Professional cyclic high mobility : modelling state transitions

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Abstract

This paper aims to investigate the combination of exogenous and dynamic endogenous variables in professional high mobility patterns. It is based on a panel dataset of the Job Mobilities and Family Lives in Europe research project conducted between 2007 and 2011 in Germany, France, Spain and Switzerland.

Cyclic professional high mobility is often considered as an emerging phenomenon since it has not been a lot investigated yet. The general idea that people flows are increasing with time is very common. Analyzing professional mobility states with a dynamic multinomial logit model with individual random effects permits to developp this statement. To do that, we account for previous situations as explanatory variables to focus on the state transitions in the labour market. Moreover, we approximate an initial state to avoid any endogeneity issue. Ongoing research also combine quantitative and qualitative analysis with a latent lifestyle variable model.

The individual choice set consists of three states (alternatives) which are not being highly mobile for work, being a long distance commuter or being an overnighter. First results show significant disparities between men, who are more impacted by the context of the labour market, and women, who are more subject to household characteristics. We find the presence of a state dependence that is also not the same across the different cyclic professional (non-)mobile states. Estimations suggest that overnighting is a more temporary pattern than long-distance commuting.

Keywords

Dynamic Multinomial Logit, Initial Conditions, High Mobility

1 Introduction

This paper aims to analyze the characteristics that influence so called professional mobility state accounting for past situation. When only considering exogenous variables, we may omit important processes contributing to the outcome. To avoid such bias, we consider two concepts that may play an important role for a durable situation : experience and lifestyle (or tastes). Experience can be modelled with a lagged endogenous variable. Lifestyle can be incorporated with latent variables based on indicators (e.g. degree of careerism in this case). In this paper, we focus on the former.

Recent works often question about the role of mobility in the labour market. Evidences have been made that showing willingness or ability to be mobile may lead to a situation progression, that is getting a job or being promoted. Moreover, urban space is getting more and more spatialized as cities develop. People now live further to the place they work, especially at the end of their careers as they seek for reversibility. This is also possible due to the significant improvements that have been made in the different means of transportation (highways, high-speed trains, low-cost flights). This has increased feasible distances without costing more time. In this context, the activity of high mobility related to work is no surprise even if it still represents a small portion of the population.

"High mobility" may be a very subjective definition that is different between each and every research. As we are only focusing on some type of highly mobile people in this paper, we explicitly talk about "professional cyclic high mobility". Professional means that we are not interested in any form of mobility that is not *directly* related to the labour market, whether it is *for* work or *at* work. That is, we do not consider long leisure trips for example. Cyclic refers to the degree of reversibility of mobility patterns. Moving in a new city is showing a form of high mobility but it is not reversible. In contrast, commuting every day or spending nights away (e.g. abroad) on a weekly basis is reversible as these people often return to their place of living. From now on, when we talk about "high mobility", we refer to people that do spend more than 1 hour one-way to their place of work or that sleep at least 30 nights out of their place of living. Individuals in the first category are "Long Distance Commuter" (LDC) while individuals in the second are "OverNighters" (ON). Along with "Non Mobile" (N), those are the three possible states (alternatives) considered in the presented dynamic multinomial logit model.

The dataset we have at our disposal consist of a two waves telephone survey conducted in four European countries : Germany, France, Spain and Switzerland. It was part of the Job Mobilities and Family Lives in Europe (JobMob) research project. The first wave took place in 2007 for all the countries. The second wave was done in 2010 in Germany, in 2011 in Spain and Switzerland and until 2012 in France. These waves took place within a weakened European economic context. Adults aged between 25 and 54 (in 2007) were in particular asked about their everyday life, their job and job mobility, their family situation and several qualitative notions (attitudes, lifestyle, satisfaction). The same questionnaire was used for the two different waves of the research project, constituting panel data. In addition, their job mobility biography was collected during the second wave. As high mobile people are not a majority in the population, oversampling techniques were used both in the 2007 and the 2010-2012 surveys in order to capture more variability.

First we present a brief review of both the methodological and the sociological literature (see Section 2). Next we introduce the JobMob research project and its associated database (see Section 3) and the theory for the modelling approach we use (see Section 4). Results are then presented (see Section 5) before discussing perspectives and ongoing work for this project Section 6).

2 Literature review

This literature review is subdivided into two main parts. In the first part, different works on professional high mobility are presented (see Section 2.1). In the second part, some of the important literature on dynamic modelling (see Section 2.2) are mentioned.

