.5) 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.5) 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:

$$\sqrt{n_1}(\hat{\beta}_1 - \beta_0) \quad \rightarrow \quad \mathcal{N}(0, \text{Vas}(\hat{\beta}_1)) \tag{B.6}$$

$$\sqrt{n_2}(\hat{\beta}_2 - \beta_0) \quad \rightarrow \quad \mathcal{N}(0, \text{Vas}(\hat{\beta}_2)) \tag{B.7}$$

and $\hat{\beta}_1$ and $\hat{\beta}_2$ are independent. Hence, it follows that under H_0,

$$DA = (\hat{\beta}_1 - \hat{\beta}_2)' \left(\frac{1}{n_1} \text{Vas}(\hat{\beta}_1) + \frac{1}{n_2} \text{Vas}(\hat{\beta}_2) \right)^{-1} (\hat{\beta}_1 - \hat{\beta}_2) \rightarrow \chi^2(2k). \tag{B.8}$$

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

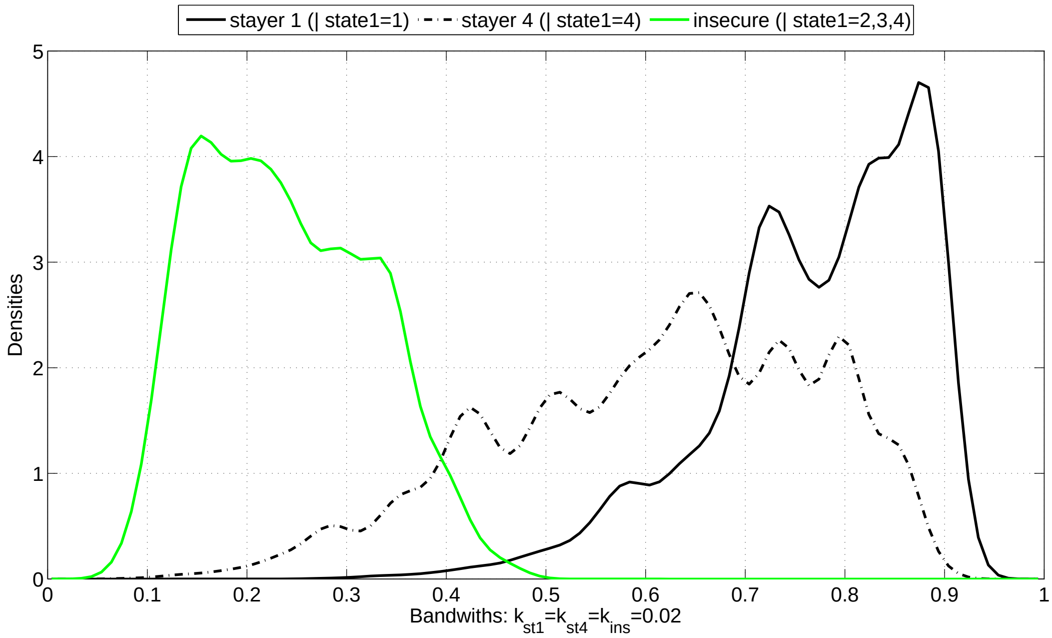
Women between 30 and 49, 4 states : out of the labor market (4), unemployed (3), short-term contract (2), long-term contract (1). Asymptotic standard-errors are obtained by bootstrap (design matrix bootstrap centered around the sample estimate) with 100 sample replicates.

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

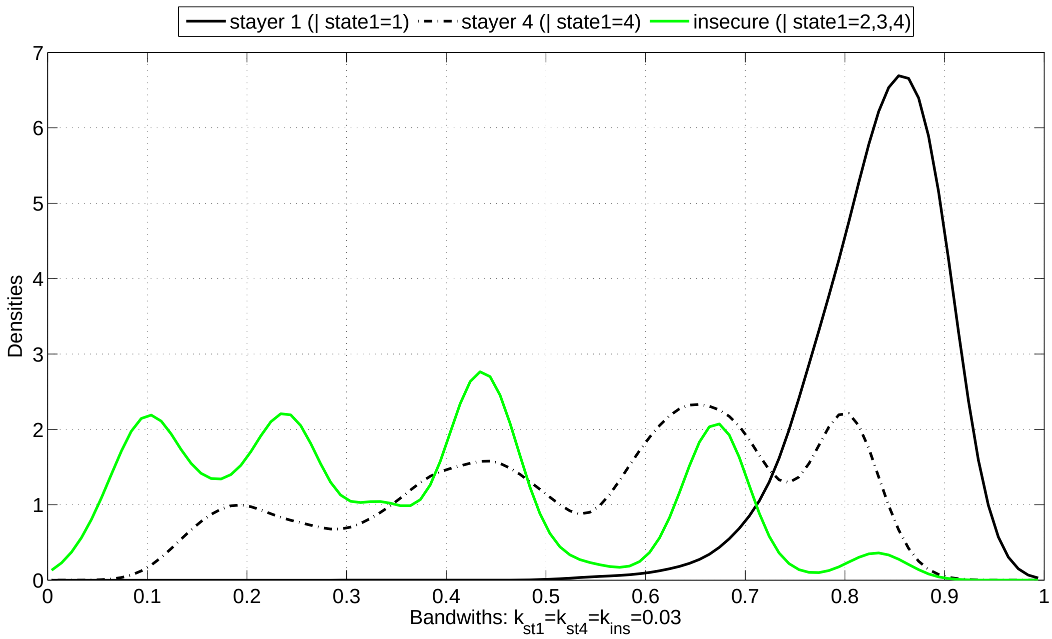


Table 15. Coefficients: men between 30 and 49.

	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:

$T \to T+1$	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:

$T \to T+1$	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	0.650	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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