2.1 High mobility

As mobility is a powerful revealer of the society (Kaufmann, 2002), its patterns evolve in time. With the intensification of daily activities (Limmer *et al.,* 2010), people are now subject to be in situations of "high mobility" to conciliate them in a single day. Having a lot of mobility projects can nowadays amount of social success (Kaufmann, 2008). Still, the part of the population actually high mobile is rather small (about one out of ten) even though almost half of the active population has already experienced this situation (Ravalet *et al.,* 2015). Previous works on the topic could yet not conclude on a statistical progression of these kind of extreme patterns in time. Professional high mobility also finds a meaning as a consequence of a potential mobility injunction in the European labour market (Kesserling, 2011, Bacqué and Fol, 2008, Vignal, 2005). It seems that some employers indeed wait for higher flexibility from their employees (Ravelet *et al.,* 2016, Jouffe, 2014) resulting in commuting or overnighting.

The political answer to give towards high mobility is also not clear. It has been shown that it has both several advantages and drawbacks. On the one side, it enables people to access the labour market and permits a kind of insurance against unemployment (Vincent-Geslin and Ravalet, 2016). On the other, it tends to strengthen mobility related inequalities (Giza-Poleszczuk *et al.*, 2010) and foster a traditional repartition of the household roles (Meil, 2010).

The probably most important point that has been highlighted in the previous works is the differences of profiles confronted to high mobility. It seems that the classical image of the young single businessman travelling for work is not representative. Because the potential of mobility, or the motility as defined by (Kaufmann, 2011), is not equally distributed among the population, some people may not accept their mobile status (Joly and Vincent-Geslin, 2016). (Dubois *et al.*, 2015) argue that the people with the highest motility may keep this capital as a potential and prefer to stay non-mobile for work. Thus, some social classes are underrepresented in the world of professional cyclic high mobility. For example, women are by far less numerous than men (Ravalet *et al.*, 2015, Collet and Dauber, 2010, Meil, 2010). The formers also show that people that did have their first child between the two waves of the study often stop any form of high mobility. Spatially, the proper characteristics of the countries play a role in the general tendency to the practice of professional high mobility but are less important than social distinctions (Meil, 2010). Together, highly mobile people share unexpected travel preferences compared to the more “classic” active population. For example, some may prioritize comfort over speed (Crozet, 2011) as they seek to enhance their significant travel time (Joly and Vincent-Geslin, 2016).

Another reason for this diversity stands in the two forms of cyclic professional high mobility that are long-distance commuting and overnighting. If both of them permit a residential anchoring (Kaufmann, 2008), their target population and their implications are not the same. For example, (Limmer *et al.*, 2010) showed that long-distance commuters express less general satisfaction than other working categories. The division of these patterns of high mobility has rarely been studied in the literature.

2.2 Panel data and dynamic modelling

Dynamic models based on panel surveys, even if these are no easy task to collect, are already widely used. This is also the case because a lot of them deal with pseudo-panel data by aggregating repeated cross-sectional informations (Verbeek, 1992). They are recommended when emerging phenomena are under study, especially for the means of prediction related to some context evolutions (Tourangeau *et al.*, 1997). (Ortúzar *et al.*, 2011) advise collectivities to monitor continuous mobility informations about citizen in order to enhance sustainable development. Utilizing dynamic models based on panel data permits more statistical efficiency and capturing transitions effects that are omitted by static models (Kitamura, 1990). In particular, some of these take a random or fixed agent effect into account specifying individuals unobserved heterogeneity for a better comprehension of the behaviour (Baltagi, 2013). On the other hand, these authors mention possible biased estimations and the growing complexity of the models as drawbacks of dynamic modelling. In particular, the endogeneity caused by the initial conditions problem is often reported in the literature (Wooldridge, 2005, Hsiao, 2003, Heckman, 1981). Working on unemployment, (Hujer and Schneider, 1989) insist on the temporal dimension of such dynamic analysis.

Dynamic models in the framework of the labour market are quiet common when it comes to large horizon choices (i.e. sector formality, relocation). In particular, transitions between different states are often under study with discrete choice models. (Gong *et al.*, 2004) model transitions between formal and informal sectors of the labour market in Mexico while (Tasci and Tansel, 2005) do the same in Turkey. In Sweden, (Hanser and Lofstrom, 2008) analyzes transition between employment, unemployment and social assistance for immigrants compared to natives. Works also focus on interactions between labour market and general wellbeing (Bardasi and Francesconi, 2004). (Winkelmann and Winkelmann, 1998) show why unemployment is a factor to unhappiness based on panel data. (Verme *et al.*, 2016) and (Graham, 2003) use panel data and dynamic modelling to highlight social inequalities on job mobility and satisfaction. Most of these study directly or indirectly deal with the notion of habits and experience. Using retarded endogenous variables enables to account for historical preferences and past situations (experience) of the decision maker, which may have a much more significant impact than any other exogenous variable.

3 JobMob research project and dataset

This section presents the data we have at our disposal. Section 3.1 introduces the JobMob research project while Section 3.2 discusses the oversampling techniques that have been used and the way we deal with them. Finally, Section 3.3 gives insights of the variables in the panel dataset.

3.1 Framework

In 2007, the European Commission launched in its Sixth Framework Program for research and technological development the "Job Mobilities and Family Lives in Europe" research project. It was conducted in six European countries : Germany, France, Spain, Switzerland, Belgium and Poland. Its aim was mainly to understand the conditions under which spatial mobility is realized and capture the mobile lifestyle requirements in order to propose economic and/or political solutions for this particular demand. Three main areas were considered : phenomenology, decision process and consequences of professional mobility. Individuals were both questioned regarding stated personal characteristics (e.g. socioeconomics) and about more discursive general opinion about labour market and job mobility (e.g. expectations, lifestyle). The JobMob project specifically considers different cases of high mobility, which can be punctual (i.e. migrations, relocations) or cyclic (i.e. long-distance commuting, overnighting). We only consider the latter in this paper. We also only focus on the first four countries aforementioned since they all participated on their own initiative to a second wave conducted between 2010 and 2012 enabling longitudinal analyses.

In 2007, the survey was conducted on 7'220 individuals aged between 25 and 54 years in the six countries using telephone interviews (CATI), except in Poland where face-to-face interviews (CAPI) were realized. The duration of the interviews was about 30 minutes.

In 2010, Germany was the first country to replicate the experience with a very similar questionnaire to the first one in order to create a panel dataset. Spain and Switzerland did the same in 2011, while France completed its second wave in 2012. The timing is such that the situation of the labour market substantially changed in between the two waves because of the European economic crisis. For this follow-up survey, 1'735 individuals interviewed during the first one could be reached again in those four countries. In addition, Germany and France also completed additional non-panel surveys that aimed to increase the number of high mobile observations in the sample. 499 randomly selected individuals not interviewed in 2007 were concerned by these additional surveys.

3.2 Oversampling

People showing long-distance commuting or overnighting patterns are not a majority in the population (about one out of ten). For this reason, oversampling techniques were used in order to capture more variability for the sample. We consider three groups of individuals depending on how they were chosen to be part of the sample. We deal with the bias generated by the non-random sampling by modifying the alternative availability conditions for every individual being part of an oversampled group.

The first group, or "Wave S1" in the research project, consist of people randomly selected in 2007 that are part of both of the surveys. There is no selection bias for this group (except that they needed to be interviewed in 2007 in order to get recontacted in 2011).

The second group, or "Wave S2" in the research project, is also part of the two surveys. The difference is that these people were oversampled high mobiles in 2007. For this reason, they cannot have been in a non-mobile situation at this time period. However, they can have stopped their high mobility between the two surveys and find themselves in a non-mobile situation by the time they were interviewed again. This oversampling was done using a screening process at the beginning of the questionnaire. For this wave, as soon as individuals were identified as being non-mobile, the interview was stopped.

Finally, the third group consist of high mobile people that have only been interviewed for the additional survey in Germany and France during the second wave. This has two implications. First, individuals in this group cannot be non-mobile in 2011. Second, the informations (e.g. choice, socio-economic variables) regarding these people are not directly observed in 2007. However, some of them can be extrapolated since the questionnaire include "biographical" sections where the individuals relate their job and household history. In order to increase the variability of the two oversampled mobile alternatives, we merge this group in the panel dataset. We controlled for the eventual "discursive bias" by comparing estimations of the model run only on this part of the sample. No significant differences were found. The segmentation in three groups is resumed in Table 1.

3.3 Dataset and variables

The final sample we use for the model estimation is a subsample of the panel JobMob dataset. As we are specifically interested in the dynamics of high mobility, we consider two time periods ($t_1 = 2007, t_2 = 2011$). In addition, we use a third time period ($t_0 = 2003$) based on stated preferences of the individuals. This "initial state" is used for an approximation of the reduced form marginal probability in order to correct the initial conditions problem (see Section 4.2). The endogenous variable is the professional mobility situation at each time period (y_{0t} = non-mobile for work, y_{1t} = long-distance commuter, y_{2t} = overnighter). All the variables included in the models are either revealed (in 2011 for each group and in 2007 for groups 1 and 2) or stated

Table 1: Segmentation of the sample in three groups depending on the selection process and "availability" of the three possible states at each time period.

		Time periods 2003	2007	2011	# individuals
Group 1					
	N	x	x	x	
	LDC	x	x	x	972
	ON	x	x	x	
Group 2					
	N	x		x	
	LDC	x	x	x	85
	ON	x	x	x	
Group 3 *					
	N	x	x		
	LDC	x	x	x	323
	ON	x	x	x	

x Professional mobility state is possible at the given period.
* Only Germany and France are reprensented in this group

(in 2007 for group 3 and in 2003 for each group). In that way, we have informations about all individuals at the three time periods. To avoid complex dynamics, we only focus on individuals who were already in the labour market at the first time period (t_0 = 2003). As gender plays a significant role in professional cyclic high mobility (see (Ravalet *et al.,* 2015) or (Meil, 2010) for example), further analysis are always done for man and woman separately. That leads to a 1'381 individuals sample, with 698 men and 683 women. Combining the three different time periods, this leads to 4'143 observations (the panel is balanced).

Table 2 presents the professional cyclic mobility type evolution through the three time periods, only accounting for non-oversampled individuals (group 1). As said before, high mobility is minority in the population with about one person out of ten being a long-distance commuter or an overnighter. Long-distance commuters are slightly more represented than overnighters, even if people exercising both are considered as being overnighters. Non-mobile people increase from 85.7% in 2003 to 90.4% in 2011, showing that state high-mobility seems to decrease in time. Interestingly, there is no big difference for long-distance commuters between men (from 7.5% in 2003 to 5.6% in 2011) and women (from 6.7% in 2003 to 5.5% in 2011). On the other hand, we can see important differences regarding the overnighters. In 2003, one man out of ten is an overnighter, while there is only about one woman out of twenty. This relation keeps somewhat constant over time.

Table 2: Cross-sectional professional mobility states percentages through periods separated by genders and for the non-oversampled group.

		Year		
		2003	2007	2011
All				
	N	85.7%	89.0%	90.4%
	LDC	7.5%	6.1%	5.6%
	ON	6.8%	4.9%	4.0%
Men				
	N	81.7%	85.9%	87.6%
	LDC	8.5%	6.5%	5.6%
	ON	9.8%	7.6%	6.7%
Women				
	N	89.1%	91.6%	92.8%
	LDC	6.7%	5.7%	5.5%
	ON	4.2%	2.7%	1.7%

Table 3: Professional mobility states transitions percentages between 2007 and 2011 separated by genders and for the non-oversampled group.

		2011		
2007		N	LDC	ON
All				
	N	94.5%	2.8%	2.7%
	LDC	45.8%	47.6%	6.8%
	ON	70.8%	4.2%	25.0%
Men				
	N	93.0%	2.3%	4.7%
	LDC	37.9%	48.3%	13.8%
	ON	70.6%	5.9%	23.5%
Women				
	N	95.9%	3.1%	1.0%
	LDC	53.3%	46.7%	0.0%
	ON	71.4%	0.0%	28.6%

Table reads for example : 93% of non-mobile men in 2007 are still non-mobile in 2011. 3.1% of non-mobile women in 2007 became long-distance commuters in 2011.

Table 4: Percentages separated by genders and for the non-oversampled group to transit between professional mobility states or to stay in the same one as the previous period.

		Year	
		03 07	07 11
All			
	Stable	92.9%	88.3%
	Transit	7.1%	11.7%
Men			
	Stable	92.4%	84.9%
	Transit	7.6%	15.1%
Women			
	Stable	93.3%	91.2%
	Transit	6.7%	8.8%

Table 3 relates the state transitions between two consecutive waves for the non-oversampled individuals (here 2007 and 2011 as they are both stated observations for this group). We can see that 94.5% of the population stays non-mobile while 47.6% keeps being long-distance commuters and only 25% overnighters. This means that 88% of the individuals in the sample stay in the same state as the previous period, while 12% change. The most significant transition is going from overnighting in 2007 to the non-mobile state in 2011 (70.8%). About 3% of the population transit between the non-mobile state and both of the mobile states. Some notable distinctions regarding men and women again appear. Men are most likely to transit between the different mobile states (13.8% from long-distance commuting to overnighting and 5.9% in the other direction) compared to women (none in the randomly selected group). A lot of long-distance commuting women in 2007 stopped their high mobility to become non-mobile in 2011 (over one half of the sample).

Finally, Table 4 shows the aggregated state relations for the two four-year laps. Although it seems that professional cyclic high mobility is decreasing over the years, we see that the transitions between the different states increase. Between 2003 and 2007, only 7.1% of the sample changed their job mobility situation. Between 2007 and 2011, they are 11.7% to do so. This tendency is slightly bigger (and increased more) for men where 15.1% became (resp. stopped being) high mobile in this lap. These results are in line with (Ravalet *et al.,* 2015) longitudinal analyses.

We mainly use socioeconomic exogenous variables to explain the endogenous variable. In our models, we account for each individual marital status, presence of children in the household, age and an eventual relocation for the current job. We also take into account a context variable

Table 5: Name of the variables, description of the variables and informations about the variables in the sample.

Variable	Explanation	Sample informations
N	Non-mobile professional status	910 *(# in 2011)*
LDC	Long-distance commuting professional status	338 *(# in 2011)*
ON	Overnighting professional status	132 *(# in 2011)*
Age	Age of the respondant (in years) *	36 *(mean in 2011)*
Single	Respondant is not in a relation	273 *(# in 2011)*
Child(ren)	Respondant has at least one child	1056 *(# in 2011)*
Relocate	Respondant did relocate for his current job	170 *(# in 2011)*
DE	Country : Germany	457 *(constant)*
FR	Country : France	388 *(constant)*
SP	Country : Spain	259 *(constant)*
CH	Country : Switzerland	276 *(constant)*
Unemp	Unemployment rate (of the NUTS2 region of the respondant) **	9.7 *(mean in 2011)*
2011	Year dummy ***	-
		Individuals : 1380
		Time periods : 3

* In the model specification, only years above 40 matter (piecewise linear).
** In the model specification, this variable is interacted with the country.
*** No 2007 year dummy is used since different utility functions are used in 2003 (first time period).

to control for regional particularities. To do that, we cross a dummy country variable with the macro-regional (NUTS2 level) unemployment rate. Doing so, we differentiate individuals regarding their place of living and we also avoid some different unemployment rate definition between the countries. Those variables are reported in Table 5.

4 Methodology

This section describes the theoretical background of the model we are using. Section 4.1 introduces the general framework for a dynamic multinomial logit model with random effects. Section 4.2 extends the base model in order to correct the initial conditions endogeneity issues.

4.1 Dynamic multinomial logit

In this paper, we use a dynamic multinomial logit model with agent effect to model the probability for an individual n to be in a certain professional mobility state $i \in \{0, 1, 2\}$ at different time periods $t \in \{0, 1, 2\}$. We model the deterministic part of the utility of each alternative as follows :

$$U_{int} = \beta_i X_{nt} + \gamma_i Y_{n(t-1)} + \alpha_{in} + \varepsilon_{int} \tag{1}$$

One can notice that there is no alternative-dependent variable in Eq. (1) . X_{nt} are socioeconomics characteristics of the individual. $Y_{n(t-1)}$ gives information about the lagged dependent status of the individual. It contains two dummy variables $y_{in(t-1)}$ that takes value 1 if n was in state i at period $(t-1)$ and 0 otherwise. This vector allows us to take cross state dependence into account. That is, we can see the impact of being in a professional mobility category at time $(t-1)$ on being in another category at time t and relax any symmetric transition assumption. β_i and γ_i are parameters to be estimated.

The $\varepsilon_{int} \overset{iid}{\sim} \mathrm{EV}(0, 1)$ error terms are assumed to be independent and identically distributed, following a Type I extreme value distribution. In order to consider some time-independent unobserved heterogeneity, we introduce individual random effects α_{in} that control for the panel nature of the data. Omitting these variables would constrain us to the restrictive IIA assumption of the classical logit models. These are each assumed to follow an idependent normal distribution. We can thus write :

$$\alpha_{in} = \sigma_i \delta_{in}, \quad \delta_{in} \sim N(0, 1) \tag{2}$$

σ_i are also parameters to be estimated from the sample.

At this point, we can write the conditional probability for someone to be in a certain state at a certain period as :

$$P\left(y_{nt} = j \mid X_{nt}, Y_{n(t-1)}, \alpha_{in}\right) = \frac{\exp\left(\beta_i X_{nt} + \gamma_i Y_{n(t-1)} + \alpha_{in}\right)}{\sum_k \exp\left(\beta_k X_{nt} + \gamma_k Y_{n(t-1)} + \alpha_{kn}\right)} \tag{3}$$

4.2 Initial conditions problem

As we are using lagged dependent variables in the formulation of the utilities, we are confronted to the initial conditions problem. It comes from the fact that, at the $t = 1$ time period, we cannot assume that the lagged variable y_{in0} is independent from the agent effect α_{in} causing endogeneity. This issue is widely described in the literature (Heckman, 1981, Hsiao, 2003). In this paper, we use a solution proposed by the former to correct any bias emerging from the dynamic structure of the model. Another common solution is the one proposed by (Wooldridge, 2005), but it was shown that it may perform poorly when the number of time periods is small (see (Akay, 2011) for the discussion).

Heckman proposes to approximate the reduced form marginal probability with as much exogenous variables as possible at time $t = 0$. The whole time periods model can then be consistently estimated with a conditional maximum likelihood estimator. This has been shown to perform quiet well, even for a low number of time periods, with Monte Carlo results (both (Akay, 2011) and (Heckman, 1981) show examples of this). To do that, we estimate a static multinomial logit model with different parameters to be determined and without any transition variable at time $t = 0$. Such procedure has previously been used in the framework of dynamic multinomial logit models with random effects (Uhlendorff, 2006, Gong *et al.*, 2004). Note that this makes Eq. (3) meaningless for the initial time period.

$$U_{in0} = \lambda_i X_{n0} + \eta_{in} + \varepsilon_{in0} \tag{4}$$

$$P\left(y_{n0} = j \mid X_{n0}, \eta_{in}\right) = \frac{\exp\left(\lambda_i X_{n0} + \eta_{in}\right)}{\sum_k \exp\left(\lambda_k X_{n0} + \eta_{kn}\right)} \tag{5}$$

Rather, if we compute each alternative utility like in Eq. (4), the conditional probability of being in a certain mobility category at time period $t = 0$ is given by Eq. (5). Once again, λ_i are parameters to be estimated, η_{in} are random effects accounting for unobserved individual heterogeneity and $\varepsilon_{in0} \overset{iid}{\sim} \mathrm{EV}(0, 1)$ are independent of all explanatory variables and also of all other ε_{int} for $t > 0$. Heckman's solution allows the initial time period random effects η_{in} to be freely correlated with the other time periods ones α_{in}.

$$\eta_{in} = \rho_i \alpha_{in} = \mu_i \delta_{in}, \quad \delta_{in} \sim N(0,1) \tag{6}$$

Instead of estimating i ρ_i parameters, we directly compute i μ_i parameters that interact with the same δ_{in} random variables.

If the random effects δ_{in} were given, the contribution of an individual to the maximum likelihood function would be easy to compute as each time period probability would be independent :

$$L_n(\delta_{in}) = P(y_{n0} = j \mid X_{n0}, \eta_{in}) \prod_{t=1}^{T} P(y_{nt} = j \mid X_{nt}, Y_{n(t-1)}, \alpha_{in}) \tag{7}$$

Unfortunately, they are not observed and thus the real contribution of individual n to the maximum likelihood function is :

$$L_n = \int_{\delta} L_n(\delta_{in}) f(\delta_{in}) d\delta_{in} \tag{8}$$

This is a multi-dimension integration where $f(\delta_{in})$ is the probability density function of δ_{in}. Instead of solving Eq. (8), we approximate it with Monte-Carlo integration. We generate a sufficient number R of $N(0,1)$ draws for each δ_{in} and calculate the mean value of Eq. (7) for these draws. The literature states that if this number R tends to infinity with the number of individuals n, the maximum simulated likelihood estimator is consistent (see for example (Train, 2003)). This way, Eq. (8) is replaced by :

$$L_n^R = \frac{1}{R} \sum_{r=1}^{R} L_n^r(\delta_{in}) \tag{9}$$

Table 6: Results for the estimation of the dynamic multinomial logit model with random effects.

	Men		Woman	
Parameters	LDC	ON	LDC	ON
β_i				
Constant	-1.78 *	-4.38 *	-1.72 *	-4.38 *
>40yo	-.052 *	-.062 *	-.059 *	-.049
Single	-.246	-.24	.226	.115
Child(ren)	-.008	-.349	-.566 *	-1.34 *
Relocate	-.177	0.565 **	-.745 *	2.42 *
Unemp.x.DE	.074 *	.121 *	.013	.013
Unemp.x.FR	.19 *	.127 *	.108 *	-.001
Unemp.x.SP	-.002	-.003	-.05 **	.021
Unemp.x.CH	.066	-.051	-.106	-.214
2011	-2.25 *	.265	-1.1 *	-1.49 **
γ_i				
LDC (lag)	4.7 *	.696	3.66 *	3.27 *
ON (lag)	1.71 *	1.52 *	1.56 *	2.3 **
σ_i				
Var LDC	-.046		-.611 **	
Var ON	1.54 *		2.2 **	

The non-mobile category is the reference. *N (lag)* is omitted for means of identification. *VarLDC* and *VarON* are the respective variances of α_{2n} and α_{3n}.
* Significant at 5% level.
** Significant at 10% level.

5 Case study

In this section, the dynamic multinomial logit model with random effects rid of the initial conditions problems presented in Section 4 is run on the JobMob sample described in Section 3. Results of the estimations are first presented in Section 5.1. Further results exploiting the estimation of the model are actually under study.

5.1 Estimation

Results of the model estimation for the non-initial time periods are reported in Table 6. We normalize all the parameters related to the non-mobile professional mobility state to 0 in order to identify the model (β_0, γ_0 and $\alpha_{0n} = 0$). This way, if an alternative parameter has a positive value, it means that the related variable has a positive effect on the probability of being in this proper state compared to the non-mobile one.

The impact of age on the two forms of cyclic professional high mobility is negative for both men and women, even if non-significant for women overnighters. This may be explain by the growing residential anchorages developed by people. We recall here that this variable is defined in a piecewise linear way such that it has no influence on the state probability before 40 years old and a decreasing continuous one after this threshold. We could not find any evidence that the age has a positive or a negative effect on the mobility state for young people. Interestingly, marital status has no significant effect on men nor on women. Even if not statistically different from zero, we remark that they go in opposite ways regarding the gender, showing first signs of segmentation. An important difference appears in the impact of having a children. A woman with at least one child is less likely to live a mobile professional life while it has no clear influence on men. This is in line with several research on the topic. Some argue that the mother of a new born child is more likely to stop any form of professional mobility (if not work at all) than her husband, bringing back the question of the traditional household roles repartition (Meil, 2010). Relocation also seems to play a role for both forms of high mobility but in opposite ways, especially for women. While relocating for the current job implies a lower probability for this one to ask for long-distance commuting, it is the contrary for the overnighting mobility pattern. The former result is expected as people often relocate in order to get closer to their job location. Still, we see that this effect is not significant for men. The latter may be less anticipated. We raise two arguments that go in that sense. First, overnighting is a situation that may require a high motility, only few spatial anchorages and especially good adaptability (Ravalet *et al.,* 2015). All of these characteristics may also be characteristics of familiar relocators. Second, jobs requiring spending nights away from home can be synonym of a “higher prestige” and a socio-professional progression (Bonnet and Orain, 2010). Thus, individuals may be subject to sacrifices like relocating to accept such a job offer.

Regional (NUTS2) unemployment rates have different implications regarding both the genders and the countries. In general, men seem to be more sensitive to the local labour market context than women. This is especially true in Germany where the increasing of unemployment plays a positive role on the probability of being in any of the two cyclic professional mobility states only for men. In France, impact of the unemployment is positive for both men and women regarding long-distance commuting. This result is in line with previous works highlighting the centralized character of this country and the performance of high-speed means of transportation (Bonnet *et al.,* 2010). In Spain and Switzerland, effects are for the most non-significant. Technically speaking, the fact that no additional oversampling survey has taken place in these countries certainly plays a role in this result. Practically, this can also be partially explained by the extreme positions of these two countries regarding the economic context. Switzerland had the most stable labour market among the four countries under study, explaining why no clear tendency emerges. On the contrary, Spain was the most impacted country of all during the European crisis. This can both lead to very high local anchorage or to strong mobility patterns to keep or find a job.

The parameters related to the endogenous lagged variables are all positive. This shows the presence of a state dependence and that a past situation has a positive impact on the probability to be in the same position 4 years later. For both men and women, these coefficients are especially high for long-distance commuters. For women, the impact of having been an overnighter is not as significant as the other transition effects as it is not statistically different from 0 (5% level). There is also a cross-state dependence that is clearly not symmetric. Overnighting men in 2007 are more likely to be in a long-distance commuting position in 2011 than men in a non-mobile professional situation in 2007. Women not showing any form of high mobility are less likely to be in one of the mobile situation in the next period than if they were exercising the other mobility type. Further research should go in this direction for a better understanding of the transitions mechanisms. Regarding these results, important distinctions between the two forms of cyclic professional high mobility arise. On the one hand, long-distance commuting professional mobility seems to be a more steady state situation from which it can be hard to exit. On the other hand, overnighting can be seen as a much more transitional state.

Finally, variances of the unobserved individuals random effects can be found at the bottom of the table. For the women, we can see that both of the parameters are significant at the 10% level showing presence of time-independent agent effect. For the men, although the overnighting variance term is significantly different from 0, it is not the case for the long-distance commuting one. This result requires us to take a step back as it seems unlikely that no effect due to the panel nature of the data is present. As a reminder, these terms are only estimated based on three observations per individual that can lead to the non-significance of the parameter (see Section 6 for eventual corrections of this issue).

6 Conclusion and ongoing researches

In this paper, we present the theoretical framework to study cyclic professional mobility states transitions. We develop a multinomial logit model with explanatory lagged state variables and unobserved individual random effects. By doing so, it is then possible to analyze efficiently a panel dataset considering the importance of a previous situation. We use as a case study the Job Mobilities and Family Lives in Europe research project that leads to a sample of about 1'500 individuals interviewed twice. We also extrapolate a third observation relying on stated biographical informations in order to deal with endogeneity. First results shows significant differences across the two cyclic professional high mobility states under study (long-distance commuting and overnighting) and among social classes. In particular, men and women are not driven by the same characteristics, showing traditionalist signs of the household structure. We also show that long-distance commuting and overnighting can be two very different states even if they are often merged together in the existing literature.

Ongoing work on this topic will go in several directions. Two main aspects are to be mentioned : one is purely methodological while the other extends the framework of the study. Building dynamic models with individual random effects on a three periods panel data sample is tricky as some parameters may not be consistently estimated. An extended reflexion on the way to handle the professional high mobile situations transitions needs to be done regarding the structure of the data. We see two potential outcomes for this question. On the one hand, we can focus on the two observed waves and go with a (cross) nested logit model considering nine alternatives instead of three (that is non-mobile in 2007 and non-mobile in 2011, non-mobile in 2007 and long-distance commuter in 2011, [...], overnighter in 2007 and long-distance commuter in 2011 and overnighter in 2007 and overnighter in 2011). This way, the implication of the parameters influencing the dynamics may be better analyzed. Another advantage of this procedure is that very few data extrapolation is needed given the observed sample. On the other hand, as we did for the "zero" time period, the retrospective part of the questionnaire makes data extrapolation possible. We can thus "construct" as many observations as wanted relating to discursive answers of the respondents. We can for example imagine to do that between 2003 and 2011 and build a pseudo nine waves panel sample to be analyzed. If so, we need to be careful to treat to revealed states (2007 and 2011) and the stated states (all others) differently (Ben-Akiva *et al.,* 1994). The results given by these different methods may then be compared.

Another important aspect of this work is the yet non-exploited data of the JobMob research project. In particular, the questionnaire contains a lot of questions regarding attitudes towards high mobility. These may be precious informations and have a high explanatory power on professional high mobility states and transitions. An integrated model with a latent variable representing somebody "level of careerism" is actually under study. We can expect that someone's position in the labour market is as much dependent on his lifestyle than on exogenous socioeconomics and context variables. We have at our disposal different indicators (questions with multiple ordered Likert scale answers) that may be used in this sense.

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